The resilience of European farms

A qualitative and quantitative assessment

Thomas Slijper

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Propositions

1. Enhancing European farm resilience requires a larger budgetary shift from income support to eco-schemes than is proposed by the reform of the Common Agricultural Policy for the period 2023-2027.
(this thesis)

2. By only considering trade-offs between financial costs and benefits, one cannot fully understand farmers' risk management decisions.
(this thesis)

3. Mixed methods are needed to improve our understanding of dynamic and complex concepts, such as farm resilience.

4. A dark side of the promising development towards Open Access publishing is that article processing charges (APCs) will continue to be exploited by predatory journals.

5. The Dutch government should regulate a reduction in livestock to meet climate targets.

6. Self-efficacy is at least as important as talent for ultra-runners.

7. Society will benefit from a reduction in religious privileges, such as the exceptional and protected status of places of worship.

Propositions belonging to the thesis, entitled

The resilience of European farms: A qualitative and quantitative assessment

Thomas Slijper
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1 General introduction

1.1 Background

European farms face increasingly complex and interrelated shocks and stresses, including price volatility (Frick and Sauer 2020), climate change (Wreford and Topp 2020), changing consumer preferences (Maggio, Van Criekinge and Malingreau 2014), and Common Agricultural Policy (CAP) reforms (Bozzola and Finger 2021). In addition, farms face unanticipated crises, such as the COVID-19 pandemic (Meuwissen et al. 2021). Dealing with these shocks and stresses requires farms to be resilient. To this end, the EU's Common Agricultural Policy (CAP) for the period 2021-2027 underlines the importance of enhancing the resilience of farms (European Commission 2020a).

1.2 Conceptualising resilience

Resilience is a multi-dimensional concept, and how resilience is understood depends on what system is studied. For investigating farm resilience, two dominant understandings are engineering and social-ecological resilience. Engineering resilience describes a reactive view on resilience by assessing the stability of a system near the status quo and studying resistance to shocks and stresses, including the recovery speed to return to the existing equilibrium (Pimm 1984, Bond et al. 2015). Social-ecological resilience studies the interplay of numerous shocks and stresses, emphasising the need for change in a dynamic environment with interactions between humans and ecosystems (Folke 2006). Two key principles of social-ecological resilience are (i) to expect the unexpected (Berkes 2007) and (ii) to successfully deal with the unexpected makes systems more resilient (Folke 2016). As recent developments in agriculture highlight unpredictability and increasing societal pressure to change, the more comprehensive social-ecological understanding of resilience appears to be the most appropriate to assess the resilience of European farms.

This thesis defines farm resilience as the ability to provide the desired farm functions (i.e. generating private and public goods) while facing interrelated and accumulating shocks and stresses by exploiting the resilience capacities of robustness, adaptability, and transformability (adapted from Meuwissen et al. 2019). Robustness relates to maintaining the status quo and absorbing shocks and stresses (Folke 2016). Adaptability and transformability require flexibility and the ability to change (Darnhofer 2014). Adaptability is the capacity to adjust to shocks and stresses by changing the composition of inputs, production, marketing, and risk management (Meuwissen et al. 2019). Transformability is the capacity to more radically change the internal structure of farms to cope with severe shocks and enduring stresses (Darnhofer 2014, Meuwissen et al. 2019). This definition of farm resilience underlines three building blocks: (i) shocks and stresses, (ii) resilience capacities, and (iii) functions.

The first building block describes the shocks and stresses to be considered when assessing resilience. Specified resilience considers the resilience to *a particular shock or stress*, which inherently implies that a fair amount of information is available. General resilience is conceptually more closely related to social-ecological resilience thinking as it studies the ability to deal with *a whole range of shocks and stresses, including novel and unknown ones* (Carpenter et al. 2012).

The second building block describes how the resilience capacities of robustness, adaptability, and transformability can be understood. The three complementary resilience capacities support farmers to cope with shocks and stresses by providing strategies to respond or prepare for change (Folke 2016). However, the relative importance of each resilience capacity depends on the context in which farmers operate (Darnhofer 2014). In a stable period where farmers do not face any major changes or surprises, being robust may be sufficient, while adaptation and transformation are required when fundamental stresses or unexpected changes may occur.

The third building block evaluates the performance of farm functions over time. These farm functions are private and public goods. Examples of farm functions are ensuring a viable farm income, delivering high-quality food, protecting biodiversity, or maintaining natural resources in good conditions, (Meuwissen et al. 2019). Investigating the performance of the desired farm functions over time reveals how well farms have dealt with shocks and stresses through their resilience capacities.

1.3 Problem statement

The impact of shocks and stresses may restrict farmers' access to credit and constrain opportunities to invest (Mutabazi, Amjath-Babu and Sieber 2015), reduce the willingness to continue farming or find successors (Pitson et al. 2020), and introduce more uncertainty (Folke 2016). These potential impacts threaten the delivery of several farm functions, including food production, biodiversity or the maintenance of natural resources. Resilient farms are able to cope with shocks and stresses and continue to secure the delivery of the desired farm functions. This may require farms to adapt or transform rather than to remain robust (Ghahramani and Bowran 2018).

To understand how the delivery of farm functions can be secured, the European Commission (2020a) calls for a better operationalisation and assessment of resilience. Operationalising and assessing resilience is challenging due to its multi-dimensional and latent character, which requires an understanding of the three buildings blocks of farm resilience (shocks and stresses, resilience capacities, and functions). Most existing studies have investigated farm resilience through the lens of specified resilience. For instance, these studies provide useful insights into assessing the resilience of farms to climate change (Burke and Emerick 2016), price volatility (Thorsøe et al. 2020), or yield volatility (Reidsma, Ewert and Oude Lansink 2007). As general resilience considers the unknown, it is more difficult to assess than specified resilience (Walker and Salt 2012). This resulted in less scientific attention to the concept of general resilience (for some examples on general resilience, see Darnhofer 2014, Meuwissen et al. 2019, Perrin et al. 2020), especially in the field of agricultural economics. A possible explanation for this could be that studying general farm resilience using quantitative methods (e.g. econometrics or multivariate statistics) is data-demanding and likely requires longitudinal datasets to investigate changes over time.

Assessing the resilience capacities requires multiple indicators, likely acquired by combining insights from interdisciplinary research (Meuwissen et al. 2021). This has roughly resulted in two types of farm resilience assessments: (i) perceived resilience assessments (e.g. Marshall 2010, Béné et al. 2016, Jones and d'Errico 2019) and (ii) indicator-based resilience assessments (e.g. Cabell and Oelofse 2012, Choptiany et al. 2017, Diserens et al. 2018). These resilience assessments provide complementary insights, implying that truly understanding farm resilience requires a combination of perceived and indicator-based approaches. Perceived resilience assessments help to better understand farmers' decision-making processes under risk and uncertainty and explain how these decisions affect resilience (Clare et al. 2017). Indicator-based approaches have a more objective character and allow researchers to assess farm resilience using secondary datasets. Empirical applications based on either perceived or indicator-based approaches are often limited to studying one resilience capacity. Both approaches will be discussed in the following paragraphs.

Perceived resilience assessments often use cross-sectional surveys or semi-structured interviews (e.g. Marshall and Marshall 2007, Sutherland et al. 2017) to assess how behavioural and/or social factors—e.g. farmers' risk behaviour, social networks or learning—relate to perceived resilience. Farmers' risk behaviour shapes their perceived robustness, adaptability, and transformability, as risk perceptions, risk preferences, and the adopted risk management strategies help farmers to respond and cope with shocks and stresses (Spiegel et al. 2021b). Most previous studies on risk behaviour and perceived resilience have partially captured these relationships by considering risk perceptions, risk preferences or risk management in isolation. For instance, studies have investigated how risk perceptions shape perceived robustness (Marshall and Marshall 2007), adaptability (Grothmann and Patt 2005), and transformability (Marshall et al. 2014) or how risk management strategies, such as agricultural diversification, enhance adaptability (Lin 2011).

Furthermore, perceived resilience assessments benefit from understanding farmers' social networks and capacity to learn. Social networks have the potential to enhance farm resilience by building social capital (Barnes et al. 2017). Learning contributes to farm resilience as it helps farmers to deal with shocks and stresses by obtaining more complete information (Cundill et al. 2015). Several studies have demonstrated how learning contributes to resilience or to one of the resilience capacities. Glover (2012) showed that reflecting on past successes and failures could strengthen the resilience of UK farms as a result of a better ability to deal with adverse events. Most previous studies demonstrated how learning enhances adaptation by improving the ability to deal with the unknown (Milestad and

Darnhofer 2003, Darnhofer 2010, Milestad, Geber and Björklund 2010) resulting from increased knowledge about shocks and stresses (Darnhofer 2010, Maguire-Rajpaul, Khatun and Hirons 2020), improved reflexivity (Pelling et al. 2008), or experimentation (Tarnoczi 2011). Furthermore, studies on transformative learning investigated how learning to radically change perceptions, preferences, values, and norms may facilitate transformations (Park et al. 2012, Marshall et al. 2014, Scholz and Methner 2020). Despite the conceptual framework of De Kraker (2017) that describes how social networks and learning are related to the resilience capacities, no empirical studies exist that explore how social networks and learning contribute to farm resilience in terms of robustness, adaptation, and transformation.

Indicator-based approaches rely on a researcher's choice of indicators based on existing literature (Jones and d'Errico 2019). As the selected indicators are context-specific, most indicator-based resilience assessments apply to a specific case study. This implies that literature has not yet designed general indicators to compare farm resilience across regions or countries. Indicator-based approaches could build on panel datasets to capture dynamics over time and tease out causal relationships (Reidsma et al. 2010, Chavas and Di Falco 2017). Previous studies that assessed farm resilience over time are limited to one resilience capacity, such as investigating the robustness of French livestock farms (Sneessens et al. 2019), the adaptation of Italian arable farmers (Di Falco et al. 2014) or European agriculture (Reidsma et al. 2010, Vanschoenwinkel, Moretti and Van Passel 2019), or transformations of Australian mixed farms (Ghahramani and Bowran 2018).

The three resilience capacities enable or constrain the delivery of farm functions. Previous studies on farm functions have investigated household well-being in developing countries (Barrett and Constas 2014, Cissé and Barrett 2018, Knippenberg, Jensen and Constas 2019), wheat yields of English arable farmers (Chavas and Di Falco 2017), or viable farm incomes of Scottish farmers (Barnes, Thomson and Ferreira 2020). The CAP for the period 2021-2027 identified a viable farm income as one of the most important farm functions (European Commission 2020a) and aims to secure a viable farm income by spending the majority of the CAP budget on income support. Farm viability is important to farm continuity of European farms (Saint-Cyr et al. 2019). Also, a viable farm income supports resilience as it allows farmers to continue investing and adds to financial buffers to better cope with surprise (Cabell and Oelofse 2012, Meuwissen et al. 2019). The most important source of income support provided by the CAP is decoupled direct payments. The effectiveness of decoupled direct payments to enhance farm viability is currently being debated and subject to mixed evidence depending on the considered time horizon. For instance, Vrolijk et al. (2010) found that European farmers that receive less decoupled direct payments are more likely to be short-term viable. Ojo et al. (2020) focussed on long-term farm viability of UK farms. They found that abolishing decoupled direct payments results in less long-term viable farms by lowering farm income. To fully understand the effect of decoupled direct payments on farm viability, a dynamic econometric approach is needed that distinguishes the effects of decoupled direct payments on both short and long-term farm viability.

The previous paragraphs revealed that farm resilience assessments are often limited to one of the resilience capacities or to one of the farm functions, without combining perceived and indicator-based assessments. This calls for an integrated approach that studies general farm resilience by combining insights from all three resilience capacities and farm functions using a mix of perceived and indicator-based approaches. The contribution of this thesis is the adoption of such an integrated approach.

1.4 Research objectives

The overall objective of this thesis is to assess the resilience of European farms.

Specific research objectives (RO) are:

RO1. To explore how farmers' risk behaviour is related to perceived resilience in terms of robustness, adaptability, and transformability.

RO2. To explore how farmers' social networks and learning contribute to perceived resilience in terms of robustness, adaptation, and transformation.

RO3. To quantify the resilience of farms in terms of robustness, adaptation, and transformation.

RO4. To investigate the effect of decoupled direct payments on short and long-term farm viability.

RO1 investigates farmers' perceived ability to be robust, to adapt or to transform. Therefore, RO1 refers to robustness, adaptability, and transformability. RO2 and 3 assess the past robustness, adaptation, and transformation of farms and farmers. Hence, these research objectives refer to robustness, adaptation, and transformation. Jointly, these four research objectives contribute to a better understanding of the resilience of European farms by studying shocks and stresses, resilience capacities, and the delivery of private and public goods.

1.5 Thesis outline

This thesis consists of six chapters: the general introduction (Chapter 1), four chapters that each address one of the research objectives (Chapters 2-5), and a general discussion (Chapter 6). Figure 1.1 portrays the structure of this thesis.

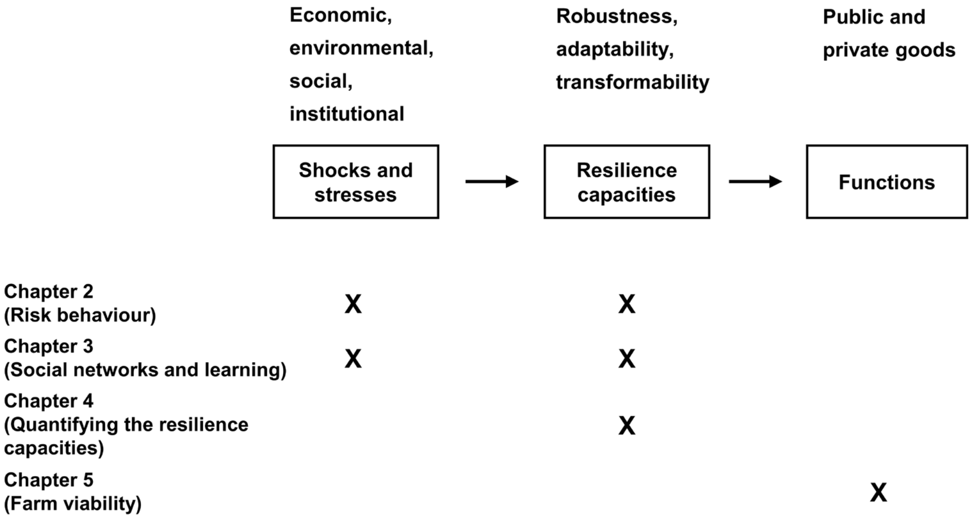

Figure 1.1 Structure of this thesis.

Chapter 2 assesses the perceived resilience capacities of Dutch farmers while facing several shocks and stresses (Figure 1.1). This chapter connects risk theory to resilience thinking. It explores how risk perceptions, preferences, and adopted risk management strategies are associated with perceived robustness, adaptability, and transformability. Data from 916 surveys are analysed using a partial least squares structural equation model (PLS-SEM) (Hair et al. 2019). Shocks and stresses are investigated by eliciting farmers' perceptions of a wide array of risks. The resilience capacities are measured using self-assessment questions to assess how resilient farmers perceive their farm. One of the advantages of these self-assessment questions is that these measures of resilience are applicable in several geographical regions, allowing comparison across regions or farm types.

Chapter 3 builds on theories of social networks and learning to explore the social setting that shapes the resilience capacities while facing several shocks and stresses (Figure 1.1). A combination of qualitative (semi-structured interviews, focus groups, and expert interviews) and quantitative research methods (farmer surveys) is used to explore the contribution of social networks and learning to the robustness, adaptation, and transformation of Dutch arable farmers from the Veenkoloniën and Oldambt. Numerous shocks and stresses, including events that were unknown in the past, are unravelled by investigating how farmers have dealt with risk and surprise in the past 10-20 years. The combination of methods investigates the resilience capacities through several lenses and allows for methodological triangulation to ensure the validity of our findings. The farmer survey uses self-assessment questions to assess the resilience capacities, while the qualitative methods are used to infer the resilience capacities by reflecting on past on-farm changes.

Chapter 4 quantifies farm robustness, adaptation, and transformation (Figure 1.1). The resilience capacities are captured by investigating changes in farm inputs and outputs over time. The revealed resilience capacities are measured using several indicators that are aggregated into a composite indicator for each resilience capacity. The Farm Accountancy Data Network (FADN) panel dataset (FADN 2018) is used to compare the resilience capacities of arable, livestock, and mixed farms from nine European countries. Furthermore, this chapter explores the effect of policy instruments and farm(er) characteristics on robustness, adaptation, and transformation. To this end, fractional correlated random effects probit models are estimated (Papke and Wooldridge 2008). Correlated random effects are a flexible extension of random effects, allowing for correlation between the exogenous explanatory variables and time-invariant unobserved heterogeneity to closely reproduce fixed effects and address the unobserved and omitted variables problem similarly. Any remaining time-variant sources of endogeneity that are not captured by correlated random effects are accounted for using a control function approach (Wooldridge 2015).

Chapter 5 assesses the performance of a farm function—i.e. farm viability—over time (Figure 1.1). Using the rich FADN panel dataset that contains data from 11 European countries, we assess the effectiveness of decoupled direct payments to enhance both short and long-term farm viability. These decoupled direct payments are the EU's main source of income support and make up for about three-quarters of the CAP budget (European Commission 2020a). Farms can be either viable or non-viable, indicating that farm viability is a dichotomous variable (Barnes, Thomson and Ferreira 2020). Often, state dependence is present as a farm that is viable at year *t-1* is more likely to remain viable at year *t* than a non-viable farm (Bartolucci, Nigro and Pigini 2018). To account for state dependence, dynamic correlated random effects probit models are estimated (Rabe-Hesketh and Skrondal 2013). The remaining time-variant sources of endogeneity, caused by the non-random assignment of several CAP payments, are accounted for using a control function approach (Wooldridge 2015).

Table 1.1 provides an overview of the research approaches adopted in this thesis. It explains if a chapter assesses perceived or indicator-based resilience, introduces which farms are studied, and provides an overview of the data and methods used.

Table 1.1 Overview of the research approaches adopted in this thesis.

Chapter	Resilience assessment	Selected farms	Data	Methods
2 (Risk behaviour)	Perceived	Dutch farms	Surveys	Multivariate statistics: Partial Least Squares Structural Equation Modelling (PLS-SEM)
3 (Social networks and learning)	Perceived	Dutch arable farms (Veenkoloniën and Oldambt)	Semi-structured interviews, focus groups, expert interviews, and surveys	Combination of methods: thematic coding and several non-parametric tests
4 (Quantifying the resilience capacities)	Indicator-based	Farms from several farm types (9 European countries)	FADN[1]	Econometrics: Fractional correlated random effects probit model with control function approach
5 (Farm viability)	Indicator-based	Farms from several farm types (11 European countries)	FADN, FAO[2], Eurostat[3], SCB[4], and ECB[5]	Econometrics: Dynamic correlated random effects probit model with control function approach

Notes: [1] Data from FADN (Farm Accountancy Data Network) are a panel data set that aims to monitor farm income and business activities of EU farms (FADN 2018). [2] Data from FAO (Food and Agriculture Organization) are used to obtain yearly producer price indices in several European countries (FAO 2020). [3] Data from Eurostat are used to obtain minimum hourly wages in several European countries except for Sweden (Eurostat 2020b). [4] Data from SCB (Statistics Sweden) are used to obtain minimum hourly in Sweden (SCB 2020). [5] Data from ECB (European Central Bank) are used to obtain long-term interest rates in several European countries (ECB 2020).

2 From risk behaviour to perceived farm resilience: A Dutch case study

This chapter is based on the paper: Slijper, T., de Mey, Y., Poortvliet, P. M., Meuwissen, M. P. M. (2020). From risk behavior to perceived farm resilience: a Dutch case study. *Ecology and Society* 25 (4).

Abstract

In an era where farmers face considerable levels of intertwined risks and uncertainties, farm resilience is developing into a focal point for agricultural policies. Using survey data from 916 Dutch farmers, we explore how risk behaviour relates to perceived resilience. We capture the dynamics of resilience thinking by investigating past risk-management portfolios, current risk preferences, future risk perceptions, and perceived resilience. Partial least squares structural equation models (PLS-SEM) indicate that higher perceived robustness, adaptability, and transformability relate to these farmers with a more resilient future. Additionally, results show the importance of risk management in assessing perceived resilience. More specifically, we find that more diverse risk-management portfolios are associated with (i) higher perceived adaptability and (ii) in specific cases, higher perceived transformability.

Keywords

Risk management, risk perception, risk preference, resilience, robustness, adaptability, transformability Partial Least Squares Structural Equation Model (PLS-SEM).

2.1 Introduction

In an unpredictable world with changing economic, environmental, social, and institutional conditions, dealing with risk and uncertainty has always been a ubiquitous feature of agricultural production (Chavas 2011). To cope with these interrelated risks and uncertainties, farm adaptation and transformation are becoming increasingly relevant (Ghahramani and Bowran 2018). Moreover, stimulating farm adaptation and transformation requires a shift from dealing with the expected to the unknown future. Depending on farmers' ability to overcome the consequences of risks and uncertainties, farm resilience is potentially threatened (Darnhofer 2014). As farmers' risk management strategies, risk perceptions, and risk preferences determine how farmers cope with risks (Van Winsen et al. 2016, Meraner and Finger 2019), risk behaviour is inherently related to resilience. To this end, this chapter explores the role of farmers' risk behaviour in assessing perceived farm resilience.

Resilience thinking acknowledges the role of complexity and the unknown in a dynamic farm operating environment (Cabell and Oelofse 2012, Darnhofer 2014). Our understanding of farm resilience is adapted from Meuwissen et al. (2019), who defined resilience as the ability to ensure the provision of functions while facing increasingly complex and accumulating economic, environmental, social, and institutional shocks and stresses through the resilience capacities of robustness, adaptability, and transformability. Robustness relates to the capacity to withstand expected and unexpected shocks and stresses (Walker et al. 2009). Adaptability is the capacity to adjust to shocks and stresses by changing the composition of inputs, production, marketing, and risk management (Meuwissen et al. 2019). Transformability is the capacity to radically change the internal farm structure to cope with severe shocks and enduring stresses, which might also imply the delivery of alternative and/or additional farm functions (Meuwissen et al. 2019). While this social-ecological understanding of resilience underlines the importance of adaptation and transformation, empirical assessments of these capacities remain challenging due to the abstract nature of resilience (Cumming et al. 2005).

As resilience is a latent concept (Clare et al. 2017), indirect assessment methods are required. These assessments can be classified into two approaches; the first approach captures the multidimensionality of resilience by defining several indicators (Resilience Alliance 2010, Cabell and Oelofse 2012, Choptiany et al. 2017, Jones and Tanner 2017, Diserens et al. 2018, Jones and d'Errico 2019). Despite their implicit objective orientation, operationalization and quantification of the resilience indicators remains complex, as these resilience assessments are context-specific, resulting in incomparable assessments across different regions (Pelling 2011, Jones 2018). The second approach assesses perceived farm resilience (Marshall, Gordon and Ash 2011, Béné et al. 2012, Marshall and Smajgl 2013, Marshall et al. 2014, Peerlings, Polman and Dries 2014, Jones, Samman and Vinck 2018, Jones and d'Errico 2019). This approach recognizes farmers' ability to judge their own resilience capacities (Jones 2018) and explains behaviour and decision-making under risk and uncertainty (Jones and d'Errico 2019). Additionally, perceived resilience assessments allow for comparison across regions, as the questions are applicable in other contexts (Clare et al. 2017). Our perception-based approach uses self-assessment questions to measure farmers' robustness, adaptability, and transformability.

While perceived resilience and risk behaviour are evidently related (Ansah, Gardebroek and Ihle 2019), no empirical applications exist that simultaneously investigated how risk management, preferences, and perceptions are associated with perceived farm resilience. Previous studies succeeded to partially capture these relationships, including how single risk management strategies might enhance specified farm resilience—the resilience to deal with one specific risk (Carpenter et al. 2001, Folke 2016). For instance, there is mixed evidence on how diversification might enhance perceived resilience to cope with agricultural policy changes. Peerlings, Polman and Dries (2014) found that specialized farmers perceived themselves as more resilient, while Sutherland et al. (2017) showed that Scottish crofters applied diversification into agri-tourism and forestry as an adaptation strategy to agricultural policy changes. However, these studies did not account for the unknown as they target one specific risk. We investigate general resilience, which is more complex than specified resilience as it embodies dealing with risk in general (Folke 2016) and the unknown (Carpenter et al. 2012). A broad view on risk management, which embraces a portfolio of strategies, is likely to be required to prepare farmers for an unknown future. While several empirical investigations explain why farmers adopt certain risk management portfolios (Coffey and Schroeder 2019, Meraner and Finger 2019, Vigani and Kathage 2019), none of these studies connected farmers' risk management portfolios to general resilience. To fill this research gap, this study investigates how farmers' risk behaviour is associated with general resilience.

A decent farm income helps ensuring farm continuity (Saint-Cyr et al. 2019) and fostering resilience (Cabell and Oelofse 2012). In resilience thinking, farm income is considered as one of the functions provided by farmers (Meuwissen et al. 2019). Other examples of farm functions are maintaining natural resources in good conditions, managing animal welfare or providing employment and good working conditions. Farmers often pursue a combination of economic and non-economic functions (Anderson and McLachlan 2012); however, a decent farm income is required to facilitate other functions (Ten Napel, Bianchi and Bestman 2006). Therefore, it is worth investigating how farm income shapes perceived resilience.

Against this background, we aim to explore how farmers' risk behaviour is related to perceived resilience in terms of robustness, adaptability, and transformability. This chapter expands the current literature in two ways: (i) we examine how farmers' risk management portfolios, perceptions, and preferences are related to perceived general resilience in terms of robustness, adaptability, and transformability and (ii) we explore how farm income explains differences in perceived resilience. Our empirical application focuses on Dutch farmers, who have recently faced a complex mix of risks. Therefore, Dutch farmers are a relevant population for resilience research.

2.2 Conceptual framework

We build upon agricultural risk behaviour (Hardaker et al. 2015) and resilience theory (Holling 1973, Darnhofer 2014, Folke 2016) to explore how risk management, perceptions, and preferences relate to perceived resilience (Figure 2.1). Our conceptual framework describes (i) the relationship between risk management portfolios, perceptions, and preferences, (ii) how perceived robustness, adaptability, and transformability relate to perceived resilience, (iii) the relationship between risk behaviour and perceived resilience, and (iv) how several control variables relate to risk behaviour and perceived resilience. Capturing backward- and forward-looking system dynamics is required to assess resilience (Folke 2016). Therefore, we investigate farmers' past perceptions (t-k), current perceptions (t), and perceptions of future events (t+k), where t-k refers to the past five years, t refers to the current year, and t+k refers either to the next 5 or 20 years. The next sub-sections will discuss the various building blocks of the conceptual framework.

2.2.1 Risk behaviour

Risk behaviour theory uses static approaches to investigate the complex interactions between farmers' current risk management decisions, perceptions, and preferences (Meuwissen, Huirne and Hardaker 2001, Meraner and Finger 2019). This simplified representation of risk behaviour does not account for the influence of past behaviour on current or future decision making under risk (Van Winsen et al. 2016). To this end, we use a dynamic approach that accounts for farmers' risk management portfolio in the last five years, current risk preferences, and future risk perceptions in the next 20 years. As past risk management decisions cannot be explained by current or future perceptions, we investigate the role of past risk management strategies in shaping current risk preferences and future risk perceptions.

Traditional understandings of risk management primarily underlined the economic dimension of risk coping. For instance, Schmit and Roth (1990) defined risk management as the strategies to minimize the costs of risks regarding potential losses, while considering the costs of risk reduction. In the context of resilience, we understand risk management as the portfolio of strategies that farmers adopt to minimize the impact and potential costs of risk on economic, environmental, and social farm functions. Risk perceptions are farmers' subjective interpretations of domain-specific risks (Meraner and Finger 2019). To account for domain-specificity, we selected eight pre-defined risk perception domains (Figure 2.1). Risk preferences are a farmer's orientation towards taking or avoiding risk (Gardebroek 2006, Van Winsen et al. 2016). Farmers can range from risk-averse, over risk-neutral to risk-taking, and most empirical findings suggest that farmers are to some degree risk-averse (Iyer et al. 2019). Therefore, more risk-averse farmers will be referred to as farmers with low risk preferences and less risk-averse farmers are these farmers with high risk preferences. Heterogeneity in risk preferences is shaped by differences in wealth or farm income (Dohmen et al. 2011, Van Winsen et al. 2016), and can be further explained by several other farm and

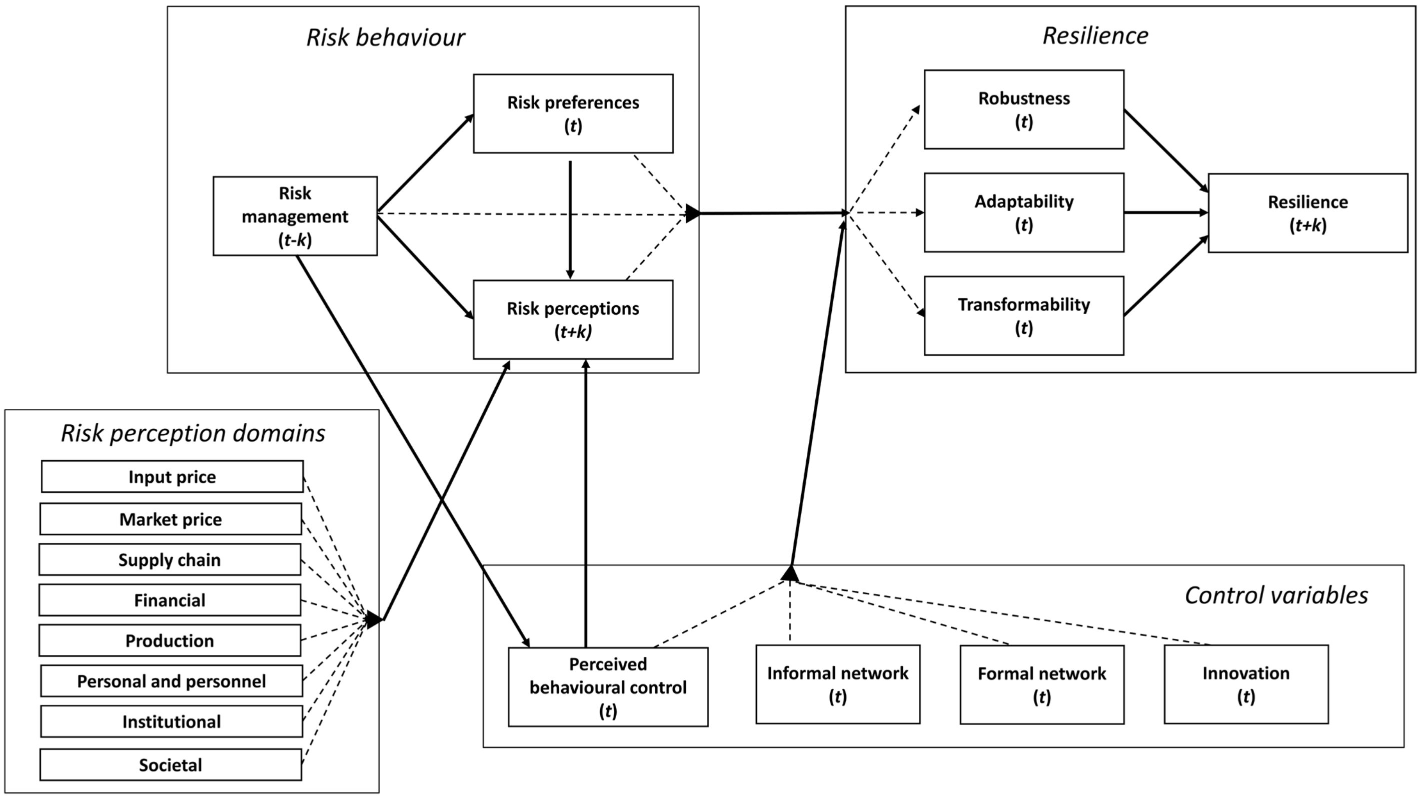

Figure 2.1 Conceptual framework to assess perceived farm resilience. Past (*t-k*), current (*t*), and future (*t+k*) variables are included. The arrows from the control variables and risk behaviour boxes to resilience indicate that all variables within the corresponding box relate to perceived robustness, adaptability, and transformability.

farmer characteristics, including age (Dohmen et al. 2017), gender (Dohmen et al. 2011), and farm size (Van Winsen et al. 2016).

We expect that farmers who have adopted a more diverse risk management portfolio in the last five years have taken more actions to reduce the presence of risk (Van Winsen et al. 2016). Therefore, they will be better equipped to cope with future risks. Hence, hypothesis 1a (H1a) states that farmers with a more diverse risk management portfolio in the last five years will perceive lower future risk (Table 2.1). Furthermore, a more diverse risk management portfolio in the last five years allows farmers to take more risks as it widens response options to risks. We hypothesize that farmers with more diverse risk management portfolios in the last five years are less risk-averse (H1b). Several lines of evidence suggest that less risk-aversion results in lower perceived risk (Keil et al. 2000, Cho and Lee 2006, Van Winsen et al. 2016). Therefore, we argue that less risk-averse farmers are expected to have lower future risk perceptions, as they perceive future risky situations as less severe (H1c).

Table 2.1 Overview of the hypothesized relationships and their expected signs. + positive relationship, - negative relationship, -/+ the relationship will be determined by the study.

	Relationship	Expected sign
H1a	Risk management (*t*-*k*) → risk perceptions (*t*+*k*)	−
H1b	Risk management (*t*-*k*) → risk preferences[1] (*t*)	+
H1c	Risk preferences (*t*) → risk perceptions (*t*+*k*)	−
H2a	Robustness (*t*) → resilience (*t*+*k*)	+
H2b	Adaptability (*t*) → resilience (*t*+*k*)	+
H2c	Transformability (*t*) → resilience (*t*+*k*)	+
H3a	Risk management (*t*-*k*) → robustness (*t*)	+
H3b	Risk management (*t*-*k*) → adaptability (*t*)	+
H3c	Risk management (*t*-*k*) → transformability (*t*)	+
H4a	Risk perceptions (*t*+*k*) → robustness (*t*)	−
H4b	Risk perceptions (*t*+*k*) → adaptability (*t*)	−
H4c	Risk perceptions (*t*+*k*) → transformability (*t*)	−
H5a	Risk preferences (*t*) → robustness (*t*)	−
H5b	Risk preferences (*t*) → adaptability (*t*)	−/+
H5c	Risk preferences (*t*) → transformability (*t*)	+

Notes: [1] In this study, risk preferences are understood as a scale ranging from risk-averse to risk-taking. Therefore, the positive sign indicates that farmers with more (less) diverse risk management portfolios are expected to be less (more) risk-averse farmers. This applies to all hypotheses.

2.2.2 Resilience

Resilience theory describes how robustness, adaptability, and transformability are exploited to manage a dynamic and uncertain world (Folke 2016). The importance of the three complementary resilience capacities depends on the context in which farms operate, the timescale, and the depth of change (Cabell and Oelofse 2012, Termeer et al. 2019). In a predictable era of slow and marginal changes, the farm focus will be more on robustness and adaptability, while farmers' need to emphasize the ability to transform in a period of radical change (Darnhofer 2014, Béné and Doyen 2018). Our conceptual framework describes how these resilience capacities jointly shape farmers' perception of future resilience. To this end, we expect that an improved ability to absorb, adapt or radically change ensures the provision of farm functions (Meuwissen et al. 2019). Therefore, we hypothesize that higher perceived robustness, adaptability or transformability are related to higher future farm resilience (H2a–2c).

Besides describing how farmers exploit their resilience capacities, resilience theory emphasizes the importance of delivering essential farm functions (i.e. the delivery of public and private goods) (Walker et al. 2004, Meuwissen et al. 2019). We account for farm functions by considering how farm income might explain differences in perceived resilience. Several studies have begun to examine how farmers with different financial goals and functions differ in terms of risk behaviour (Greiner, Patterson and Miller 2009, Greiner and Gregg 2011, Bopp et al. 2019). We will expand this conceptual lens by comparing the perceived resilience of two groups; a group of farmers that perceived obtaining farm income as more important and a group that perceived obtaining farm income as less important.

2.2.3 From risk behaviour to perceived resilience

Understanding the relationship between risk behaviour and perceived resilience requires thorough insights into the interactions among risk management, perceptions, preferences, and perceived resilience capacities. Both risk and resilience literature describe how risk-related variables help to explain resilience (Scholz, Blumer and Brand 2012, Park et al. 2013, Aven 2017, Aven 2019). Therefore, we describe how risk management, preferences, and perceptions are related to perceived resilience (Grothmann and Patt 2005, Marshall and Marshall 2007, Marshall and Stokes 2014).

Farmers with more diverse risk management portfolios enhance their response diversity, which helps them to deal with unknown future risks (Resilience Alliance 2010). An increased response diversity to risks will help farmers to improve their capacity to absorb negative consequences, adjust responses or radically change their farm. Therefore, farmers with a more diverse portfolio of risk management strategies in the last five years are expected to perceive themselves as more robust, adaptable, and transformable (H3a–3c).

Ansah, Gardebroek and Ihle (2019) described that risk perceptions negatively shape all perceived resilience capacities because farmers with higher risk perceptions struggle more to overcome the consequences of risks. The separate relationship between risk perceptions and perceived robustness (Marshall and Marshall 2007), adaptability (Marshall and Stokes 2014) or transformability (Marshall et al. 2014) has been examined. For instance, Marshall et al. (2014) found that higher risk perceptions restricted farmers' ability to identify new transition opportunities, constraining perceived transformability. Extrapolating the findings of Marshall et al. (2014) to all perceived resilience capacities, we expect farmers' future risk perceptions to be negatively related to perceived robustness, adaptability, and transformability (H4a–4c).

More risk-averse farmers are less likely to make big and risky investments and are more likely to maintain the status quo (Ansah, Gardebroek and Ihle 2019), while less risk-averse farmers are expected to more easily introduce radical changes and are better able to transform. Although some transformations might result in less risky production systems, the radical change towards a new production system is risky and requires willingness to take risk. We expect less risk-averse farmers to perceive themselves as less robust (H5a). The relationship between risk preferences and perceived adaptability could be either positive or negative (H5b), while less risk-averse farmers are expected to perceive higher transformability (H5c).

2.2.4 Control variables

We control for farmers' perceived behavioural control, openness to innovation, and formal and informal networks in relation to perceived resilience. First, perceived behavioural control reflects the perceived ability to overcome obstacles in reaching one's goals (Ajzen 2002). In this study, perceived behavioural control is framed as a farmer's perceived ability to deal with risk. Therefore, perceived behavioural control is expected to be positively related to perceived resilience (Ansah, Gardebroek and Ihle 2019) and negatively associated with risk perceptions (Van der Linden 2015). Second, more innovative farmers are more likely to try out new farm practices or technologies, which makes them better equipped to change (Glover 2012). We expect a positive relationship between openness to innovation and all perceived resilience capacities. Finally, having a larger informal or formal network improves farmers' social capital (Hunecke et al. 2017) and is therefore expected to enhance resilience (Cabell and Oelofse 2012).

2.3 Empirical model

To explain the relationship between risk behaviour and resilience theory (Figure 2.1), a partial least squares structural equation model (PLS-SEM) was estimated using Smart PLS 3 (Ringle, Wende and Becker 2015). Most of the elicited constructs are latent, indicating that they cannot be directly observed and measured. PLS-SEM is a non-parametric multivariate technique that investigates latent constructs by combining the structural model, which specifies the relationships between latent constructs, and the measurement model (Hair et al. 2016). Measurement models specify how each latent construct was formatively or reflectively measured. Formative measurement models present a relationship from indicators to latent constructs, where changing indicators cause the construct to change (Diamantopoulos and Winklhofer 2001, Sarstedt, Ringle and Hair 2017). Reflective measurement models explain the relationship from the latent construct to the indicators, where a change in the latent construct reflects on the indicators (Bollen and Lennox 1991, Diamantopoulos and Siguaw 2006). As our study is exploratory and combines formative and reflective measurement models into a complex model, PLS-SEM is the most suitable estimation approach (Hair et al. 2017). We followed the measurement invariance of the composite models (MICOM) procedure (Henseler, Ringle and Sarstedt 2016) to account for observed heterogeneity based on the perceived importance of farm income. This procedure determines if the dataset is suitable for multi-group analysis (MGA).

2.4 Data

A survey among Dutch farmers was conducted to assess how risk behaviour is associated with perceived resilience. Two experts of the Dutch Farmers Union and an interdisciplinary group of researchers provided feedback on the survey. Subsequently, four Dutch farmers pre-tested the survey, after which some statements were reformulated or omitted. The finalized survey was sent out by e-mail in November 2018 to about 9,000 randomly selected Dutch farmers, using a database of an agricultural publisher. To the best of our knowledge, the readership of this publisher can be considered to cover the diversity of the Dutch farming sector and comprehensively reflect the sector as a whole. Additionally, we placed advertisements on the website of this publisher and sent a reminder in December 2018 to increase response rates. This resulted in 1,537 responses (17% response rate) of which 926 (60.25%) completed surveys without any missing data. The high dropout rate (39.75%) can be explained by the relatively long duration of the survey. We randomly raffled one tablet and 24 vouchers of €25 among the respondents. Ten respondents indicated to be agricultural contract workers and were left out for further analysis, resulting in a final sample of 916 farmers. This sample meets the sample size requirements of Barclay, Higgins and Thompson (1995) who recommend a sample size of ten times the largest number of formative indicators in a construct or ten times the largest number of paths going from a construct into the structural model.

The survey was designed to measure six constructs: (1) perceived resilience, (2) risk management portfolios, (3) risk perceptions, (4) risk preferences, (5) farm functions, and (6) other farmer characteristics. Unless stated otherwise, all items were measured on a 7-point Likert scale. The scores of the negatively worded items were reversed during the analysis. Table 2.2 presents the item wordings and summary statistics.

Table 2.2 Item wordings and summary statistics (*N* = 916).

Item[1]		Mean	St dev
Risk behaviour			
Risk management (RM) – single item. 8-point scale, ranging from 0 (no risk management) to 7 (all seven categories in risk management portfolio)			
rm	The number of different risk management categories adopted by farmers. The following categories are distinguished: flexibility of farm activities, cooperation with others, diversification, specialization, learning, financial risk management, and measures to control environmental risks.	3.98	1.35
Risk perception (RISK PERC) – second-order formative			
Input price risk perception (RISK PERC_1) – first-order formative			
riskperc_1	Persistently high input prices.	4.44	1.53
riskperc_2	Input price fluctuations.	4.16	1.47
Market price risk perception (RISK PERC_2) – first-order formative			
riskperc_3	Persistently low market prices.	4.91	1.62
riskperc_4	Market price fluctuations.	4.78	1.45
Supply chain risk perception (RISK PERC_3) – first-order formative			
riskperc_5	Low bargaining power towards processors and retailers.	4.93	1.70
riskperc_6	Low bargaining power towards input suppliers.	4.02	1.54
Financial risk perception (RISK PERC_4) – first-order formative			
riskperc_7	Limited access to loans from banks.	4.17	1.74
riskperc_8	Late payments from buyers.	3.42	1.75
Production risk perception (RISK PERC_5) – first-order formative			
riskperc_9	Persistent extreme weather events.	4.50	1.61
riskperc_10	Pest, weed, or disease outbreaks.	4.38	1.56
Personal and personnel risk perception (RISK PERC_6) – first-order formative			
riskperc_11	Limited availability of skilled farm workers.	3.71	1.95
riskperc_12	Limited ability to work on the farm due to illness, divorce or other personal circumstances.	3.20	1.67
riskperc_13	Uncertainty about succession.	3.68	1.99
Institutional risk perception (RISK PERC_7) – first-order formative			
riskperc_14	Strict regulations.	5.51	1.50
riskperc_15	Reduction in direct payments of the Common Agricultural Policy (CAP).	4.36	1.92
Societal risk perception (RISK PERC_8) – first-order formative			
riskperc_16	Public distrust in agriculture.	4.87	1.62
riskperc_17	Low societal acceptance of agriculture.	4.84	1.69
Risk preferences (RISK PREF) – formative			
	I am willing to take more risks than other farmers in terms of...		
riskpref_1	Production.	4.08	1.49
riskpref_2	Marketing and prices.	4.39	1.50
riskpref_3	Financial risks.	4.15	1.40
riskpref_4	Innovation.	4.35	1.35
Risk preferences (RISK PREF) – reflective. 11-point Likert scale ranging from 0-10			
riskpref_5	How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?	5.99	2.03
Resilience			
Robustness (ROB) – reflective			
rob_1	After something challenging has happened, it is easy for my farm to bounce back to its current profitability.	4.21	1.43
rob_2	As a farmer, it is hard to manage my farm in such a way that it recovers quickly from shocks.	3.90	1.54
rob_3	Personally, I find it easy to get back to normal after a setback.	4.44	1.47
rob_4	A big shock will not heavily affect me, as I have enough options to deal with this shock on my farm.	4.02	1.53

Table 2.2 (continued) Item wordings and summary statistics ($N = 916$).

Item[1]		Mean	St dev
Adaptability (ADAP) – reflective			
adap_1	If needed, my farm can adopt new activities, varieties, or technologies in response to challenging situations.	3.97	1.71
adap_2	As a farmer, I can easily adapt myself to challenging situations.	4.58	1.42
adap_3	In times of change, I am good at adapting myself and facing up to agricultural challenges.	4.65	1.37
adap_4	My farm is not flexible and can hardly be adjusted to deal with a changing environment.	4.57	1.59
Transformability (TRANS) – reflective			
trans_1	For me, it is easy to make decisions that result in a transformation.	3.84	1.58
trans_2	I am in trouble if external circumstances would drastically change, as it is hard to reorganize my farm.	4.08	1.56
trans_3	After facing a challenging period on my farm, I still have the ability to radically reorganize my farm.	3.98	1.46
trans_4	If needed, I can easily make major changes that would transform my farm.	3.72	1.57
Resilience (RES) – formative			
res_1	For the next 5 years, I expect my farm to be resilient to agricultural challenges.	4.87	1.47
res_2	For the next 20 years, I expect my farm to be resilient to agricultural challenges.	4.37	1.59
Farm functions (FUNC) – formative. 100 points			
	Number of points distributed to farm income		
func_1	Ensure a sufficient farm income.	36.64	20.25
Control variables			
Innovation (INNO) – reflective			
inno_1	Compared to other farmers, I am among the first to try out a new practice on my farm.	4.15	1.58
inno_2	I like to try out all kinds of new technologies or varieties.	4.12	1.58
Informal network (NET INF) – reflective			
net_1	I know a lot of other farmers in my region.	5.62	1.31
net_2	Concerning farming, I often interact with neighboring farmers.	4.98	1.47
net_3	Farmers in my region tend to support each other when there is a problem.	4.28	1.52
Formal network (NET FOR) – reflective			
net_4	I know a lot of agricultural professionals, experts, or value chain actors.	5.09	1.35
net_5	When I attend agricultural events and meetings, I interact a lot with professionals, experts, or value chain actors.	4.56	1.49
net_6	I feel I can receive support from agricultural professionals, experts, or value chain actors in my network.	4.66	1.50
Perceived behavioural control (PBC) – reflective			
pbc_1	If I wanted to, it would be easy for me to deal with agricultural challenges on my farm.	4.64	1.30
pbc_2	It is mostly up to me whether or not I can deal with the challenges on my farm.	4.78	1.43
pbc_3	I have a lot of control about agricultural challenges affecting my farm.	3.96	1.45
pbc_4	For me, it is difficult to deal with the challenges that affect my farm.	4.43	1.46

Notes: [1]Unless otherwise stated, all items are measured on a 7-point Likert scale. Reversed scores of the negatively worded items are presented.

First, farmers selected their adopted risk management strategies in the past five years (*RM*) from a list of 22 risk management strategies (Meuwissen, Huirne and Hardaker 2001, Flaten et al. 2005, Van Winsen et al. 2016, Meraner and Finger 2019). These risk management strategies were classified into 7 categories: flexibility, cooperation with others, financial risk management, measures to control environmental risks, specialization, diversification, and learning (see Appendix 1; Table A1.1 for more details). An index of farmers' risk management portfolios was created by counting in how many categories at least one strategy was selected.

Second, we used a subjective approach to elicit farmers' future risk perceptions (*RISK PERC*) with respect to 17 risk sources. The selected risk sources were based on a literature review (Meuwissen, Huirne and Hardaker 2001, Van Winsen et al. 2016, Meraner and Finger 2019). Farmers were asked to indicate their expectations about how challenging certain risks would become in the next 20 years in the following domains: input price, market price, financial, supply chain, production, personal and personnel, institutional, and societal (Table 2.2). We controlled for farmers' domain-specific risk perceptions as first-order constructs and combined them into a second-order construct that represents general risk perception.

Third, we elicited farmers' risk preferences (*RISK PREF*) using a combination of self-assessment and business statements (Iyer et al. 2019). Farmers were asked to provide a general self-assessment of their risk preferences using one reflective item on an 11-point Likert scale (Dohmen et al. 2011). Additionally, we elicited domain-specific risk preferences using five formative business statements (Meuwissen, Huirne and Hardaker 2001, Meraner and Finger 2019). These statements elicited farmers' relative risk preferences—risk preferences relative to other farmers—regarding the following subjects: (1) production, (2) marketing and prices, (3) financial risks, (4) innovation, and (5) farming in general. The fifth statement was excluded from further analysis because it does not represent a specific domain. Therefore, this statement is not suitable to fit into a formative construct that composes farmers' general risk preferences based on different domains.

Fourth, perceived farm resilience was measured using an indirect and direct method. Building upon several resilience frameworks (Marshall and Marshall 2007, Clare et al. 2017, Jones and d'Errico 2019), the indirect approach measured farmers' perceived robustness (*ROB*), adaptability (*ADAP*), and transformability (*TRANS*) using four statements per category. All resilience capacities were introduced with a non-agricultural example to ensure that farmers understood the statements. Additionally, we used two items to directly elicit farmers' future resilience (*RES*) for the next 5 and 20 years.

Fifth, farmers were asked to distribute 100 points over nine farm functions (*FUNC*). We grouped farmers based on the perceived importance of income as a farm function. The group *Low* consists of farmers who perceived income as relatively unimportant compared to other farm functions; these farmers distributed less than the median (less than 30 points) to farm income. The group *High* represents farmers who perceived income as one of the main farm functions (30 or more points).

Finally, we included several statements about farmers' openness to innovation (*INNO*), informal networks (*NET INF*), formal networks (*NET FOR*), and perceived behavioural control (*PBC*). Openness to innovation was measured using two items (Aubert, Schroeder and Grimaudo 2012). Two sets of three statements were used to measure farmers' formal and informal networks (Hunecke et al. 2017). Based on Armitage and Conner (1999) and Ajzen (2002), perceived behavioural control was measured as a four-item construct.

2.5 Results

The PLS-SEM evaluation consists of the measurement and structural model assessment. The measurement model assessment examines the reflective and formative indicators that are used to operationalize the latent constructs. If sufficient measurement quality is confirmed, the structural model evaluation tests the hypothesized associations between the latent constructs (Hair et al. 2016). Finally, the results of the MGA will be presented.

2.5.1 Measurement model assessment

Evaluating the reflective measurement model includes an assessment of internal consistency reliability, convergent validity, and discriminant validity (Hair et al. 2016). Following the recommendations of Hair et al. (2018) for PLS-SEM with a second-order formative-formative construct, we used the repeated indicators approach with a factor weighting scheme, a maximum of 300 iterations, and a stop criterion of 10^{-7} as algorithm settings. The evaluation of the full model showed a lack of internal consistency reliability as PBC and ROB obtained Cronbach's alpha values smaller than 0.7 (Appendix 1; Table A1.2). Furthermore, the outer loadings of adap_4 (0.566), pbc_2 (0.695), pbc_4 (0.510), rob_2 (0.180), and trans_2 (0.227) are lower than 0.7, potentially causing low convergent validity. After removing adap_4, pbc_4, rob_2, and trans_2, the internal consistency reliability and convergent validity improved. All Cronbach's alpha values were larger than 0.7 and all composite reliability values ranged between 0.8 and 0.95 (Table 2.3). Additionally, all average variance explained (AVE) values exceed 0.5, confirming convergent validity. Discriminant validity is obtained as none of the 95% bias-corrected and accelerated (BCa) confidence intervals of the heterotrait-monotrait (HTMT) ratio include 1 (Henseler, Ringle and Sarstedt 2016) (Appendix 1;Table A1.3).

Table 2.3 Internal consistency reliability and convergent validity of the reduced model.

	Cronbach's alpha			Composite reliability			AVE[1]		
	All	Low	High	All	Low	High	All	Low	High
ADAP	0.795	0.811	0.785	0.879	0.887	0.874	0.710	0.725	0.701
INNO	0.856	0.851	0.858	0.933	0.930	0.933	0.874	0.869	0.875
NET FOR	0.813	0.768	0.831	0.888	0.866	0.897	0.726	0.684	0.744
NET INF	0.774	0.792	0.765	0.869	0.877	0.861	0.689	0.707	0.675
PBC	0.713	0.743	0.693	0.837	0.852	0.826	0.632	0.657	0.615
ROB	0.726	0.713	0.730	0.846	0.838	0.847	0.646	0.634	0.649
TRANS	0.846	0.860	0.835	0.907	0.915	0.901	0.765	0.782	0.752

Notes: [1]AVE = average variance explained.

The formative measurement model assessment evaluates convergent validity, collinearity, and the significance of outer weights (Hair et al. 2016). First, a redundancy analysis was conducted to assess convergent validity between the formative and reflective *RISK PREF* measures. This resulted in a path coefficient with a magnitude of 0.805—exceeding the critical threshold of 0.70 (Sarstedt, Ringle and Hair 2017)—convergent validity was obtained. No redundancy analysis was conducted for *RISK PERC* and *RES* because these constructs were respectively a second-order construct or directly elicited. Second, all formative items obtained variance inflation factors (VIF) below 5 (Appendix 1; Table A1.4), indicating that collinearity is not present at critical levels. Finally, we assessed the significance of outer weights and the relevance of outer loadings using a bootstrapping procedure (4,000 samples, no sign changes option, BCa, two-tailed testing at α=0.05). Except farmers' financial risk preferences (*riskpref_3*), all formative items obtained significant outer weights (Appendix 1; Table A1.4). The factor loading of *riskpref_3* exceeds the critical value of 0.50, indicating an absolute contribution to *RISK PREF* (Hair et al. 2016). Furthermore, previous research confirmed the theoretical importance of financial risk preferences (Reynaud and Couture 2012, Iyer et al. 2019). Therefore, we decided to keep *riskpref_3* in the measurement model. We continued with the structural model assessment because the reflective and formative measurement model assessments suggest satisfactory levels of reliability and validity.

2.5.2 Structural model assessment

The structural model assessment evaluates the potential presence of collinearity and the predictive capacity of the PLS-SEM. As the highest VIF value of all predictor constructs is 1.76, we found no indication of the presence of collinearity at critical levels. The second and sixth columns of Table 2.4 present respectively the direct and the total effects, which is the sum of the direct and indirect path coefficients.

Table 2.4 Path coefficients of the PLS-SEM. Direct and total effects are reported. Variables that revealed significant differences between low and high are in bold (p =0.05) or italics (p=0.10). This refers to p-values of the permutation test.

	Direct effects			Total effects		
	All (N = 916)	Low (N = 329)	High (N = 587)	All (N = 916)	Low (N = 329)	High (N = 587)
Risk behaviour						
RM → RISK PREF	0.237***	0.225***	0.253***	0.237***	0.225***	0.253***
	(0.033)	(0.055)	(0.042)	(0.033)	(0.055)	(0.042)
RM → PBC	0.109***	0.174***	0.076*	0.109***	0.174***	0.076*
	(0.034)	(0.055)	(0.043)	(0.034)	(0.055)	(0.043)
PBC → RISK PERC[1]	-0.141***	-0.132	-0.143***	-0.141***	-0.132	-0.143***
	(0.044)	(0.088)	(0.051)	(0.044)	(0.088)	(0.051)
RISK PREF → RISK PERC	0.082*	0.209***	-0.007	0.082*	0.209***	-0.007
	(0.047)	(0.076)	(0.054)	(0.047)	(0.076)	(0.054)
RM → RISK PERC	0.162***	0.145**	0.149***	0.162***	0.145**	0.149***
	(0.036)	(0.060)	(0.045)	(0.036)	(0.060)	(0.045)
Robustness						
RISK PERC → ROB	-0.098**	-0.002	-0.139***	-0.098**	-0.002	-0.139***
	(0.039)	(0.074)	(0.045)	(0.038)	(0.074)	(0.045)
RISK PREF → ROB	0.096**	0.205***	0.026	0.088**	0.205***	0.027
	(0.042)	(0.073)	(0.052)	(0.041)	(0.071)	(0.051)
RM → ROB	-0.018	-0.045	0.005	0.027	0.063	0.017
	(0.032)	(0.055)	(0.039)	(0.037)	(0.063)	(0.046)
INNO → ROB	-0.044	-0.085	-0.036	-0.044	-0.085	-0.036
	(0.040)	(0.069)	(0.048)	(0.040)	(0.069)	(0.048)
NET FOR → ROB	0.093**	-0.017	0.149***	0.093**	-0.017	0.149***
	(0.044)	(0.073)	(0.054)	(0.044)	(0.073)	(0.054)
NET INF → ROB	-0.013	0.067	-0.049	-0.013	0.067	-0.049
	(0.038)	(0.061)	(0.051)	(0.038)	(0.061)	(0.051)
PBC → ROB	0.351***	0.356***	0.350***	0.365***	0.356***	0.370***
	(0.041)	(0.073)	(0.049)	(0.040)	(0.072)	(0.048)
Adaptability						
RISK PERC → ADAP	-0.028	0.017	-0.059	-0.028	0.017	-0.059
	(0.033)	(0.057)	(0.041)	(0.033)	(0.057)	(0.041)
RISK PREF → ADAP	0.156***	0.141**	0.164***	0.153***	0.145**	0.164***
	(0.039)	(0.063)	(0.049)	(0.039)	(0.062)	(0.049)
RM → ADAP	0.057**	0.049	0.056	0.130***	0.150***	0.116***
	(0.029)	(0.048)	(0.036)	(0.034)	(0.055)	(0.043)
INNO → ADAP	0.106***	0.058	0.132***	0.106***	0.058	0.132***
	(0.038)	(0.066)	(0.047)	(0.038)	(0.066)	(0.047)
NET FOR → ADAP	0.073*	0.136**	0.041	0.073*	0.136**	0.041
	(0.041)	(0.064)	(0.051)	(0.041)	(0.064)	(0.051)
NET INF → ADAP	0.031	0.062	0.019	0.031	0.062	0.019
	(0.037)	(0.056)	(0.048)	(0.037)	(0.056)	(0.048)
PBC → ADAP	0.371***	0.386***	0.358***	0.375***	0.383***	0.367***
	(0.037)	(0.060)	(0.047)	(0.037)	(0.059)	(0.046)

Notes: [1]The domain-specific (first-order) effects of RISK PERC and most indirect effects are omitted for the sake of brevity. These results can be consulted in Table A 1.10 of Appendix 1. * p≤0.10 ** p≤0.05; *** p≤0.01.

Table 2.4 (continued) Path coefficients of the PLS-SEM. Direct and total effects are reported. Variables that revealed significant differences between low and high are in bold (p =0.05) or italics (p=0.10). This refers to p-values of the permutation test.

	Direct effects			Total effects		
	All (N = 916)	Low (N = 329)	High (N = 587)	All (N = 916)	Low (N = 329)	High (N = 587)
Transformability						
RISK PERC → TRANS	-0.047	-0.054	-0.035	-0.047	-0.054	-0.035
	(0.036)	(0.057)	(0.046)	(0.036)	(0.057)	(0.046)
RISK PREF → TRANS	0.212***	0.202***	0.212***	0.209***	0.191***	0.212***
	(0.044)	(0.068)	(0.055)	(0.044)	(0.067)	(0.055)
RM → TRANS	-0.027	0.000	-0.045	0.057	0.112*	0.031
	(0.030)	(0.051)	(0.038)	(0.038)	(0.061)	(0.048)
INNO → TRANS	0.012	-0.051	0.045	0.012	-0.051	0.045
	(0.047)	(0.072)	(0.058)	(0.047)	(0.072)	(0.058)
NET FOR → TRANS	0.062	0.055	0.071	0.062	0.055	0.071
	(0.041)	(0.067)	(0.053)	(0.041)	(0.067)	(0.053)
NET INF → TRANS	-0.020	0.050	-0.065	-0.020	0.050	-0.065
	(0.037)	(0.057)	(0.050)	(0.037)	(0.057)	(0.050)
PBC → TRANS	0.385***	0.422***	0.367***	0.392***	0.429***	0.372***
	(0.038)	(0.065)	(0.048)	(0.038)	(0.063)	(0.049)
Resilience						
ROB → RES	0.267***	0.245***	0.289***	0.267***	0.245***	0.289***
	(0.041)	(0.066)	(0.050)	(0.041)	(0.066)	(0.050)
ADAP → RES	0.230***	0.284***	0.200***	0.230***	0.284***	0.200***
	(0.046)	(0.070)	(0.057)	(0.046)	(0.070)	(0.057)
TRANS → RES	0.114**	0.113	0.108*	0.114**	0.113	0.108*
	(0.047)	(0.071)	(0.060)	(0.047)	(0.071)	(0.060)
RISK PERC → RES				-0.038**	-0.001	-0.056**
				(0.018)	(0.035)	(0.022)
RISK PREF → RES				0.083***	0.113***	0.063**
				(0.021)	(0.035)	(0.027)
RM → RES				0.043**	0.071**	0.031
				(0.019)	(0.034)	(0.024)
INNO → RES				0.014	-0.010	0.021
				(0.019)	(0.035)	(0.022)
NET FOR → RES				0.049**	0.041	0.059**
				(0.022)	(0.037)	(0.027)
NET INF → RES				0.001	0.040	-0.017
				(0.018)	(0.029)	(0.024)
PBC → RES				0.229***	0.245***	0.220***
				(0.024)	(0.047)	(0.026)

Notes: [1]The domain-specific (first-order) effects of RISK PERC and most indirect effects are omitted for the sake of brevity. These results can be consulted in Table A 1.10 of Appendix 1. * p≤0.10 ** p≤0.05; *** p≤0.01.

Our results indicate that a more diverse risk management portfolio in the last five years is associated with higher future risk perceptions, leading to the rejection of H1a. This suggests that farmers who have adopted risk management strategies did so to cover the major perceived risks. However, while a more diverse risk management portfolio might be beneficial to cope with present risks, future risk perceptions remain high as farmers could still be unaware of the consequences. We found support for H1b, indicating that farmers with a more diverse risk management portfolio in the past are less risk-averse. This suggests that a more diverse risk management portfolio helps farmers to reduce the exposure to risk, which makes farmers less risk-averse. As less risk-averse farmers experienced higher future risk perceptions, we rejected H1c. It could be that the current degree of risk aversion reflects on current risks, while the consequences of these risks arise in the future. Ultimately, this might increase farmers' future risk perceptions. Our findings contradict Van Winsen et al. (2016), who found domain-specific relationships between risk preferences and perceptions.

The results support H2a-H2c as they suggest that farmers use their capacities to absorb, adapt, or transform in response to future risks, resulting in higher perceived future resilience. Our findings are in line with Darnhofer (2014), Folke (2016), and Meuwissen et al. (2019), who described that higher levels robustness, adaptability or transformability are needed to improve resilience.

The non-significant relationship between farmers' past risk management portfolio and perceived robustness led to the rejection of H3a. The high costs involved in obtaining a diverse risk management portfolio could restrain farmers from absorbing shocks (Vigani and Kathage 2019). This might indicate that individual financial risk management strategies are more efficient tools to boost robustness. More diverse risk management portfolios are positively related to perceived adaptability (accept H3b), suggesting that wider response options to future risks increase the manoeuvring space of farmers. We reject H3c, as more diverse risk management portfolios were not related to perceived transformability. A diverse risk management portfolio alone might not be sufficient to enhance transformability because farmers need to be both able and willing to transform (Tong, Niu and Fan 2016).

We found support for H4a, as future risk perceptions are negatively related to perceived robustness. Surprisingly, we found that future risk perceptions are unrelated to perceived adaptability and transformability, leading to the rejection of H4b and H4c. These findings contradict previous studies that described how higher risk perceptions partly explain farm adaptation (Grothmann and Patt 2005, Marshall and Stokes 2014) or transformation (Marshall et al. 2014). A potential explanation for this could be that robustness describes the capacity to recover from shocks, which could be perceived as dealing with risks (Bené et al. 2016). Perceived adaptability and transformability are related to respectively adjustments or radical changes, which are not reflected by risk perceptions.

Risk preferences are positively associated with perceived robustness, adaptability, and transformability, indicating that less risk-averse farmers perceive higher resilience capacities. Hence, we rejected H5a and found support for H5c. This suggests that less risk-averse farmers have an improved confidence to overcome the negative consequences of risks, which could enable them to better exploit their resilience capacities.

The largest path coefficients were found from perceived behavioural control to perceived robustness (0.351), adaptability (0.371), and transformability (0.385). This suggests that farmers with higher perceived behavioural control were more certain about their ability to tackle risks using their resilience capacities (Clare et al. 2017). Farmers' formal networks were positively related to robustness and adaptability, while informal networks were related to none of the resilience capacities. These findings suggest that farmers could use their formal networks to implement robustness and adaptation strategies, while informal networks are not exploited. Finally, a positive association between innovation and adaptability was found, suggesting that more innovative farmers are better able to adapt. This is line with Anderson and McLachlan (2012), who found that innovative Canadian farmers were able to improve adaptability to overcome mad cow disease.

R^2 values of 0.186, 0.282, 0.334 were obtained for respectively perceived robustness, adaptability, and transformability (Appendix 1; Table A1.5). The exploratory aim of this study in combination with the complexity of resilience explains the relatively low R^2 values. Consequently, the f^2 effect sizes are relatively low as well (Appendix 1; Table A1.6). The out-of-sample predictive relevance is confirmed as all Q^2 values are above zero (Appendix 1; Table A1.5).

2.5.3 Multi-group analysis

The MICOM-procedure confirmed partial measurement invariance (Appendix 1; Table A1.8 and A1.9), indicating that the subsets *Low* and *High* are suitable for MGA to investigate the importance of farm income in predicting differences in perceived resilience (Henseler, Ringle and Sarstedt 2016). Table 2.3 shows that the Cronbach's alpha values of perceived behavioural control for the group *High* (0.693) is slightly below the threshold of 0.7. No adjustments to the measurement model were made, as it is important to compare exactly the same models while conducting a MGA PLS-SEM. Therefore, we conclude that satisfactory reliability and validity levels of the reflective and formative measurement model were obtained.

Some path coefficients are significant for either *Low* or *High*, indicating that both groups have different constructs associated with the perceived resilience capacities (Table 2.4). The results of the permutation test with 3,000 permutations (Chin and Dibbern 2010) indicate significant differences between *Low* and *High* for the path coefficients *RISK PREF → RISK PERC*, *RISK PERC → ROB, RISK PREF → ROB,* and *NET FOR → ROB*. Noteworthy are the path coefficients *RM → TRANS* and *RM → RES*, which are only significant for the group *Low*. To ensure robust estimation results, a sensitivity analysis with different threshold values for *High* (i.e. 35, 40, and 45 points) was conducted. No threshold values lower than 30 were selected as this would have resulted into extremely unequal sample sizes of both groups. Almost all path coefficients maintained the same direction and level of significance, indicating fairly robust estimation results. We will further detail the relationship between risk management and perceived transformability.

Only for farmers who perceived obtaining farm income as less important, a more diverse risk management portfolio is positively related to perceived transformability. Note that only the total effects are significant, indicating that the sum of the direct and indirect effects together shape perceived transformability. A possible explanation for this could be that farmers who prioritized income less, found a mix of other functions, including the provision of public goods, more important. This could imply that these farmers use risk management strategies to become better aware of potential opportunities for radical change. Additionally, farmers who prioritized income less, perceived themselves as better able to transform and obtained higher perceived behavioural control than those farmers who perceived income more important (Appendix 1; Table A1.11). These differences in intrinsic motivations shape farmers' decision-making (Greiner and Gregg 2011) and might be associated with differences in perceived transformability.

2.6 Discussion and conclusions

This chapter explores how risk behaviour is related to perceived farm resilience. First, we have examined how farmers' perceived resilience capacities are associated with future resilience and how risk management, perceptions, and preferences are related to perceived resilience. All perceived resilience capacities are positively associated with perceived future resilience, indicating that the most resilient future farms obtain high levels of perceived robustness, adaptability, and transformability. Additionally, more diverse risk management portfolios are associated with farmers with higher perceived adaptability and future resilience. Second, we have investigated differences in terms of perceived resilience between farmers who perceive farm income as being less important and those who prioritize farm income. Higher perceived transformability is obtained for farmers who perceive farm income as being less important. Only for these farmers, a more diverse risk management portfolio is positively associated with perceived transformability.

To ensure the validity of our findings, a successful translation of the complex and latent nature of perceived resilience into a comprehensible and measurable construct is needed. In other words, it requires translation validity, i.e. the degree to which the operationalized construct is translated into measurable items (Onwuegbuzie et al. 2016). Three actions were taken to ensure translation validity. First, we based our perceived resilience statements on previous frameworks (Marshall and Marshall 2007, Clare et al. 2017, Jones and d'Errico 2019). Second, all resilience capacities were introduced with a short non-agricultural example to ensure that all statements were commonly interpreted. Third, we received feedback from an interdisciplinary group of researchers and specifically asked farmers to review all resilience statements when we pre-tested the survey. Several statements were rephrased based on the received feedback. Jointly, these three actions ensure translation validity (Netemeyer, Bearden and Sharma 2003).

A limitation of this study is that it did not consider the potential trade-offs between perceived robustness, adaptability, and transformability. For instance, improving perceived robustness by creating financial buffers, might result in farms that perceive themselves as being less able to adapt or transform. These additional insights are valuable to understand the potential costs of improving one resilience capacity. This motivates future research, which could investigate the potential trade-offs between robustness, adaptability, and transformability using panel data approaches.

Our findings have implications for agricultural policy makers and farmers. First, our results indicate that more diverse risk management portfolios, consisting of a combination of economic environmental and social strategies, associate with higher perceived adaptability and transformability. Most current European agricultural policies primarily consider robustness and emphasize how to tackle short-term risks (Candel, Termeer and Meuwissen 2018). However, to ensure a resilient future for farmers, policies should also stimulate farm adaptation and transformation (Ohlund, Zurek and Hammer 2015). To this end, policy makers could consider shifting from a narrow-minded view on risk management, where one specific tool is emphasized aiming to enhance robustness, to a holistic approach that highlights the importance of diverse risk management portfolios (Coffey and Schroeder 2019, Meraner and Finger 2019, Vigani and Kathage 2019). In this way, risk management has the potential to enhance adaptability and transformability. Second, this study has implications for farmers because our findings show that resilient farmers combine robustness, adaptability, and transformability to overcome unknown future risks using a diversity of risk management strategies.

3 Exploring the contribution of social networks and learning to the resilience of Dutch arable farmers

This chapter is based on the paper: Slijper, T., Urquhart, J., Poortvliet, P.M., Soriano, B., Meuwissen, M.P.M. (2021). Exploring the contribution of social networks and learning to the resilience of Dutch arable farmers. Submitted to a journal.

Abstract

Enhancing farm resilience has become a key policy objective of the EU's Common Agricultural Policy (CAP) to help farmers dealing with numerous interrelated economic, environmental, social, and institutional shocks and stresses. A central theme in resilience thinking is the role of the unknown, inherently implying that knowledge is incomplete and that change, uncertainty, and surprise are inevitable. Important strategies to enhance resilience are engaging in social networks and learning as these contribute to building social capital, improving knowledge, and preparing farmers for change. This chapter explores how social networks and learning contribute to farm resilience along the dimensions of robustness, adaptation, and transformation. We study the resilience of Dutch arable farmers from the Veenkoloniën and Oldambt using a combination of four methods. Qualitative data from semi-structured farmer interviews, focus groups, and expert interviews are combined with quantitative data from farmer surveys. The qualitative data are analysed using thematic coding. Non-parametric tests are used to analyse the quantitative data. Based on methodological triangulation, we mostly find convergence in our qualitative and quantitative datasets, which increases the validity of our findings. The results reveal that social networks and learning mostly help farmers to adapt and, in certain cases, also foster robustness and transformation. Robustness-enhancing strategies include exploiting farmers' informal social networks to build bonding social capital, acquiring knowledge about agriculture, and developing financial skills. Farmers undertaking adaptation benefit from bonding and bridging social capital obtained by formal and informal networks, are early adopters of innovation, and have high self-efficacy. Transformations are enhanced by linking social capital from formal networks. This allows farmers to learn radical new ideas and critically reflect on current farm business models. This study contributes to a deeper understanding of the dynamic relationship between farmers' social networks and learning and how these concepts affect decision-making and enhance resilience. We make a theoretical contribution by presenting a revised conceptual framework on how social networks and learning contribute to farm resilience. Our findings are relevant for agricultural policy makers, as we provide recommendations on how social networks and learning can enhance farm adaptation and transformation and improve information exchange in Agricultural Knowledge and Innovation Systems (AKIS) by exploiting farmers' social capital.

Keywords

Learning, social network, social capital, resilience, robustness, adaptation, transformation

3.1 Introduction

In an unpredictable world where farmers face numerous economic, environmental, institutional, and social shocks and stresses, enhancing resilience has become a key policy objective of the EU's Common Agricultural Policy (European Commission 2020a). Resilience involves a farm's ability to provide functions (i.e. public and private goods) while facing shocks and stresses through the resilience capacities of robustness, adaptability, and transformability (Meuwissen et al. 2019). While robustness relates to stability and the maintenance of current production practices, adaptation and transformation require the ability to change and to be flexible (Folke 2016). Adaptation is reflected by changes in a farm's input and output composition as a response to shocks and stresses (Meuwissen et al. 2019). Transformation involves more radical changes in the farm structure (Darnhofer 2014). Resilience theory recognises the role of the unknown in the complex and dynamic farm operating environment (Cabell and Oelofse 2012, Darnhofer 2014), inherently implying that knowledge is incomplete and that change, uncertainty, and surprise are inevitable. Farmers, therefore, need various anticipating, coping, and responding strategies to deal with shocks and stresses across economic, environmental, and social dimensions (Mathijs and Wauters 2020). Developing these strategies requires social networks and learning, as these contribute to building social capital, improving knowledge, and preparing farmers for change, uncertainty, and surprise (Cundill et al. 2015).

The aim of this chapter is to explore how farmers' social networks and learning contribute to perceived resilience in terms of robustness, adaptation, and transformation. Social networks are directly and indirectly related to resilience. The direct relationship describes how social networks enhance resilience by improving farmers' self-organisation (Cabell and Oelofse 2012). However, this relationship does not consider the dynamic interplay between social networks and learning. These dynamics are captured by the indirect relationship that describes how social networks allow knowledge to be exchanged and are a source of information, which fosters farmers' ability to learn (Dolinska and d'Aquino 2016, Skaalsveen, Ingram and Urquhart 2020, Thomas, Riley and Spees 2020) and builds social capital, ultimately enhancing resilience (Barnes et al. 2017, Barnes et al. 2020). This chapter focuses on this indirect relationship among social networks, learning and resilience.

A large array of conceptual studies have addressed how learning can be embedded in a resilience framework, including how social networks enable social learning (De Kraker 2017, Phuong, Biesbroek and Wals 2017), transformative learning (Tarnoczi 2011, Pahl-Wostl et al. 2013), normative, cognitive, and relational learning (Huitema, Cornelisse and Ottow 2010, Baird et al. 2014), and single, double, and triple-loop learning (Pahl-Wostl et al. 2013, Cundill et al. 2015, De Kraker 2017). This resulted in several empirical studies that have investigated how learning contributes to resilience or to one of the resilience capacities. For instance, Glover (2012) found that learning from both successes and failures strengthened the resilience of English farms by increasing the ability to deal with adverse events. However, most of the existing studies focus on how learning enhances farm adaptation. These studies provide useful insights into how learning enhances farm adaptation by improving farmers' ability to deal with uncertainty, dynamics, and complexity (Milestad and Darnhofer 2003, Darnhofer 2010, Milestad, Geber and Björklund 2010), increasing knowledge about challenges (Darnhofer 2010, Maguire-Rajpaul, Khatun and Hirons 2020), improving reflexivity (Pelling et al. 2008), or stimulating experimentation (Tarnoczi 2011). Recently, other scholars explored the role of learning in facilitating transformations and demonstrated how radically changing perceptions, preferences, values, and norms may facilitate transformations (Park et al. 2012, Marshall et al. 2014, Scholz and Methner 2020).

Barring a notable exception of Spiegel et al. (2020), none of these studies considered how learning contributes to resilience along the dimensions of robustness, adaptation, and transformation simultaneously. It is important to consider all three resilience capacities to fully understand how farmers cope and respond to shocks and stresses. The contribution of this chapter is twofold. First, this chapter expands the framework of Spiegel et al. (2020)—who described the learning attributes and strategies that enhance robustness, adaptation, and transformation in 11 European farming systems—by exploring the relationships between social networks and learning. We build on the conceptual framework of De Kraker (2017) that emphasises the current learning setting, learning processes, and learning outcomes to provide a more systematic view on how learning contributes to resilience. Second, based on our findings, we introduce a revised framework to better capture the dynamic nature of learning. This chapter builds on data originating from four methods. It draws on qualitative data from semi-structured interviews, focus groups, and expert interviews and quantitative data from farmer surveys to explore how farmers' social networks, learning processes, and outcomes have the potential to facilitate robustness, adaptation, and transformation. We focus on Dutch arable farmers from the Veenkoloniën and Oldambt. These farmers face several interrelated shocks and stresses, including droughts, societal pressure to change towards less intensive production systems, and changing regulations. Farmers have demonstrated an openness to change as a response to these shocks and stresses (Coopmans et al. 2021). This makes this case study suitable for studying resilience. We contribute to a better understanding of the role of social networks and learning in shaping farmer decision-making and facilitating the anticipating, coping, and responding strategies employed by farmers. This makes our findings of interest to agricultural policy makers.

3.2 Conceptualising how social networks and learning contribute to the resilience capacities

This section describes how social networks and learning may contribute to resilience. First, we explain how social networks stimulate farmers to learn by encouraging knowledge sharing (Figure 3.1). Second, the conceptual framework describes how learning may impact farm resilience. Many existing studies conceptualise how learning relates to decision-making or changes in behaviour without considering how learning affects resilience (see e.g. Gerlak and Heikkila 2011, Siebenhüner, Rodela and Ecker 2016, Suškevičs et al. 2018). These studies underline the importance of the setting to foster learning, learning processes, and learning outcomes to change behaviour or affect decision-making. Following Cundill et al. (2015) and

De Kraker (2017), we expand these frameworks by describing how decision-making affects resilience (Figure 3.1). Section 3.2.1 describes the relationship between social networks and learning and section 3.2.2 elaborates on how learning is associated with resilience.

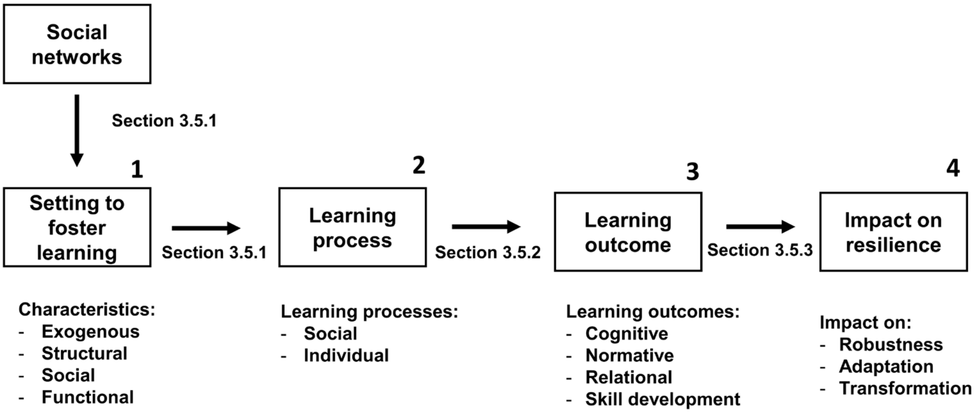

Figure 3.1 Conceptual framework that describes how learning relates to farm resilience, adapted from De Kraker (2017). Sections refer to the sections discussing a specific stage of the framework.

3.2.1 Social networks, learning, and resilience

Social networks are the social relationships between individuals and/or groups (Barnes et al. 2017), which can be divided into informal and formal networks. Informal and formal networks are concepts without clear boundaries and can be understood as a continuum ranging from most informal to most formal relationships (Pautasso et al. 2012). Informal networks are farmers' relationships to close friends, family, and farming colleagues that mostly contribute to farmers' agricultural knowledge (Hunecke et al. 2017). Formal networks reflect relationships with actors that could provide new information sources about radically new ideas, such as cooperatives or local government institutions (Hunecke et al. 2017). Furthermore, social networks may facilitate social learning processes in which farmers learn from others as larger networks with stronger ties increase the adoption of learning processes (Thomas, Riley and Spees 2020). Figure 3.1 portrays how social networks create a setting to foster learning that facilitates knowledge sharing (Barnes et al. 2017).

The interplay between social networks and learning can contribute to resilience by building three types of social capital: bonding, bridging, and linking social capital (Szreter and Woolcock 2004). Bonding social capital mostly relates to informal relationships with similar actors that are trusted, willing to cooperate, and have strong ties (Klerkx and Proctor 2013). For example, relationships with farming colleagues could help to build bonding social capital. Bridging social capital refers to relations between actors that are less similar and consist of more formal relationships with less trust and weaker ties (Cofré-Bravo, Klerkx and Engler

2019). Such relationships could be between farmers and agronomists or other advisors. Linking social capital is described by farmers' most formal relationships with actors or institutions that share few similarities and often differ in terms of power, reflecting vertical relationships rather than horizontal ones (Szreter and Woolcock 2004)—e.g. communication between farmers' and local governments. All three types of social capital have the potential to enhance resilience. Bonding social capital stimulates learning with peers about agricultural practices, resulting in more complete information about existing farm practices. This helps farmers to make better-informed decisions related to agriculture and has the potential to enhance robustness. Bridging and linking social capital are important to obtain new sources of information and to learn about (radically) new ideas, potentially fostering, respectively, adaptation and transformation (Barnes et al. 2017, Barnes et al. 2020).

3.2.2 Moving from learning to resilience

Figure 3.1 illustrates the four stages that explain how learning can contribute to resilience: (i) the setting to foster learning, (ii) learning processes, (iii) learning outcomes, and (iv) impact on resilience.

The setting to foster learning describes the physical and social context that stimulates or constrains learning processes (Pahl-Wostl et al. 2007, Diduck et al. 2012). Exogenous factors, such as the risks faced by farmers or new regulations, affect the setting to learn. These exogenous factors determine a farmer's motivation to learn by affecting the perceived frequency, severity, and direct involvement with risk (Leeuwis and van den Ban 2004). Furthermore, we distinguish three physical and/or social characteristics that affect the setting to learn: (i) structural characteristics, (ii) social characteristics, and (iii) functional characteristics (Gerlak and Heikkila 2011). First, structural characteristics describe how learning is structured between farms and other actors. This is affected by the institutional design describing the formal rules in which farms operate (e.g. policies, regulations, and market structures) and the degree of integration between actors, which is shaped by farmers' formal and informal networks (Pahl-Wostl et al. 2013, De Kraker 2017, Joffre, Poortvliet and Klerkx 2019). Second, social characteristics are the relationships and communication patterns among actors that are shaped by farmers' social networks (Gerlak and Heikkila 2011). Examples of these social characteristics are trust (Ensor and Harvey 2015, Joffre et al. 2020), the willingness to share information, take risk, or experiment with others (Lipshitz, Popper and Friedman 2002), and the existence of leaders (Gerlak and Heikkila 2011). Leaders are early adopters of innovations that may or may not facilitate learning processes depending on their willingness to share information. Third, the functional domain determines what and how information can be shared (Gerlak and Heikkila 2011). Social networks may facilitate learning platforms to share information in order to foster both social learning (e.g. study clubs) and individual learning (e.g. having access to information on the internet).

The second stage describes the social and individual learning processes adopted by farmers. Learning processes exploit the setting to foster learning by describing how and with whom farmers learn. Examples of learning processes are experimentation (Ingram 2010, Kummer et al. 2012, Darnhofer et al. 2016, Šūmane et al. 2018), being open to new ideas (Darnhofer 2010, Cofré-Bravo, Klerkx and Engler 2019), learning from others (Ingram 2010, Dolinska and d'Aquino 2016), seeking out new information (Suškevičs et al. 2018), learning new skills (Conley and Udry 2010), being flexible (Carlisle 2014), and reflexivity (Sinclair et al. 2017).

The third stage investigates how learning processes result in learning outcomes. Learning outcomes can be changes in the structural, social, and functional characteristics described in stage 1. We distinguish four types of learning outcomes: (i) cognitive changes, (ii) normative changes, (iii) relational changes, and (iv) skill development. While the classification of cognitive, normative, and relational learning has been developed in earlier studies (e.g. Huitema, Cornelisse and Ottow 2010, Haug, Huitema and Wenzler 2011, Baird et al. 2014), we add skill development as a fourth learning outcome because farmers often learn by doing, trial-and-error, and experimentation to develop practical skills. Cognitive learning outcomes reflect changes in knowledge acquisition and creation (Albert et al. 2012) or an increased understanding of risk and uncertainty (Baird et al. 2014, Hordijk, Sara and Sutherland 2014). Normative learning outcomes are changes in perceptions, preferences, attitudes, values or norms that potentially affect decision-making (Baird et al. 2014). Relational learning outcomes are changes in attitudes and/or perceptions towards existing relationships (Siebenhüner, Rodela and Ecker 2016, Suškevičs et al. 2018) or changing relationships—e.g. building trust or solving conflicts (Muro and Jeffrey 2008). Relational learning outcomes could also affect social networks and help to build social capital. Finally, skill development leads to improved social and communicative skills (Albert et al. 2012), a better ability to deal with uncertainty and change (Armitage et al. 2011, Folke 2016), and acquired task-oriented and/or technical skills, including learning to use new technologies for improved production (Sinclair et al. 2017). It is still being debated whether the four learning outcomes are hierarchically interrelated or can be studied in isolation. Studies that have described this hierarchical interrelationship are embedded within single, double, and triple-loop learning literature. Single-loop learning tends to be associated with cognitive learning outcomes, while double and triple-loop learning may require 'deeper' normative learning outcomes (Armitage, Marschke and Plummer 2008). However, Baird et al. (2014), describe that these interrelations in learning outcomes do not always hold and can be in conflict with other learning outcomes. For instance, normative learning outcomes do not necessarily have to be the result of cognitive learning outcomes. Therefore, we study the four learning outcomes in isolation without considering any hierarchical interrelationships.

The fourth stage explains how learning outcomes change behaviour and decision-making that potentially affect farm resilience. These changes in behaviour and decision-making reveal how farmers have responded to shocks and stresses. The combination of decision-making strategies ultimately affects farm resilience along the dimensions of robustness, adaptation, and transformation (De Kraker 2017). One should be aware that not all learning outcomes necessarily lead to behavioural changes or affect decision-making (Muro and Jeffrey 2008). Hence, learning does not always have an impact on resilience. Furthermore, decision-making is not solely shaped by learning outcomes, as other factors, such as farm characteristics or past experiences, also play a role in decision-making.

3.3 Data and methods

We used a combination of four methods from the SURE-Farm[1] project: (i) semi-structured farmer interviews, (ii) farmer surveys, (iii) a focus group with farmers and other local stakeholders, and (iv) expert interviews with local experts who had extensive knowledge about past and current developments in the case study region. Data collection took place between April 2018 and November 2019. All methods discussed the following: farmers' capacity to learn, social networks, regional shocks and stresses, and resilience. All respondents participating in any of the methods were provided with information about the study to enable them to decide whether to take part and were asked to sign a consent form before data collection to indicate their willingness to participate.

Table 3.1 provides a chronological overview of the methods and data collection. Each stage of the conceptual framework has been addressed by at least two methods. Section 3.3.1–3.3.4 provide more details on each method. The chosen methods to investigate learning (Urquhart et al. 2019, Spiegel et al. 2020), social networks (Oreszczyn, Lane and Carr 2010, Bertolozzi-Caredio et al. 2021), and resilience (Urquhart et al. 2019, Slijper et al. 2020) were used in previous studies, ensuring that their validity and reliability have been established previously.

Datasets were separately analysed and compared for convergence, complementarity, and divergence (Nightingale 2009). The validity of our findings increases if triangulation revealed that results converged into a common understanding across methods (Carter et al. 2014). To identify sufficiently large sample sizes for the qualitative methods, criteria based on data saturation were adopted. Data saturation occurs if increasing the sample size does not introduce new themes or findings (Saunders et al. 2018). Although the presented sample size of each qualitative method in Table 3.1 (i.e. semi-structured interviews, focus group, and expert interviews) could be considered small, we argue that data saturation can still be obtained if triangulation reveals convergence across methods (Fusch and Ness 2015). This implies that a common understanding that is verified by different methods can be used to secure the overall validity of our findings, despite being limited by the small sample size of each qualitative method.

[1] SURE-Farm: towards SUstainable and REsilient FARMing systems.

Table 3.1 Overview of methods and data collection, ordered chronologically.

Method	Actors involved in a method	Timing	Number of respondents	Stages conceptual framework
Semi-structured interviews	Farmer	June–December 2018	10	1, 2, 3, and 4
Survey	Farmer	November–December 2018	71	1, 2, 3, and 4
Focus group	Farmer and local stakeholders (2 arable farmers, policy maker, agricultural insurer, crop protection producer	September 2019	5 participants (1 focus group)	1, 2, and 3
Expert interviews	Local experts (regional innovation platform and starch potato cooperative)	April 2018 and November 2019	2	1

3.3.1 Semi-structured interviews

Ten qualitative semi-structured interviews with arable farmers were conducted; participants were recruited with the assistance of gatekeepers from (young) farmer organisations, local study clubs, and innovation platforms. 49 farmers were approached by e-mail, followed up by phone calls resulting in a response rate of 20%. Purposive sampling was used to cover a diverse range of farmers, of which some farms went through big changes while other farms have remained stable over time. This variety of farms helps to understand robustness, adaptation, and transformation. The interviews lasted between 50 and 95 minutes and were conducted in the period June–December 2018. All interviews were audio-recorded and transcribed verbatim. An analytical memo was written to briefly reflect on each interview and summarise key findings. The interviews discussed the farm history, on-farm changes in the past 10–20 years, farmers' experience with learning, and social networks. Social networks were elicited using influence maps, which captured farmers' networks of influence to better understand the setting in which social learning takes place by interactively mapping the main influencers that shape decision-making (Oreszczyn, Lane and Carr 2010). Farmers were asked to place all actors influencing their daily decision-making on a circular grid consisting of six circles. The most influential actors were placed in the central circle of the grid (1) and the least influential actors were placed in the most outside circle (6). The completed influence maps were photographed and the data was recorded in an Excel-file.

The interviews were thematically analysed based on a pre-designed codebook (Urquhart et al. 2019). The codebook identified the four stages of the conceptual framework by classifying: (i) how farmers have dealt with shocks and stresses and who influenced decisions (stage 1), (ii) learning processes (stage 2), (iii) learning outcomes (stage 3), and (iv) on-farm changes in the past 20 years (stage 4). Stage 4 was inferred from the interviews, indicating that we derived the revealed resilience capacities of a farm by studying the changes or stability of a farm over time. We distinguished between farms that absorbed and maintained the status quo despite facing shocks and stresses (robustness) from farms that changed inputs and outputs over time (adaptation), such as experimenting with new crops or early-adopting innovations. Finally, those farms that went through radical changes were classified as being transformed. ATLAS.ti (version 9.0) was used to code the interviews (Muhr 2013).

3.3.2 Survey

The quantitative survey measured farmers' (i) informal and formal networks, (ii) learning processes adopted in the last five years, (iii) learning outcomes, and (iv) perceived robustness, adaptability, and transformability. The survey used closed questions; most of them were based on a 7-point Likert scale. The specific wording of all statements and descriptive statistics can be found in Appendix 2. Farmers completed the survey in the period November–December 2018. The survey was sent out by email to a random sample of about 9,000 Dutch farmers by a major agricultural publisher. Note that the survey was sent out to Dutch farmers in general, including farmers that were not located in the case study region and/or different farm types. This resulted in a total sample of 1,537 respondents (17% response rate) of which a subset of 71 arable farmers from Northern and Eastern Netherlands was selected to match our case study. The low response rate can be explained by the fact that the survey has been sent out by e-mail, which can be easily ignored. It took approximately 30 minutes to complete the survey. For more details on the survey design, pre-testing, data availability and assessments of internal consistency reliability, convergent validity, and discriminant validity, see Slijper et al. (2020).

We investigated if farmers' informal networks were larger than their formal networks (stage 1) using the Wilcoxon signed-rank test for paired measurements. An overview of the most adopted learning processes was presented in stage 2. Furthermore, we explored if farmers who had actively learned in the past five years differ from farmers who had not learned in terms of several learning outcomes (stage 3) and perceived resilience capacities (stage 4) using the Mann-Whitney U test. Non-parametric tests were used because of the ordinal measurement scale resulting from Likert items.

3.3.3 Focus group

The qualitative focus group sets out to investigate how farmers and other regional stakeholders perceived (i) the setting to foster learning by studying shocks and stresses, (ii) social networks, and (iii) learning processes and outcomes. Participants were recruited using the network of a local innovation platform and experimental farm. Purposive sampling yielded five participants (two arable farmers, a local policy maker, a representative from an agricultural insurance company, and a crop protection producer), representing different stakeholders of farmers' social networks. The focus group was conducted in September 2019 and lasted approximately 3 hours. The researchers took notes during the focus group. Participants were asked to complete forms to individually describe the existing social networks and the role of each actor in the social network. Afterwards, a plenary discussion followed to reflect on the findings and look for convergence of results. The data was analysed using thematic coding based on a pre-designed codebook to investigate the role of each social network actor in the setting to foster learning, learning processes, and learning outcomes. Bertolozzi-Caredio et al. (2021) provide more details on the methodology and analysis of the focus group.

3.3.4 Expert interviews

Two expert interviews were conducted. The first expert worked at the research and development department of a large starch potato cooperative; the second expert worked for a local innovation platform. Both experts had a good overview of past developments in the case study region and had assisted arable farmers in the past. Both interviews lasted approximately 60 minutes; interviews were audio-recorded and summarised afterwards. Short analytical memos were taken directly after each interview to summarise key findings. The first expert interview was conducted before the start of all other data collection (April 2018). We discussed the current setting to learn, social networks, and the most important shocks and stresses in the region. During the second expert interview (conducted in November 2019), we verified the findings from the other methods and reflected on recent changes in the regional learning setting and learning platforms.

3.4 Case study

We study the resilience of intensive arable farms from the Veenkoloniën and Oldambt, a region located in the north-east of the Netherlands (Figure 3.2). Most of the agricultural land is used for arable farming practices. The region follows the general trend of reducing farm numbers, while the remaining farms increase in farm size (Spiegel et al. 2021a). Furthermore, the region is characterised by different soil types ranging from peat soils that are mixed with sand to heavy clay soil, where only limited crop rotation schemes are possible (Prins et al. 2011). Starch potato and winter wheat function as main crops, rotated with mostly sugar beet and rapeseed (Immenga, Munneke and Lamain 2012). Recently, arable farmers started experimenting with new crops, including onions, blueberries, carrots, and bulb flowers. More regional details will be presented in section 3.5.1, where we discuss the regional setting to foster learning.

Figure 3.2 Map of the Netherlands, highlighting the Veenkoloniën and Oldambt with diagonal lines.

3.5 Results

The results describe how learning and social networks contribute to farm resilience. We structured the results based on the four stages of the conceptual framework (Figure 3.1). Section 3.5.1 discusses how social networks and the regional setting fosters or constrains learning processes. Section 3.5.2 presents how learning processes shape learning outcomes. Section 3.5.3 describes how social networks and learning outcomes enhance farm resilience.

3.5.1 Social networks, the setting to foster learning, and learning processes

This section provides an overview of farmers' social networks (section 3.5.1.1) and presents how the setting to foster learning influences learning processes (section 3.5.1.2).

3.5.1.1 How social networks shape the setting to foster learning

We investigated which network actors facilitate learning on a continuum ranging from informal to formal networks. Table 3.2 shows that there were seven key actors involved in farmers' social networks: (i) people on the farm and farming colleagues, (ii) advisors, (iii) cooperatives, (iv) insurance companies, (v) banks, (vi) media, and (vii) local, regional, and national governments. Most findings converged across methods, as all network actors were consistently identified by at least two methods in terms of mutual dependence or a unilateral relationship. Power differences were reflected by unilateral relationships, which imply that a network actor affected farmers but that farmers did not affect the network actor. We briefly discuss two actors that were subject to divergence across methods: advisors and insurance companies. During the focus group, advisors were excluded from social networks as participants indicated that there was an overlap between the role of advisors and cooperatives. Cooperatives often employed representatives who regularly visited farms to provide advice. During the semi-structured interviews, farmers indicated that insurance companies were not considered as network actors and had no influence on their decisions, while the focus group and expert interviews with non-farmers suggested that insurance companies were part of farmers' networks. Several farmers described high insurance premiums and high levels of own risk when defaulting as constraining factors to buy insurance. During one of the semi-structured interviews, a farmer mentioned negative experiences with filing insurance claims as a trigger to end his insurance: "*We had big losses on our farm and then you need to submit such an insurance claim. Well... that was a tough negotiation process with the insurance company. We put a lot of effort into this claim... eventually, it worked out. But for me, that was the trigger to end my insurance*" (R2).

In line with Klerkx and Proctor (2013), we found that farmers' informal networks contributed to bonding social capital resulting from informal relationships with strong ties, high levels of trust, and shared norms and values. Informal networks had a greater influence on decision-making than actors that were part of formal networks. Often, informal actors facilitated learning by providing agricultural-related information. Relationships that moved in the direction of formal networks were characterised by slightly weaker ties and lower trust. Hence, these actors had less influence on daily decision-making. If farmers learned from their formal networks, it typically contributed to bridging and linking social capital by providing new sources of information, sometimes even leading to radically new ideas. In general, we found that less formal relationships contributed to bonding social capital and that the most formal relationships contributed to linking social capital (Cofré-Bravo, Klerkx and Engler 2019). However, not all farmers were able to build linking social capital. Often, red tape and too formal ties, as a result of large power differences, were listed as constraining factors by farmers to learn from their formal networks.

Results from the survey indicated that farmers perceived their informal networks (mean = 5.70, median = 6.00), as being larger than their formal networks (mean = 5.35, median = 5.00). The Wilcoxon signed-rank test confirmed that the median ranks of farmers' informal network size were larger than the median ranks of formal networks (p = 0.018). However, the tie strength of the informal (mean = 4.87, median = 5.00) and formal networks (mean = 4.79, median = 5.00) were comparable, as the Wilcoxon signed-rank test revealed no significant differences (p = 0.620).

Table 3.2 Comparison of the actors involved in farmers' social networks, ranging from informal relationships (informal network) to formal relationships (formal network). Mutual or unilateral reflects the influential nature of the relationship. Mutual indicates that the farm and the actor both influence each other. Unilateral indicates that the actor influences the farm, but the farm does not influence the actor.

	Actor	Semi-structured interviews[1]	Focus group	Expert interviews[2]
Informal network	People on the farm and farming colleagues	Mutual	Mutual	Mutual
↓	Advisors (e.g. agronomist, accountant)	Mutual		Mutual
	Cooperatives	Mutual	Mutual	Mutual
	Insurance company		Unilateral	Unilateral
	Bank	Unilateral	Unilateral	Unilateral
	Media (e.g. social media, news)	Unilateral		Unilateral
Formal network	Local, regional, and national government	Unilateral	Unilateral	

Notes: [1]Actors are included if they were mentioned by at least 50% of the influence maps. [2] Based on the first expert interview.

3.5.1.2 How the current setting to foster learning influences learning processes

Table 3.3 describes the current setting to foster learning and how the setting to foster learning shapes farmers' learning processes, which is based on the semi-structured interviews, focus groups, and expert interviews. In general, our findings converged into a common description of the setting to foster learning. The results revealed that the most important exogenous factors affecting the setting to foster learning were extreme weather events and climate change. We also found some differences across methods. For instance, low societal acceptance of intensive agricultural practices was listed by participants of the semi-structured interviews and focus groups as an important exogenous factor, whereas experts listed changing and volatile market conditions.

The structural characteristics described the integration and engagement in social networks and the regulations affecting farmers. Our results revealed that engaging in social networks stimulated farmers to start new learning processes by having improved access to information and being better able to learn from others. Change in regulations that affected farmers were the shift from coupled to decoupled CAP-payments, which decreased the payments from 450-750 €/ha to 350-400 €/ha (Spiegel et al. 2021a) or new crop protection regulations, such as the recent ban on neonicotinoids and glyphosate. Both were perceived as barriers to learn.

Three social characteristics were consistently mentioned to describe the setting to foster learning: having an entrepreneurial spirit, high levels of trust, and high willingness to cooperate. These characteristics fostered farmers' learning processes and were affected by social networks. Furthermore, farmers' willingness to take risks and self-efficacy—an individual's belief in their capacity to succeed in a task (Bandura 1977)—were sometimes listed as factors fostering the setting to learn. Our findings also revealed some divergence across methods. For instance, on the role of strong self-identities. The semi-structured interviews indicated that farmers with a strong self-identity were less open to learn, while the expert interviews illustrated that farmers who strongly identified themselves with agriculture could be either more or less open to learn, depending on what is learned. Strong agricultural self-identities fostered the setting to learn about agricultural practices, while it constrained farmers to learn about new ideas or business models. Two factors that constrained learning processes were identified. First, traditional subjective norms or values (e.g. the son should take over the farm and not the daughter or a farm should not diversify into non-agricultural activities) constrained farmers' openness to new ideas. Second, some innovative farmer leaders were not willing to share information with other farmers. For example, one of the first introducers of blueberries was not keen on sharing production details. While many farmers indicated an interest in learning about blueberries, the leader was not willing to share information to protect his status as the main supplier of blueberries.

The functional characteristics described existing learning platforms that were frequently used by farmers. Access to information on the internet and study clubs were consistently listed as good starting points to foster learning. Additionally, the semi-structured interviews revealed that farmers appreciated informal information exchange on social media and WhatsApp with peers. Social learning and networks were of importance to motivate farmers to seek out new information and learn from others (Phuong, Biesbroek and Wals 2017). For instance, new information was often acquired in the context of study clubs with other farmers and/or advisors. These interactions with social network actors created a setting to foster learning and enabled farmers to start learning processes.

Table 3.3 Comparison of key characteristics of the current setting to foster learning across methods. + indicates that a characteristic fosters the adoption of learning processes. - indicates that a characteristic constrains the adoption of learning processes +/- indicates that characteristics could either foster or constrain the adoption of learning processes. Empty cells imply that a characteristic was not discussed.

	Key characteristics	Semi-structured interviews	Focus group	Expert interviews
Exogenous factors	Climate change and/or extreme weather events	+	+	+
	Low societal acceptance of agriculture	-	-	
	Market circumstances			+
Structural characteristics	High engagement in social networks	+	+	+
	Strict and/or changing regulations	-	-	-
Social characteristics	Traditional subjective norms	-		
	Entrepreneurial spirit	+	+	+
	Leaders who were not willing to share information on innovations		-	-
	High self-efficacy	+		
	Strong self-identity as a farmer	-		+/-
	Trust	+	+	+
	Willingness to cooperate	+	+	+
	Willingness to take risk	+	+	
Functional characteristics	Access to information on social media and WhatsApp	+		
	Access to information on the internet	+	+	+
	Study clubs	+	+	+

3.5.2 Moving from learning processes to learning outcomes

Learning outcomes are changes in knowledge, behaviour, social networks, or skills. In line with Ensor and Harvey (2015), we identified that not all learning processes necessarily resulted in learning outcomes. Table 3.4 presents an overview of successful learning processes and the related categories of learning outcomes based on the semi-structured interviews, focus group, and surveys.

The survey revealed three key learning processes that were adopted by a high percentage of farmers—seeking out information (62%), learning from others (59%), and reflexivity (58%). Other learning processes were adopted at a much lower rate. In general, our findings converged across methods as the semi-structured interviews revealed that all ten farmers had adopted these three learning processes. These learning processes were also discussed during the focus group. However, we also observed some complementary findings as two learning processes were discussed during the semi-structured interviews and surveys but not during the focus group—i.e. the ability to be flexible and learning new skills. A possible explanation for this could be that the focus group combined the views of regional stakeholders and farmers on current learning processes, while the semi-structured interviews and survey elicited learning processes that were adopted in the past. The combination of different stakeholders and time horizons could make some learning processes less relevant. Furthermore, Table 3.4 shows that learning processes mostly resulted in cognitive learning outcomes, while normative, relational, and skill development were less often listed as learning outcomes. It could be that cognitive learning outcomes were easier to describe by farmers and were, therefore, more often identified. More detailed examples of learning outcomes and their impact on resilience will be discussed in section 3.5.3.

Table 3.4 Comparison of learning processes and outcomes across methods.

Learning process	Examples demonstrating learning processes[1]	Learning outcome(s)[2]	Semi-structured interviews	Focus group	Survey (%)[3]
Seeking out information	- Individually seeking out information (e.g. (social) media, internet) - Seeking out information with others (e.g. study clubs, cooperating with colleagues)	Cognitive	X	X	62%
Learning from others	- Visiting farming fairs or network events - Learning from farming colleagues - Learning from family members - Learning from specialists and experts (e.g. agronomist, accountant, bank, contractor)	Relational, skill development	X	X	59%
Reflexivity	- Learning from mistakes and successes - Reflecting on the current financial position - Reflecting on past and current farming practices (e.g. agricultural practices, diversification, financial position, openness to change)	Cognitive, normative	X	X	58%
Ability to be flexible	- Ability to respond flexibly to unexpected events - Ability to respond flexibly to expected risk (e.g. flexibility in harvesting to deal with weather risk)	Cognitive, skill development	X		35%
Learning new skills	- Learning about radically new farming practices (e.g. drastically reorganising the farm, how to run a Bed & Breakfast) - Learning how to use new technologies (e.g. precision agriculture) - Learning social skills (e.g. chairing social events, decision-making, negotiating with supply chain partners) - Learning new skills by attending agricultural education or specialised courses	Cognitive, relational, skill development	X		27%

Table 3.4 (continued) Comparison of learning processes and outcomes across methods.

Learning process	Examples demonstrating learning processes[1]	Learning outcome(s)[2]	Semi-structured interviews	Focus group	Survey (%)[3]
Experimentation	- Experimentation with new crops - Experimentation with non-agricultural activities to spread risk (e.g. solar panels) - Experimentation with more sustainable technologies to improve soil health, farm inputs or farm practices	Cognitive, skill development	X	X	23%
Being open to new ideas	- Openness to adopt new technologies - Openness to learn about agricultural shocks, stresses, and risks - Openness to new agricultural practices	Cognitive, normative	X	X	7%

Notes: [1] The examples of learning processes are included in Table 3.4 if at least 3 farmers mentioned this learning process during the semi-structured interviews or if it was discussed during the focus group. [2] Learning outcomes refer to the most occurred outcomes. If a learning outcome is not listed in this column, this implies that these learning outcomes are less often mentioned than the presented learning outcomes. [3] The percentage of farmers who had adopted a learning process is presented.

Additionally, the survey investigated if farmers who had actively learned about agricultural risk in the past five years differ in terms of several learning outcomes from farmers who had not learned about agricultural risk in the past five years. Table 3.5 reveals that the median of farmers who had learned was significantly higher in terms of knowledge about risk, openness to innovation, and perceived behavioural control—i.e. a person's perceived ability to overcome obstacles in reaching one's goals (Ajzen 2002)—while there were no significant differences in terms of willingness to take risk. Table A.1 of Appendix 2 provides more details on how the survey measured each of the latent constructs described in Table 3.5.

Table 3.5 Descriptive statistics to compare cognitive and normative learning outcomes of farmers that had actively learned with farmers who had not actively learned. Based on the farmer survey.

		Mean		Median		p-value[1]
Category	Learning outcome	Not learned	Learned	Not learned	Learned	
	N	35	36	35	36	
Cognitive	Knowledge about challenges	4.77	5.22	5.00	6.00	0.076*
	Openness to innovation	3.81	4.50	4.00	4.25	0.078*
Normative	Perceived behavioural control	4.34	4.72	4.25	4.88	0.082*
	Willingness to take risk	4.19	4.51	4.80	4.60	0.416

Notes: [1]p-values of the Mann-Whitney U test are reported. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

3.5.3 How learning outcomes affect the resilience capacities

Most of the findings demonstrating how learning enhanced resilience revealed that learning most often contributed to adaptation, while there were fewer cases that describe how learning enhanced robustness or transformation. Table 3.6 presents an overview of the learning outcomes associated with each resilience capacity and provides examples of the revealed resilience capacities.

Robust farms maintained and optimised current production processes by persevering a stable financial position, having buffers, or making required investments to continue current production processes. These farmers accumulated agricultural knowledge and often developed agricultural-related skills, had strong self-identities, low willingness to take risk, and complied with traditional norms and values. Examples of these traditional norms are that farmers should primarily focus on agriculture and a strict division between conventional and organic farming. During one of the semi-structured interviews, a farmer indicated that he felt societal pressure to change towards more sustainable and organic farming practices. However, he was not open to these changes: "*If they wanted me to become an organic farming and I get stared at every birthday party if I tell them that I am a normal farmer... then I'd rather quit farming... yeah, I won't change my farm*." (R4). Furthermore, robustness-enhancing learning outcomes helped to build bonding social capital with other arable farmers. Some robust farmers struggled with the uncertainty about or the lack of a successor, often leading to maintaining the status quo (Inwood and Sharp 2012). For instance, by delaying investments in technologies or innovations.

Some farmers adapted by changing their agricultural inputs (e.g. labour) and outputs (e.g. introducing new crops), while others adapted to societal pressure towards more sustainable production by installing solar panels or providing agricultural education to teach citizens about sustainable farm practices. Furthermore, changing consumer demands resulted in altered marketing strategies. Farmers dealt with these changing consumer demands by creating direct sales channels to retailers. In line with previous studies, we found that adaptation-enhancing learning outcomes include being an early adopter of innovation resulting from increased knowledge or positive attitudes towards new technologies (Cofré-Bravo, Klerkx and Engler 2019, Spiegel et al. 2020), having high self-efficacy (Grothmann and Patt 2005), and willingness to take risk to some extent (Slijper et al. 2020).

For instance, during one of the semi-structured interviews a farmer indicated the need to take risk to experiment with new crops: "*Yeah, farming is weighting risks and deciding. You either take risks or you cover them. Or you don't take any risks. These are the three possibilities. But I like to take risks and try out new things*" (R3). This reveals that trying out new things or experimenting with new crops are adaptations with risky outcomes that require some willingness to take risk. Adaptations were often supported by bonding and bridging social capital from informal and formal networks (Barnes et al. 2017). For instance, informal networks were often used to build bonding social capital by learning primarily from colleagues about improving labour flexibility, sharing machinery or changing crop rotations, while bridging social capital from more formal relationships (e.g. cooperatives or agronomists) facilitated adaptation by introducing farmers to new crops.

Farms that have transformed revealed changes in farm type (e.g. from mixed farming to arable farming) or radical changes in the farm business focus (e.g. a Bed & Breakfast with agriculture as secondary activity). Consistent with the literature, we found that normative learning outcomes facilitating transformations were radical changes in beliefs and values (De Kraker 2017), progressive subjective norms after critical reflection on current farm practices (Tarnoczi 2011), and a high willingness to take risk (Barnes et al. 2020). Additionally, farms that have transformed acquired knowledge of radically new ideas that often resulted in agricultural and non-agricultural skill development. Transformations potentially require unlearning existing skills, knowledge, ideas or views (see e.g. Morais-Storz and Nguyen 2017). Unlearning is often triggered by crises that force farmers to transform. An example of this was changing local regulations that forced a farmer to sell his farm. This farmer had to start farming at a different location and changed from mixed farming practices to a specialised arable farm. This radical change required unlearning knowledge about livestock farming to be able to learn about starting a new farm business and the related regulations of starting a new business. In line with Barnes et al. (2017), we found that transformations were associated with the exploitation of linking social capital from formal network actors (e.g. external or institutional actors). For instance, one of the farmers visited tourism fairs to meet local policy makers and tourist offices. The radically new ideas acquired from these actors facilitated a change in business focus from primarily farming to a Bed & Breakfast with agriculture as secondary activities, illustrating the importance of linking social capital to facilitate transformations.

Table 3.6 Overview of the learning outcomes that enhance the resilience capacities based on the semi-structured interviews.

Resilience capacity	Examples revealing a resilience capacity	Learning outcome (category)	Examples of learning outcomes associated with a resilience capacity
Robustness	- Having buffers (e.g. machinery, labour, financial) - Small or required investments that maintain the current business focus (e.g. replacing depreciated buildings or machinery) - Stable financial position and performance despite facing shocks (e.g. droughts)	Cognitive	- Increased knowledge of innovations, but being a late adopter - Increased knowledge of existing agricultural practices
		Normative	- Traditional subjective norms and values - Low willingness to take risk - Strong self-identity as a farmer
		Relational	- Increased openness to agricultural ideas as a result of increased trust in informal networks (bonding social capital) - Uncertainty about or not having a farm successor
		Skill development	- Developing financial management or agricultural-related skills
Adaptation	- Adapting to societal expectations regarding sustainability (e.g. installing solar panels or providing agricultural education) - Introducing new crops (e.g. onions or mustard) or technologies - Labour or farm input flexibility (e.g. cooperating with neighbours or having access to multiple input suppliers) - New marketing strategies (e.g. on-farm direct sales or direct sales to retailers)	Cognitive	- Increased knowledge of innovation and being an early adopter
		Normative	- High self-efficacy and perceived behavioural control - Medium willingness to take risk - Positive attitude towards new technologies
		Relational	- Combining bonding and bridging social capital from formal and informal networks to increase openness to new ideas
		Skill development	- Improved ability to be flexible (labour, harvesting) - Improved ability to cultivate new crops

Table 3.6 (continued) Overview of the learning outcomes that enhance the resilience capacities based on the semi-structured interviews.

Resilience capacity	Examples revealing a resilience capacity	Learning outcome (category)	Examples of learning outcomes associated with a resilience capacity
Transformation	- Changing farm type (e.g. changing from mixed farming to specialised arable farming) - Radically changing the business focus (e.g. from primarily arable farming to Bed & Breakfast)	Cognitive	- Increased knowledge of radically new ideas
		Normative	- Critical reflection on long-term business focus, resulting in radically new beliefs and values - High willingness to take risk - Progressive subjective norms - Unlearning existing skills, knowledge, ideas or views
		Relational	- Building linking social capital from formal networks, resulting in increased openness to radically new ideas
		Skill development	- Developing agricultural and non-agricultural related skills, including social skills

Table 3.7 compares the perceived robustness, adaptability, and transformability of farmers who had learned to those who had not learned, drawing on the survey data. Appendix 2 provides more details about the items used to measure the three resilience capacities. Our findings revealed that farmers who had learned obtained significantly higher medians for adaptation. Although the mean and median scores of robustness and transformability from farmers who had learned were slightly higher, no significant differences were found. It remains uncertain if these findings confirm the results of the semi-structured interviews—which revealed that learning was associated most often with adaptation and that the contribution of learning to robustness and transformation was less often observed in our data—as no significant differences in terms of robustness and transformability were found.

Table 3.7 Summary statistics comparing the perceived resilience of farmers that have actively learned to farmers who have not actively learned. Based on the farmer survey.

	Mean		Median		p-value[1]
	Not learned	Learned	Not learned	Learned	
N	35	36	35	36	
Robustness	4.29	4.59	4.33	4.67	0.283
Adaptability	4.60	5.19	4.33	5.17	0.040^{**}
Transformability	4.32	4.39	4.33	4.67	0.786

Notes: [1]p-value of the Mann-Whitney U test are reported. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

3.6 Discussion

The discussion consists of two sections; section 3.6.1 discusses a revised framework on how learning and social networks contribute to farm resilience. Section 3.6.2 reflects on the combination of methods used in this study and discusses the limitations of this study.

3.6.1 A revised framework on how social networks and learning contribute to resilience

When comparing our findings to the conceptual framework of De Kraker (2017), we found three additional relationships that are important to understand how social networks and learning contribute to farm resilience. Figure 3.3 presents a revised framework that includes the following changes to describe that learning is an iterative and cumulative process: (i) (relational) learning outcomes sometimes result in changes in social networks, (ii) learning outcomes and learning processes are interrelated, and (iii) learning outcomes may affect the setting to foster learning. These three changes underline the importance of *what* is learned by farmers (learning outcomes) instead of focussing on *how* farmers learn (learning processes), as similar learning outcomes can be the result of different learning processes.

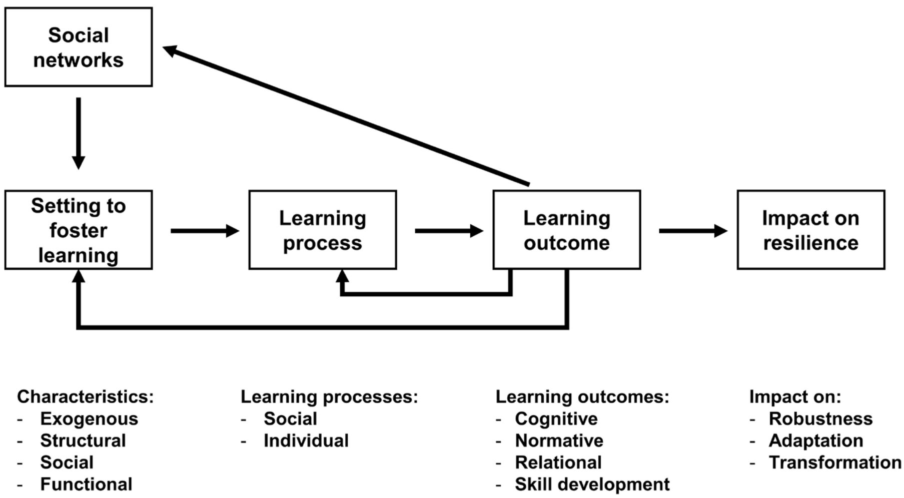

Figure 3.3 Revised framework describing how learning and social networks contribute to farm resilience.

First, our results revealed a dynamic interplay between social networks and learning. On the one hand, social networks shaped the setting to foster learning in terms of structural and functional characteristics as the mix of formal or informal relationships determine how farmers learn. This inherently relates to the adoption of learning processes as a result of sharing knowledge and information across network actors (Klerkx and Proctor 2013, Thomas, Riley and Spees 2020). These learning processes may stimulate learning outcomes that potentially enhance resilience (Knickel et al. 2018, Šūmane et al. 2018). On the other hand, some of the learning outcomes may affect social networks. For instance, relational learning outcomes, such as increased trust in farming colleagues or building social capital, shape farmers' social networks. However, social capital does not always enhance resilience. In line with King et al. (2019), we found that a drawback of bonding social capital is the creation of lock-ins resulting from strong social connections with a small number of actors. These lock-ins reduce farmers' openness to change and constrain adaptation and transformation.

Second, our findings revealed that learning is a non-linear and cumulative process, which is often shaped by multiple iterations and interactions between learning processes and learning outcomes (see e.g. Leeuwis and van den Ban 2004, Sinclair, Diduck and Fitzpatrick 2008, Diduck et al. 2012, Ensor and Harvey 2015). This was demonstrated by a farmer who had learned about installing solar panels after multiple iterations of learning processes and outcomes. The farmer learned from others by visiting farms with solar panels, resulting in an increased interest in solar panels (normative learning outcome). Based on this increased interest in solar panels, the farmer started a new learning process by seeking out financial information about the costs and benefits of solar panels, leading to a cognitive learning outcome—i.e. improved financial knowledge about solar panels. This iterative process shaped the farmer's decision to install solar panels, revealing an adaptation to sustainable energy sources.

Third, we observed that learning outcomes often affect the setting to foster learning, as was previously found by Gerlak and Heikkila (2011). Especially normative and relational learning outcomes shaped the social characteristics of the setting to foster learning. For instance, a relational learning outcome was that agronomists employed by cooperatives gained farmers' trust after successfully introducing a new variety of starch potatoes that increased yields. This learning outcome affected the setting to foster learning as this increased trust made farmers more willing to learn from these agronomists.

3.6.2 General discussion on triangulation

This study explored the contribution of social networks and learning to farm resilience by comparing several qualitative and quantitative datasets. Qualitative data was used for an in-depth description of the dynamic relationships among social networks, learning, and resilience. These qualitative methods furthered our understanding of what farmers learn and how social networks affect learning. Quantitative methods complemented these findings by testing for statistical differences between farmers who had learned and had not learned. By comparing results across methods, methodological triangulation revealed mostly a convergence towards a common understanding, which increased the validity of our findings (Carter et al. 2014). However, we also found some cases of complementarity or divergence in our findings. We briefly discuss these findings and provide possible explanations. Complementarity was found when investigating learning processes, as two learning processes—i.e. the ability to be flexible and learning new skills (Table 3.4)—were discussed during the semi-structured interviews and survey but not during the focus group. This highlights the added value of combining several methods because a more complete picture of farmers' learning processes was created. The comparison of farmers' social networks revealed some contradictions (Table 3.3). These diverging findings occurred for advisors and insurance companies that were classified as being part of farmers' social networks in two methods but were not understood as network actors in one method. This could be the result of differences in the actors involved that were involved in the methods. The semi-structured interviews were conducted with farmers, whereas the focus group contained farmers and local stakeholders. The expert interviews were conducted with regional experts. It could be that some issues were highly relevant for experts and stakeholders while being less important for farmers or vice versa.

Finally, we discuss two limitations of this study. First, a limitation of this study is that no mixed methods design was used. Mixed methods require a common research design before data collection, while we first collected the data and later compared these datasets to a conceptual framework. Second, the qualitative methods employed in this study were based on small samples (10 semi-structured interviews, 1 focus group, and 2 expert interviews). This may raise the question if data saturation is reached—i.e. if collecting more data would have improved our understanding of farmers' social networks, learning, and resilience. We have dealt with this limitation by considering methodological triangulation, which mostly revealed convergence across methods, and by clearly stating that this chapter has an explorative character, implying that we aim to develop a conceptual framework that describes how social networks and learning relate to resilience.

3.7 Conclusions

This chapter explored the contribution of social networks and learning to the resilience of Dutch arable farmers from the Veenkoloniën and Oldambt. We used a combination of qualitative and quantitative data from semi-structured interviews, surveys, focus groups, and expert interviews. Methodological triangulation resulted mostly in convergence, indicating that there was a common interpretation of the findings of all methods that improved the validity of our findings. We have shown that social networks contribute to farm robustness, adaptation, and transformation. Social networks enhanced robustness by building bonding social capital, increasing farmers' trust in informal networks. Farms that revealed adaptations benefitted from a combination of bonding and bridging social capital, which increased their openness to new ideas from both informal and formal networks. Transformations were fostered by linking social capital, which enabled farmers to connect with their formal network and increased their openness to radically new ideas. Social networks facilitated farmers' learning processes and outcomes, ultimately enhancing their resilience capacities. Learning contributed to resilience as it helped farmers to acquire more complete information, which made them better able to deal with the unknown. While our results revealed that the impact of learning on farm adaptation was mostly observed, we also found some cases where learning helped farmers to remain robust or to transform. Robust farmers learned mostly about existing agricultural practices, while adapting farms were interested in adopting innovations and new technology. Farms that have transformed were mostly characterised by farmers who were open to radically new ideas, potentially involving changes towards non-agricultural activities. To enhance farm resilience, more attention should be paid to *what* farmers learn (i.e. learning outcomes) instead of focussing on *how* farmers learn (i.e. learning processes). Finally, we presented a revised framework that accounts for the dynamic and cumulative relationships among social networks, learning, and resilience.

This study has implications for European agricultural policy makers who aim to enhance farm resilience. The current CAP does not sufficiently address how social factors, including social networks and learning, play a role in facilitating robustness, adaptation and transformation. We have shown under which circumstances social networks and learning provide farmers more complete information. This has implications for designing better Agricultural Knowledge and Innovation Systems (AKIS), as we have described how farmers' social networks can improve their information exchange. Our results revealed that linking social capital, often built by farmers' formal ties (e.g. governments or insurance companies), plays a key role in providing radically new ideas, potentially stimulating farm adaptation or even transformation. However, the current relationship between farmers and formal network actors was perceived as being bureaucratic and impersonal, reducing farmers' willingness to learn. To enhance farm resilience, policy makers should stimulate a shift towards more personal ties of farmers' formal networks. Policy makers should try to reduce red tape to promote efficient and less formal information exchange by facilitating social learning with formal network actors or joint innovation programmes. For instance, by creating a resilience-enabling policy environment that establishes farmer-scientists or farmer-other businesses networks.

4 Quantifying the resilience of European farms using FADN

This chapter is based on the paper: Slijper, T., de Mey, Y., Poortvliet, P.M., Meuwissen, M.P.M. (2021). Quantifying the resilience of European farms using FADN. *European Review of Agricultural Economics*.

Abstract

Agricultural policy makers call for the operationalisation of farm resilience as a dynamic concept. Therefore, we quantify farm resilience along the dimensions of robustness, adaptation, and transformation. Using the rich Farm Accountancy Data Network (FADN) panel dataset, we explore which farm(er) characteristics affect resilience. We employ a control function approach to address the presence of endogeneity in correlated random effects (fractional) probit models. In general, we find that decoupled payments negatively affect robustness, while rural development payments have a positive effect on robustness. Both decoupled and rural development payments have no effect on adaptation and transformation in most European regions.

Keywords

Resilience, robustness, adaptation, transformation, correlated random effects (CRE) fractional probit models.

4.1 Introduction

The concept of resilience emphasises the importance of successfully dealing with uncertainty and dynamic environments. European farmers have to cope with dynamics and uncertainty by dealing with multiple risks, including droughts (Parsons et al. 2019), climate change (Reidsma, Ewert and Oude Lansink 2007), changing regulations (Ondersteijn et al. 2002), price volatility (Hardaker et al. 2015), and previously unimaginable crises such as the COVID-19 pandemic (Darnhofer 2020, Meuwissen et al. 2021). Limited resilience renders farmers unable to deal with such risks (Knickel et al. 2018, Meuwissen et al. 2020). The 2020 Common Agricultural Policy (CAP) reform underlines the importance of resilient farms (European Commission 2020a), illustrating that farm resilience has developed into a focal point for policy makers (Darnhofer 2014, Knippenberg, Jensen and Constas 2019, Buitenhuis et al. 2020a). This has resulted in a call for the operationalisation and quantification of farm resilience to support European agricultural policy makers in developing policies that ensure farm viability.

While most economic theories assume the existence of equilibria or optima, resilience thinking offers additional insights into the importance of creating buffers, being flexible in response to change, or exploring future opportunities to adapt or transform (Darnhofer 2014). We understand resilience as the ability to provide farm functions (i.e. the delivery of public and private goods) while facing economic, social, environmental, and institutional shocks and stresses by exploiting the resilience capacities of robustness, adaptability, and transformability (Meuwissen et al. 2019). These three capacities support farmers to deal with uncertainty and are essential for resilient farms. Robustness is related to stability. Robust systems aim to absorb and persist in the face of risk to maintain the current production system (Folke 2016). In contrast, adaptation and transformation require flexibility. Adaptation represents a farm's ability to adjust production processes, while transformation reflects a radical change in business focus (Darnhofer 2014). The relative importance of the three complementary resilience capacities depends on the operational context (Folke 2016, Meuwissen et al. 2019). For instance, gradual evolution calls for a different mix of robustness, adaptation, and transformation compared to a period with radical changes (Walker et al. 2004, Darnhofer 2014, OECD 2020).

Despite the complex environment in which farmers operate, the vast majority of agricultural scholars analyse one specific type of risk in isolation (Komarek, De Pinto and Smith 2020). Several studies also assessed farm resilience to one specific risk across different regions, countries, and/or farm types (e.g. Grothmann and Patt 2005, Di Falco and Chavas 2006, Peerlings, Polman and Dries 2014, Béné et al. 2016), providing useful insights into how spatial, institutional, and agro-ecological heterogeneity affects farm resilience. However, these studies did not consider responses to multiple risks or uncertainty in general. Neither did these studies assess all three resilience capacities jointly.

Other studies simultaneously assessed robustness, adaptability, and transformability using static approaches and cross-sectional datasets. For instance, through surveys on perceived robustness, adaptability, and transformability of Ugandan households (Jones and d'Errico 2019) or Dutch farmers (Slijper et al. 2020). A dynamic study approach requires repetitive measures to account for change over time. While such studies have been conducted, none of them assessed all three resilience capacities simultaneously. For instance, recent work in agricultural and development economics captured the dynamics of resilience by studying household well-being (Barrett and Constas 2014, Cissé and Barrett 2018, Knippenberg, Jensen and Constas 2019) or wheat yield over time (Chavas 2019). Alternatively, there are several empirical papers on the dynamics of the robustness of French livestock farms (Sneessens et al. 2019), adaptability of European agriculture (Reidsma et al. 2010, Vanschoenwinkel, Moretti and Van Passel 2019) or Italian crop farms (Di Falco et al. 2014), and transformability of mixed Australian farms (Ghahramani and Bowran 2018).

The aim of this chapter to quantify the resilience of farms in terms of robustness, adaptation, and transformation. Our contribution to the existing literature is twofold. First, we explicitly capture dynamics in farm robustness, adaptation, and transformation by investigating changes over time. Using the rich Farm Accountancy Data Network (FADN) panel dataset from nine European countries, we design an indicator-based framework to measure the resilience capacities. Second, we compare farm resilience across several farm types and European countries and explore which farm(er) characteristics affect robustness, adaptation, and transformation. Understanding which characteristics contribute to resilience is important for the design of resilience-enhancing policies. This approach extends existing studies on a European scale, which only focused on adaptability (e.g. Reidsma et al. 2010, Vanschoenwinkel, Moretti and Van Passel 2019) or studies that considered self-reported resilience without uncovering the actual resilience capacities (Peerlings, Polman and Dries 2014). Our empirical application uses composite indicators to quantify farm robustness, adaptation, and transformation. The econometric approach is based on correlated random effects fractional probit models (Wooldridge 2019). We employ a control function approach to account for potential endogenous explanatory variables (Papke and Wooldridge 2008).

As this chapter contributes to the call for an operationalisation and quantification of farm resilience (European Commission 2020a), our findings are especially of interest to European agricultural policy makers. We find that the effectiveness of decoupled payments and rural developments payments to enhance resilience is heterogeneous across regions and farm types. In general, our results reveal that decoupled payments have a negative effect on farm robustness, while rural development payments enhance farm robustness. Decoupled payments and rural development payments have in most regions no significant effect on both adaptation and transformation, suggesting that alternative policy instruments, such as payments for providing public goods, are needed to support flexibility and the ability to change.

4.2 Conceptual framework

This section operationalises resilience as a multi-dimensional and dynamic concept. Our conceptual framework develops several indicators along the dimensions of robustness, adaptation, and transformation. Most previous studies assessed resilience to a specific risk (e.g. Seo 2010, OECD 2020). A limitation of this approach is that the indicators measuring resilience are only applicable to a specific context. Other studies have argued that resilience assessments should address the whole range of risks faced by farms (Meuwissen et al. 2019, Perrin et al. 2020). We follow this approach and assess farm resilience to all risks by investigating farm dynamics in terms of yearly changes in farm inputs and outputs. By describing general patterns, we study responses to change and uncertainty without targeting a specific risk. We propose a set of generic indicators that are applicable to several farm types across multiple European countries. Below, we present the robustness, adaptation, and transformation indicators (overview in Table 4.1).

4.2.1 Robustness

Robustness is the capacity to withstand, absorb, and recover from expected and unexpected risks (Meuwissen et al. 2019). To empirically assess robustness, we use three indicators that are based on farm profitability: resistance, severe shocks, and recovery rate (Figure 4.1).

Resistance describes a farm's ability to absorb the consequences of risks by minimising decreases in farm income or profitability (Urruty, Tailliez-Lefebvre and Huyghe 2016). More resistant farms are better able to absorb shocks and are hence more robust (Grafton et al. 2019, Dardonville, Bockstaller and Therond 2021). We define resistance as the decrease in profitability over time (Figure 4.1), where a lower decrease in profitability implies a more resistant farm. Higher levels of resistance result in more robust farms.

Prior to mathematically defining resistance, it is important to introduce how we benchmark farms based on profitability. The rate of return on assets (ROA) is used as profitability indicator, which is defined as the net farm income before taxes divided by the average total assets (Barry and Ellinger 2011). We benchmark farms to their peers (i.e. farms within the same farm type and country for the same year) by comparing relative profitability (Seo 2010). This is done by normalising ROA on a scale from 0 to 1, where 0 represents the least profitable farm and 1 is the most profitable farm. All robustness indicators are based on changes in normalised profitability.

Hence, we define *resistance* as:

$$resistance_t = \begin{Bmatrix} 0 & \text{if } ROA_t \geq ROA_{t-1} \\ \dfrac{ROA_t - ROA_{t-1}}{ROA_{t-1}} & \text{if } ROA_t < ROA_{t-1} \end{Bmatrix} \quad (1)$$

where, $resistance_t$ is the resistance at time *t*, and ROA is the normalised profitability.

Table 4.1 Overview of the resilience capacity indicators. Positive (negative) directions indicate that higher values of an indicator imply higher (lower) levels of a resilience capacity. +/- indicates that either a positive or negative change implies higher levels of a resilience capacity. Application indicates to what farm type a specific indicator applies. ACP = arable, crop, and perennial farms.

Resilience capacity	Resilience capacity indicator (indicator name)	Definition	Direction	Application
Robustness	Resistance (*resistance)*	Percentage decrease in profitability	+	ACP, livestock, mixed
	Shock (*shock*)	Occurs if profitability decreases with at least 30%	−	ACP, livestock, mixed
	Recovery rate after year 1 *(recovery rate)*	Degree of recovery after one year. Expressed as a percentage of the decrease in profitability	+	ACP, livestock, mixed
Adaptation	Crop diversity *(crop diversity)*	Change in crop diversity	+/−	ACP, mixed
	Fertiliser, crop protection, and energy costs *(FCE)*	Percentage change in fertiliser, crop protection, and energy costs per hectare	+/−	ACP, mixed
	Irrigation *(irrigation)*	Percentage change in irrigated area	+/−	ACP, mixed
	Labour *(labour)*	Percentage change in annual working units (AWU) per hectare	+/−	ACP, livestock, mixed
	Livestock units per hectare *(LU)*	Percentage change in livestock units per hectare	+/−	Livestock, mixed
	Feed ratio (*feed ratio*)	Percentage change in the ratio on-farm produced feed to total feed costs	+/−	Livestock, mixed
Transformation	Organic (*organic*)	Conversion from conventional to organic farming or vice versa	+	ACP, livestock, mixed
	Farm type (*farm type*)	Change in farm type (TF8-classification[1])	+	ACP, livestock, mixed
	Farm tourism (*tourism*)	Revenue from farm tourism represents at least 30% of total revenue	+	ACP, livestock, mixed

Notes: [1] TF8 classifies farm types according to the following types: 1 = fieldcrops, 2 = horticulture, 3 = wine, 4 = other permanent crops, 5 = milk, 6 = other grazing livestock, 7 = granivores, and 8 = mixed.

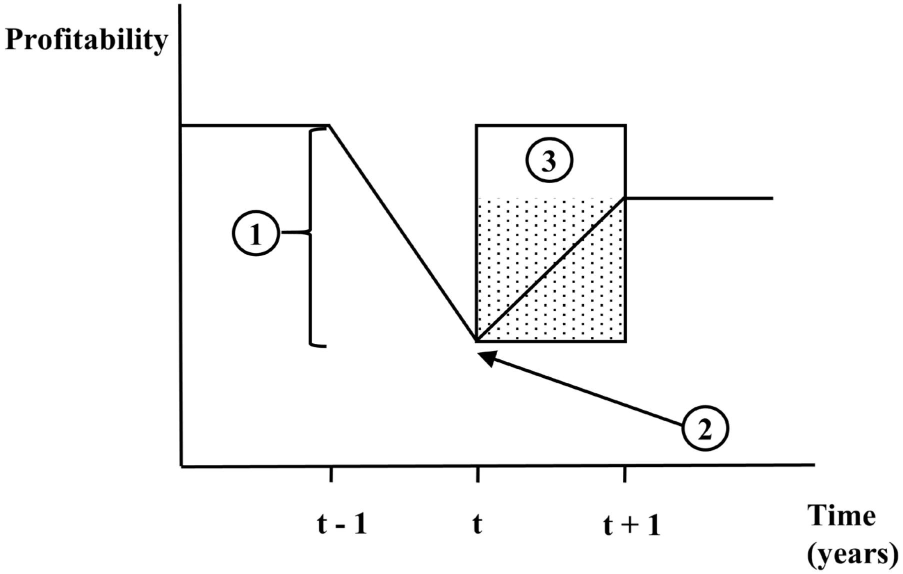

Figure 4.1 Illustration of the three robustness indicators: (1) resistance is the percentage decrease in profitability, (2) shock is a severe decrease in profitability, and (3) recovery rate is the degree of recovery after a decrease in profitability. The entire box represents the decrease in profitability and the shaded area is the degree of recovery after a year.

Resistance is a continuous variable in the domain [-1,0], where a value of -1 indicates the lowest possible resistance[2] and values of 0 are assigned to the most resistant farms. Additionally, the maximum value of 0 is assigned if there is no decrease in normalised profitability.

A severe shock in profitability (*shock*) reflects a farm's ability to withstand successive risks (Sabatier et al. 2015, Sneessens et al. 2019). Farms that face a severe shock in profitability are less able to withstand risk and are therefore less robust. Following Finger and El Benni (2014a), a severe shock is defined as a decrease in normalised profitability of at least 30%. It takes the value 1 if a severe shock occurred and 0 if not. The threshold of a 30% decrease in profitability is based on the OECD (2011), who define a 30% decrease in profitability as a catastrophic risk.

[2]In the exceptional cases where profitability decreased with more than 100%, we censored the data at -1.

The *recovery rate* describes the degree of recovery after a set amount of time, given that the normalised profitability has decreased (Urruty, Tailliez-Lefebvre and Huyghe 2016, Sneessens et al. 2019, Dardonville, Bockstaller and Therond 2021). It measures the degree to which farms can bounce back to previous levels of normalised profitability. Higher recovery rates indicate a better ability to recover from shocks. Hence, farms with higher recovery rates are more robust. In this study, we use the recovery rate after one year:

$$recovery\ rate_{t+1} = \begin{Bmatrix} 1 & \text{if } ROA_t \geq ROA_{t-1} \\ \dfrac{ROA_{t+1} - ROA_t}{ROA_{t-1} - ROA_t} & \text{if } ROA_t < ROA_{t-1} \end{Bmatrix} \tag{2}$$

where $recovery\ rate_{t+1}$ is the recovery rate after one year. The recovery rate is a continuous variable that is censored in the domain [0,1]. It takes the value 0 if there is no recovery and 1 in case of (more than) full recovery.

4.2.2 Adaptation

Adaptation is reflected by changes in a farm's input composition, production, marketing, and risk management (Meuwissen et al. 2019). These changes can be towards more or less intensive input compositions or production processes (Smit and Skinner 2002), implying that either an increase or decrease in the intensity of inputs and production processes is understood as adaptation. To this end, we investigate the absolute value of changes in inputs and production processes. The direction of change is not important for absolute values, indicating that we refrain from making normative claims about the desired direction of adaptation—i.e. if adaptation should be towards more or less intensive production practices. As different farm types use different inputs and production processes, we distinguish between adaptation indicators for arable, crop, and perennial (ACP) and livestock farms. For mixed farms that combine cropping and livestock practices, all adaptation indicators for arable and livestock farms apply (Table 4.1).

4.2.2.1 Arable, crop, and perennial farms

We investigate four ACP adaptation indicators by studying changes in: (i) crop diversity, (ii) fertiliser, crop protection, and energy costs per hectare, (iii) irrigation, and (iv) labour. First, changing a farm's *crop diversity* towards more drought-resistant crops helps farms to adapt (Di Falco, Veronesi and Yesuf 2011). Farmers can either increase or decrease their crop diversity as adaptation strategy, indicating gradual changes towards more diversified or specialised farms. On the one hand, increasing crop diversity reflects an adaptation towards more diversified farms (Reidsma et al. 2010, Cabell and Oelofse 2012, Bouttes, San Cristobal and Martin 2018, Paut, Sabatier and Tchamitchian 2019, Dardonville et al. 2020). On the other hand, under certain circumstances—e.g. favourable market conditions—changing towards more specialised and less diverse farms can also be an effective adaptation strategy

(Peerlings, Polman and Dries 2014, Matsushita, Yamane and Asano 2016). We measure crop diversity using the Shannon entropy (Shannon 1948). The Shannon diversity index (*SDI*) reflects the evenness (the proportion of land covered by a crop) and richness (the number of different crops) of a crop portfolio (Brady et al. 2009):

$$SDI_t = -\sum_{i=1}^{I} p_{i,t} \ln(p_{i,t}) \tag{3}$$

where SDI_t denotes the diversity at time t, $p_{i,t}$ is the share of land covered by crop i (i = cereals, other field crops, vegetables and flowers, vineyards, permanent crops, other permanent crops, forage crops, or woodland) at time t. The yearly change in SDI, reflects the change in crop diversity (Smit and Skinner 2002, Kremen and Miles 2012). A bigger absolute value of the change in crop diversity implies a more adaptive farm.

Second, changing the intensity of production processes also facilitates adaptation (Smit and Skinner 2002, Howden et al. 2007). We use the change in fertiliser, crop protection, and energy costs per hectare (FCE) as adaptation indicator representing farm intensity, where higher levels of FCE indicate more intensive farms (Westbury et al. 2011). The effectiveness of intensification as adaptation strategy could be either high or low, depending on local circumstances, including rainfall, the availability of water, temperature, and the current level of production (Reidsma, Oude Lansink and Ewert 2008, Ge et al. 2016, Dardonville et al. 2020, Dardonville, Bockstaller and Therond 2021). While increasing temperatures may require adaptation towards drought-resistant crops that require more intensive inputs (Reidsma, Oude Lansink and Ewert 2008, Mase, Gramig and Prokopy 2017), farmers facing less extreme weather events may adapt towards less intensive production systems by decreasing FCE (Coomes et al. 2019). Hence, adaptation is the decrease or increase in farm intensity over time, measured by the absolute value of the percentage change in FCE.

Third, *irrigation* is an adaptation strategy to manage water availability to deal with droughts and adverse weather conditions (Howden et al. 2007). The effectiveness of irrigation depends on the availability of water, national water rights regulations, and irrigation costs (Hendricks and Peterson 2012, Kahil, Connor and Albiac 2015, Li and Zhao 2018). On the one hand, farmers could adapt towards more intensive production practices by increasing the irrigated area, potentially resulting in higher farm productivity by improved water management (Reidsma et al. 2009, Foudi and Erdlenbruch 2012). On the other hand, if water scarcity occurs or irrigation costs increase, farms can adapt by reducing the irrigated area and switching to dryland farming (Deines et al. 2019). Larger absolute values of changes in irrigated areas imply bigger potential changes in water management, indicating higher levels of adaptation.

Finally, changing the amount of *labour* per hectare is an adaptation strategy reflecting a farm's flexibility to adjust to peak hours (Meuwissen et al. 2019). Farmers who can easily increase or decrease their labour force are more flexible and more adaptable (Smit and

Skinner 2002, Coomes et al. 2019). For example, they can increase their flexibility by attracting temporal labour to meet seasonal labour demand.

4.2.2.2 Livestock farms

We investigate three adaptation indicators for livestock farms by studying changes in: (i) livestock units per hectare, (ii) feed ratio, and (iii) labour. First, the stocking rate is an intensity indicator defined as the amount of livestock units per hectare (*LU*) (Howden et al. 2007, Ruiz-Martinez et al. 2015). Higher stocking rates indicate more intensive farms. Changing towards more intensive or extensive production systems is an adaptation strategy that is reflected by, respectively, increases or decreases in LU (Wreford and Topp 2020). Livestock farms can either increase or decrease LU as an adaptation measure, which is measured by the absolute value of the change in LU.

Second, livestock farms that are more flexible are better able to adapt to shocks by buying more feed if feed prices are low or producing more feed if feed prices are high (Martin and Magne 2015, Wreford and Topp 2020). This adaptation is captured by changes in the ratio self-produced feed to bought feed (*feed ratio*), reflecting the self-sufficiency of farms (Havet et al. 2014). Farms that increase their feed ratio are more self-sufficient and increased their feed production relative to the amount of bought feed, while a decrease in feed ratio implies more bought feed. A larger absolute change in feed ratio implies a more adaptable livestock farm.

Finally, *labour* refers to the flexibility to attract labour. As discussed earlier, an improved ability to change the amount of labour per hectare reflects more flexible farm practices and higher adaptability.

4.2.3 Transformation

In contrast to adaptation, transformations involve more radical and fundamental changes in the internal farm structure to cope with severe and enduring risks (Meuwissen et al. 2019). To provide a clear distinction between farm adaptation and transformation, we operationalise transformation as a considerable redistribution of the primary production factors (i.e. land, labour, and capital) and/or change in output (Vermeulen et al. 2018). We examine three transformation indicators: (i) organic farming, (ii) farm type, and (iii) farm tourism. First, the conversion from conventional to organic farming or vice versa (*organic*) is a transformation that often results in a considerable redistribution of labour practices (Rickards and Howden 2012). Second, a change in farm type (*type*) (Neuenfeldt et al. 2019) is characterised by a substantial change in output, as different farm types supply different products. Finally, obtaining a considerable part of revenue from tourism (*tourism*) implies a shift in business focus from primarily agricultural activities towards a more recreational character (Rickards and Howden 2012). This transformation occurs if revenue from tourism accounts for at least 30% of the total revenue[3].

4.3 Methods

To move from the complexity of resilience towards a measure that is easy to interpret by policy makers, we aggregate the resilience capacity indicators into composite indicators. We create a separate composite indicator for each resilience capacity and explicitly refrain from aggregating the three resilience capacities into an overall resilience indicator as there is no theoretical foundation that adequately describes the trade-offs between the resilience capacities. Our empirical application uses farm-level data from FADN, which is an unbalanced panel dataset that includes detailed farm characteristics and accounting data from nine European countries over the period 2004–2013 (FADN 2018). Section 4.3.1 describes our approach to construct composite indicators, section 4.3.2 discusses the econometric model, section 4.3.3 discusses the dataset, and section 4.3.4 introduces the control variables of the econometric model.

4.3.1 Composite indicators

Each composite indicator reflects a yearly level of robustness, adaptation, and transformation. To construct composite indicators for farm robustness and adaptation, we use principal component analysis (PCA) to obtain indicator weights. PCA is a statistical method that reveals how the resilience capacity indicators are associated with each other and converts them into a set of uncorrelated indicators (OECD 2008). PCA objectively and endogenously assigns weights to each indicator (Reig-Martínez 2012). To construct the composite indicator for transformation, we aggregate all transformation indicators into a dummy variable that takes the value 1 if at least one of the transformations occurred[4]. The procedure below describes how we obtain composite indicators for robustness and adaptation.

Table 4.1 illustrates that some indicators contribute positively to the composite indicators, while other indicators have a negative effect. In order to make them comparable, we normalise all indicators using the min-max procedure[5] (OECD 2008). After normalisation, we use PCA to assign indicator weights. We compute the composite indicators using the weighted sum of the normalised indicators. The composite indicators are fractional response

[3] To prevent the arbitrary selection of the threshold of 30%, we conducted a sensitivity analysis to compare our findings under different thresholds values (10%, 20%, 40%, and 50%). The findings are robust to alternative thresholds, see Table A32-A43 for more details.

[4] Although it is possible that a farm transforms multiple times per year, this only occurred for a very small proportion of the observations (less than 1%). Therefore, we decided to create a dichotomous variable.

[5] Min-max normalisation requires positive values for each indicator score. Therefore, negative values are rescaled to positive values by adding the absolute minimum value to the vector of each resilience capacity indicator.

variables, ranging from 0 to 1, where outcomes at 0 and 1 are allowed. These values represent farms that either score extremely low (0) or high (1) on a resilience capacity. Note that values of 0 or 1 should be treated as normal observations. Therefore, the composite indicators are not truncated or censored. Truncation or censoring would assume that values of 0 or 1 are special observations (e.g. because values below 0 or above 1 could occur but are unobserved). Table 4.2 presents an overview of the obtained composite indicators and associated econometric approach detailed in the next section.

Table 4.2 Overview of the composite indicators and econometric approach.

Resilience capacity	Composite indicator	Econometric model
Robustness	Fractional response variable [0,1]	CRE fractional probit with control function
Adaptation	Fractional response variable [0,1]	CRE fractional probit
Transformation	Dummy (1 = transformed, 0 = not transformed)	CRE probit

Notes: CRE = correlated random effects.

4.3.2 Econometric approach

The econometric approach explores which farm(er) characteristics contribute to the resilience capacities. We estimate fractional probit models with correlated random effects (CRE) for robustness and adaptation (Papke and Wooldridge 2008). An important advantage of fractional probit models is that values of 0 and 1 can be directly included in the model and are treated as normal observations[6]. CRE fractional probit models use quasi-maximum likelihood (QMLE) to obtain robust estimates. For transformation, we estimate a CRE probit model because this variable is dichotomous. We employ CRE because fixed effects specifications of (fractional) probit models result in biased estimates (Greene 2004).

[6] We also considered three alternative econometric approaches: (i) beta regressions (Ferrari and Cribari-Neto 2004), (ii) zero-inflated models (Jansakul and Hinde 2002), and (iii) double-hurdle models (Jones 1989). Limitations of these approaches are that beta regressions completely ignore values of 0 or 1, while zero-inflated and double-hurdle models assume that values of 0 and 1 are special observations originating from a different data generating process. Double-hurdle and zero-inflated models use two-stage approaches that separately explain values of 0 and/or 1 in the first stage and explain all other values in the second stage. Another limitation is that two of the alternative approaches make strong distributional assumptions about the conditional mean (beta regressions and double-hurdle models).

4.3.2.1 Econometric model

The fractional probit model investigates which farm(er) characteristics explain farm robustness or adaptation. Following Papke and Wooldridge (2008), it can be specified as:

$$\mathrm{E}(y_{i1t}|\boldsymbol{y_{i2t}}, \boldsymbol{x_{it}}, c_i, \varepsilon_{it}) = \phi(\boldsymbol{y_{i2t}\alpha} + \boldsymbol{x_{it}\beta} + c_i + \varepsilon_{it}) \tag{4}$$

where y_{i1t} is the robustness or adaptation composite indicator of farm *i* at year *t*, $\phi(\cdot)$ is the standard normal cumulative distribution function (cdf), $\boldsymbol{y_{i2t}}$ is a vector of potentially endogenous explanatory variables, $\boldsymbol{x_{it}}$ is a vector of exogenous explanatory variables, c_i is the unobserved heterogeneity of farm *i*, and ε_{it} is a time-varying error term that is potentially correlated with $\boldsymbol{y_{i2t}}$. The selected explanatory variables—ROA, asset turnover (ATO), decoupled payments, rural development payments, farmer age, land, farm type, and country—will be detailed in section 4.3.4. For transformation, we estimate a CRE probit model. The probit model follows the same specification as the fractional probit model in equation (4). The only difference is that the dependent variable y_{i1t} is dichotomous instead of a fractional response.

The current model specification likely suffers from two sources of endogeneity: (i) unobserved time-invariant heterogeneity that might affect the resilience capacities, (ii) potential reversed causality between two of the explanatory variables and our dependent variable robustness. Section 4.3.2.2 explains how CRE deals with unobserved heterogeneity and section 4.3.2.3 explains how we address reversed causality using a control function approach.

4.3.2.2 Correlated random effects

CRE is a flexible extension of the random effect estimator that provides fixed effects estimates by accounting for the time-invariant unobserved heterogeneity (Wooldridge 2005a). In this way, CRE addresses the unobserved and omitted variable problem. We apply CRE as pure random effects models are likely to be too restrictive due to the assumption that explanatory variables are completely uncorrelated with the unobserved heterogeneity.

Traditional CRE approaches (e.g. Mundlak-Chamberlain) are often only suitable for balanced panel datasets (Wooldridge 2005b, Giles and Murtazashvili 2013). However, our dataset is an unbalanced panel. Therefore, we follow the approach of Wooldridge (2019) that is also applicable to unbalanced panel datasets. This approach models the unobserved heterogeneity as a function of the number of yearly data entries of a farm and the mean of the time-varying variables interacted with dummy variables for the number of yearly data entries of a farm:

$$c_i = \sum_{r=1}^{T} \delta_{i,r}\, \psi_{0r} + \sum_{r=1}^{T} \delta_{i,r}\, \boldsymbol{\bar{x}_i \psi_{1r}} + a_i \tag{5}$$

where ψ_{0r} is a dummy variable that is 1 if a farm is r years present in the dataset, $\overline{\boldsymbol{x}}_i = \frac{1}{T}\sum_{i=0}^{T}\boldsymbol{x}_{it}$ are the within-unit averages of the time-varying exogeneous explanatory variables $\boldsymbol{x}_i$, $\boldsymbol{\psi}_{1r}$ is a vector of dummy variables that is 1 if a farm is r years present in our dataset, and a_i is a normally distributed error term: $a_i|\overline{\boldsymbol{x}}_i\boldsymbol{\psi}_{1r} \sim \mathrm{Normal}(0, \sigma_{a_i}^2)$. Including the averages of the time-varying variables in c_i absorbs correlations with the unobserved heterogeneity and hence relaxes the random effects assumption of strict exogeneity (Wooldridge 2005b, O'Brien et al. 2010).

4.3.2.3 Control function

Our model specification potentially suffers from reversed causality between one of the dependent variables (robustness) that is based on changes in profitability and two explanatory variables (ROA and ATO).

The control function (CF) approach addresses endogeneity in non-linear models using a two-stage approach (Papke and Wooldridge 2008, Wooldridge 2015). In the first stage, we estimate a reduced form equation for each endogenous variable using pooled OLS. In the second stage, we add the residuals of the reduced form equations to the correlated random effects model. We slightly adjust the CF approach of Papke and Wooldridge (2008), based on the CRE-specification of Wooldridge (2019):

(i) Estimate the reduced form equation for each endogenous explanatory variable using pooled OLS: $y_{2it} = \boldsymbol{z}_{it}\eta + \boldsymbol{x}_{it}\beta + c_i + v_{it}$, where $\boldsymbol{z}_{it}$ is a vector of instrumental variables. Year dummies are included to allow for different time period intercepts. Obtain the estimated residuals of the reduced form equations ($\hat{\boldsymbol{v}}_{it}$) for all (*i, t*) pairs.

(ii) Add $\hat{\boldsymbol{v}}_{it}$ to the second-stage model (equation 4) and estimate the correlated random effects fractional probit model using QMLE.

Second lags of the endogenous explanatory variables are used as instrumental variables[7].

The standard errors of the second-stage model are corrected for adding the first-stage residuals through bootstrapping. Following Wooldridge (2010), we present average partial effects (APE) instead of parameter estimates because of their straightforward interpretation.

[7] The dependent variable is based on changes in the resilience capacity indicators (computed as the difference between current and lagged values) and might therefore still be correlated to first lags of the endogenous explanatory variables. To overcome this, we use second lags of the endogenous explanatory variables as instrumental variables.

4.3.3 Data

Our dataset contains FADN data for the period 2004–2013 from nine European countries: Belgium, France, Germany, Italy, the Netherlands, Poland, Spain, Sweden, and the United Kingdom. We investigate heterogeneity in the dataset across two dimensions. First, we account for differences between Western (Belgium, France, Germany, the Netherlands and the United Kingdom), Southern (Italy and Spain), Northern (Sweden), and Eastern European countries (Poland). Second, we investigate differences between ACP, livestock, and mixed farms[8]. We estimate a separate model for each farm type within a region. Since we need one lagged value to compute changes in input and output and a second lag to obtain instrumental variables, as well as data on recovery rate for the year following a shock, our actual analysis is focused on the period 2006–2012.

Given the sensitivity of composite indicators for outliers (OECD 2008), we trim the upper and lower 1% of the observations from the following variables: (i) ROA (for all farm types), (ii) labour (for all farm types), (iii) FCE (for ACP and mixed farms), (iv) crop diversity (for ACP and mixed farms), (v) LU (for livestock and mixed farms), (vi) feed ratio (for livestock and mixed farms). Our final sample contains 239,483 observations representing 58,457 farms.

4.3.4 Explanatory variables

Table 4.3 presents the summary statistics of the explanatory variables[9]. We include the following farm and farmer characteristics as explanatory variables: profitability, asset turnover, decoupled payments, rural development payments, farmer age, land, the TF8-farm typology of FADN, and country. We use ROA as profitability indicator. To measure farm operational efficiency, we use the asset turnover (*ATO*). ATO is defined as total revenue divided by total assets. *Land* is the total agricultural area expressed in hectares. We take the logarithm of the total agricultural area to decrease the range in order to minimise heteroskedasticity. *Age* is the age of the farm operator which represents the farmer's experience with risk and uncertainty (Peerlings, Polman and Dries 2014). *Decoupled payments* are the share of decoupled payments that a farm receives relative to their total revenue including subsidies (Wauters and de Mey 2019). Decoupled payments are a form of government support aiming to provide a more stable income (de Mey et al. 2016). While

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[8] We categorise farm types based on the TF8-classification of FADN. The following categorisation is used: ACP includes fieldcrops, horticulture, wine, and other permanent crops farms; livestock includes dairy, other grazing livestock, and granivores; and mixed includes all mixed farms.

[9] Appendix 3 (Table A1-A5) provides summary statistics on the major farm characteristics for the initial and final sample.

decoupled payments primarily function as income support, rural development support[10] aims to enhance rural development and sustainable production. We define *rural development payments* as the share of rural development payments that farmers receive relative to their total revenue including subsidies. Furthermore, we control for heterogeneity across the TF8-typology of FADN *(farm type*), which classifies farms according to eight typologies: fieldcrops, horticulture, wine, other permanent crops, milk, other grazing livestock, granivores, and mixed farms. The farm type dummies capture differences in agro-ecological context that are heterogeneous across farm types. Finally, *country* is a dummy variable that accounts for differences in the socio-economic and institutional context across countries.

4.4 Results

4.4.1 Composite indicators

We construct composite indicators for the resilience capacities for each farm type within a region. The procedure below applies to the composite indicators of robustness and adaptation. To investigate if PCA is an appropriate method to assign indicator weights, we run the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (Kaiser 1974) and Bartlett's test of sphericity (Hair et al. 2014). We conclude that PCA is an appropriate method to obtain indicator weights because all KMO values exceed 0.5 and the Bartlett test rejects the hypothesis of no intercorrelations between indicators (all p-values < 0.01). Appendix 3 provides more details on the KMO and Bartlett test (Table A6-A14). Table A15-A20 present the weights of the resilience capacity indicators obtained from our PCA analysis. The composite indicator scores are calculated by the weighted sum of all resilience capacity indicators (Table 4.3).

Figure 4.2a–i present the spatial distribution of the composite indicators for all resilience capacities. The obtained composite indicators are heterogeneous over space and farm type. A few notable patterns arise. First, farms in countries with relatively low scores for robustness in all farm types (Sweden and Poland) are better able to adapt and transform compared to most other countries. Second, mixed farms have more often transformed than ACP and livestock farms.

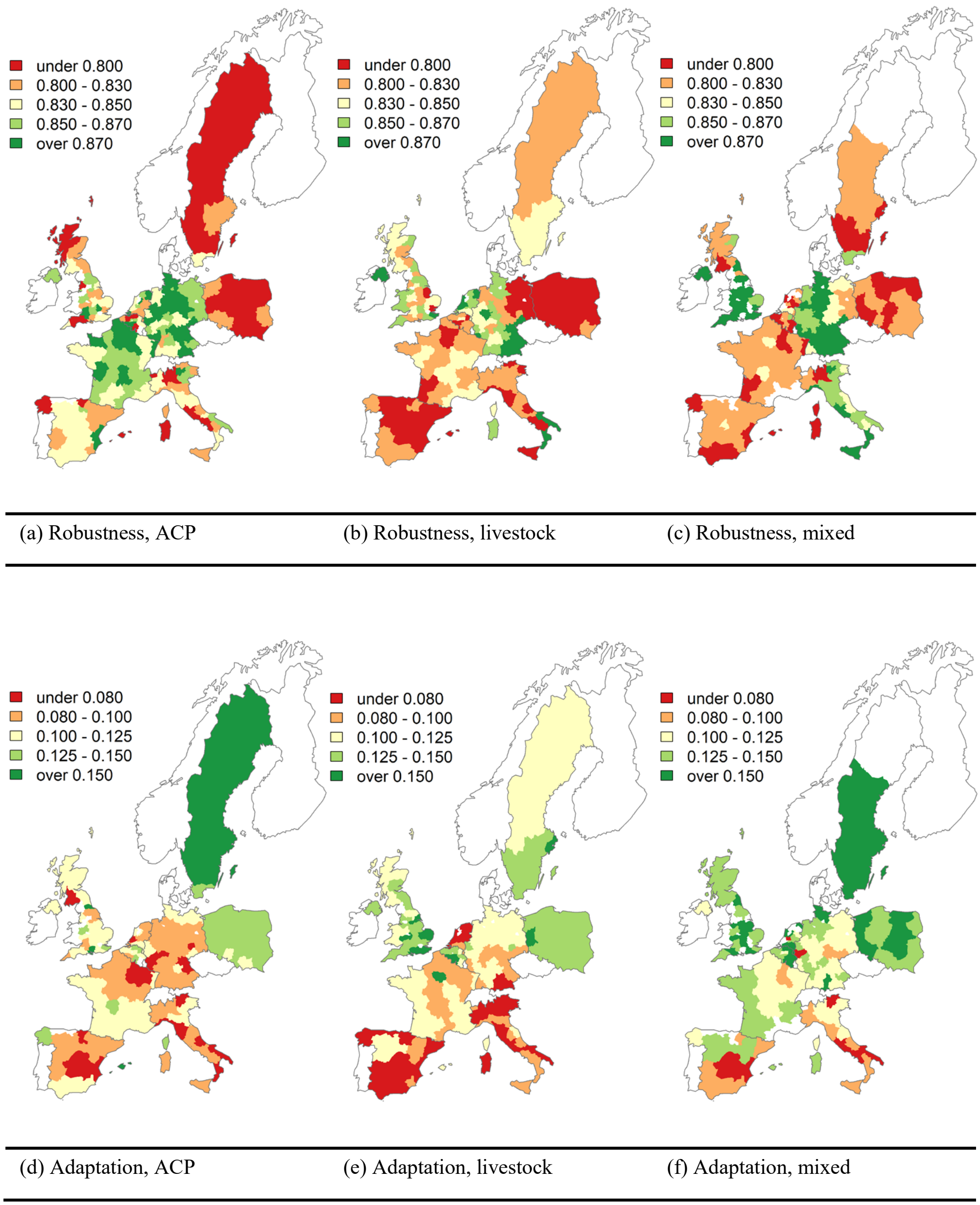
[10] Rural development support consists of environmental subsidies, subsidies for less favourite areas (LFA), and other rural development payments (European Commission 2020b).

Table 4.3 Descriptive statistics of the composite indicators and farm(er) characteristics. Standard deviations are presented in parentheses.

	Western Europe			Southern Europe		
	ACP	Livestock	Mixed	ACP	Livestock	Mixed
Robustness	0.858	0.841	0.842	0.833	0.801	0.832
	(0.224)	(0.234)	(0.240)	(0.259)	(0.270)	(0.267)
Adaptation	0.098	0.108	0.126	0.089	0.070	0.100
	(0.078)	(0.107)	(0.079)	(0.084)	(0.075)	(0.080)
Transformation[1]	0.051	0.058	0.127	0.079	0.071	0.294
ROA	0.112	0.061	0.064	0.111	0.105	0.090
	(0.138)	(0.067)	(0.075)	(0.139)	(0.088)	(0.084)
ATO	0.515	0.308	0.366	0.216	0.240	0.184
	(0.497)	(0.243)	(0.237)	(0.269)	(0.178)	(0.146)
Log(land)	3.521	4.284	4.677	2.699	3.400	3.582
	(1.746)	(0.925)	(1.034)	(1.441)	(1.181)	(1.270)
Age	50.291	49.573	49.750	55.696	51.503	54.135
	(9.377)	(9.509)	(9.359)	(12.892)	(11.824)	(12.730)
Decoupled payments	0.095	0.141	0.146	0.117	0.105	0.142
	(0.100)	(0.099)	(0.074)	(0.155)	(0.101)	(0.112)
Rural development	0.010	0.055	0.025	0.022	0.034	0.026
payments	(0.034)	(0.219)	(0.051)	(0.062)	(0.069)	(0.052)
Sample size (%) by country						
Belgium	5.076	7.750	8.339			
France	44.970	29.749	31.118			
Germany	33.144	36.382	51.038			
The Netherlands	9.342	7.936	2.330			
United Kingdom	7.468	18.183	7.174			
Spain				45.055	53.276	46.429
Italy				54.945	46.724	53.571
N	38,888	42,969	14,162	54,105	23,369	3,920

	Northern Europe			Eastern Europe		
	ACP	Livestock	Mixed	ACP	Livestock	Mixed
Robustness	0.814	0.834	0.819	0.791	0.770	0.802
	(0.261)	(0.236)	(0.257)	(0.291)	(0.299)	(0.281)
Adaptation	0.162	0.127	0.181	0.134	0.136	0.147
	(0.117)	(0.107)	(0.113)	(0.090)	(0.107)	(0.084)
Transformation[1]	0.079	0.091	0.304	0.118	0.104	0.114
ROA	0.038	0.040	0.022	0.105	0.098	0.084
	(0.076)	(0.061)	(0.058)	(0.090)	(0.062)	(0.060)
ATO	0.241	0.269	0.225	0.246	0.258	0.219
	(0.316)	(0.141)	(0.167)	(0.173)	(0.145)	(0.108)
Log(land)	4.277	4.383	4.656	3.210	3.196	3.061
	(1.249)	(0.801)	(0.789)	(1.298)	(0.680)	(0.780)
Age	56.092	52.700	53.474	44.673	43.789	44.433
	(9.306)	(9.234)	(9.110)	(9.018)	(8.726)	(9.002)
Decoupled payments	0.186	0.125	0.152	0.108	0.079	0.100
	(0.115)	(0.072)	(0.079)	(0.087)	(0.058)	(0.054)
Rural development	0.042	0.105	0.070	0.045	0.046	0.055
payments	(0.079)	(0.099)	(0.073)	(0.094)	(0.074)	(0.077)
Sample size (%) by country						
Sweden	100.000	100.000	100.000			
Poland				100.000	100.000	100.000
N	1,132	3,601	437	15,898	19,543	21,459

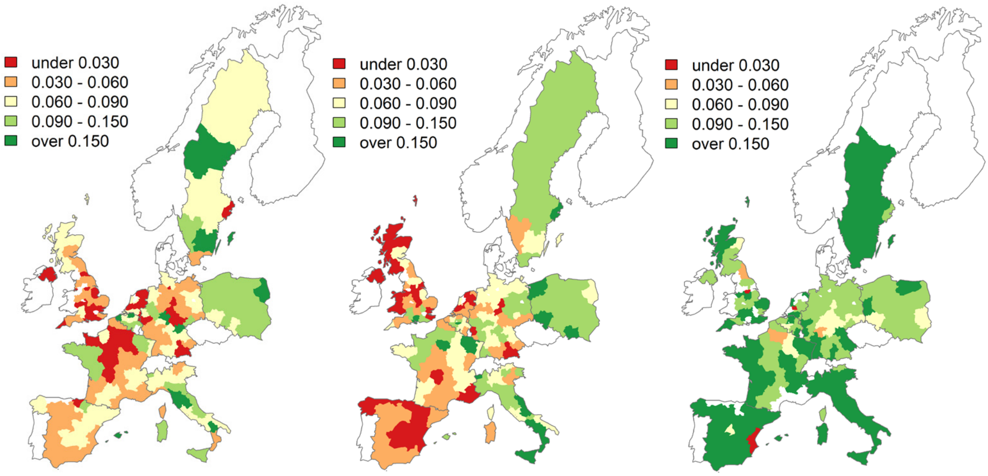
Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Transformation is a dummy variable. Therefore, no standard deviation is presented.



(a) Robustness, ACP (b) Robustness, livestock (c) Robustness, mixed

(d) Adaptation, ACP (e) Adaptation, livestock (f) Adaptation, mixed

Figure 4.2 Average scores of the resilience capacities by NUTS-2-region (Nomenclature of Territorial Units for Statistics regions). NUTS-2 regions are units at which regional policies apply. NUTS-2 regions with less than 10 observations are left blank. ACP = arable, crop, and perennial farms.



(g) Transformation, ACP	(h) Transformation, livestock	(i) Transformation, mixed

Figure 4.2 (continued) Average scores of the resilience capacities by NUTS-2-region (Nomenclature of Territorial Units for Statistics regions). NUTS-2 regions are units at which regional policies apply. NUTS-2 regions with less than 10 observations are left blank. ACP = arable, crop, and perennial farms.

4.4.2 Regression results

Prior to interpreting the results, we discuss the validity of the instrumental variables. We use second lags of the endogenous variables as instruments, indicating that the equation is exactly identified. We conclude that our instrumental variables are valid based on the following criteria: (i) the significance of the proposed instruments in the first-stage regression, (ii) the Kleibergen-Paap F-statistics[11] that are larger than 10 and exceed the critical values of Stock and Yogo (2002), and (iii) the significance of the Kleibergen-Paap rk LM-statistics. Table A21-A23 of Appendix 3 provide more details on the instrument validity tests. Furthermore, we test which of the potential endogenous variables should be treated as endogenous using a Hausman test (Papke and Wooldridge 2008). This test inspects if the residuals of the reduced form equations are significantly different from zero in the second-stage model. If the residuals have a significant effect on the dependent variable, we reject exogeneity and conclude that the variable is endogenous. A non-significant effect implies that we cannot reject exogeneity.

Table 4.4-4.6 present the average partial effects of the CRE (fractional) probit models. Additionally, we investigate the robustness of our findings to alternative model

[11] The reduced form regression is based on pooled OLS, which uses clustered standard errors at farm level. Therefore, we use the Kleibergen-Paap F-statistics instead of Cragg-Donald's F-statistics.

specifications, by estimating the following models: (i) models based on other weighting methods (equal weights) to compute composite indicators for robustness and adaptation, (ii) models based on other threshold values for farm tourism as transformation indicator, (iii) models including age squared and land squared as additional explanatory variables, (iv) models including additional economic and environmental variables, and (v) models that investigate if decoupled payments and/or rural development payments are exogenous or endogenous explanatory variables due to non-random assignment of these payments. The results of the robustness checks can be found in Appendix 3 (Table A24-A102). In general, we find that the reported results are statistically robust to alternative model specifications. Additionally, we test if the estimated parameters are significantly different across regions using seemingly unrelated estimation (Zellner 1962). Table A103-A111 of Appendix 3 show that the estimated parameters are in general significantly different across regions, supporting the estimation of regional models instead of one common European model.

Table 4.4 Average partial effects of models with farm robustness as dependent variable across different regions and farm types.

	Western Europe			Southern Europe		
	ACP	Livestock	Mixed	ACP	Livestock	Mixed
ROA	-0.059**	0.076*	-0.027	-0.377***	-0.620***	-0.786***
	(0.024)	(0.041)	(0.076)	(0.047)	(0.064)	(0.241)
ATO	0.181***	-0.086***	0.384***	0.007	0.000	1.014***
	(0.027)	(0.009)	(0.034)	(0.024)	(0.028)	(0.166)
Log(land)	0.054***	0.025***	0.006	0.021***	0.010**	-0.026**
	(0.004)	(0.006)	(0.011)	(0.004)	(0.005)	(0.012)
Age	0.001**	0.000	0.002***	0.001***	0.001	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Decoupled payments	-0.926***	-0.662***	-0.872***	-0.163***	-0.193*	-0.170**
	(0.054)	(0.051)	(0.084)	(0.062)	(0.109)	(0.067)
Rural development payments	0.481***	0.028	0.425***	-0.029	0.171***	0.446***
	(0.091)	(0.074)	(0.110)	(0.030)	(0.061)	(0.125)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	No	Yes	Yes	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes
CRE[4]	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	ROA	ROA, ATO	ROA	ROA, ATO	ROA, ATO	ROA
N	38,888	42,969	14,162	54,105	23,369	3,920

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE indicates if the correlated random effects parameters are included in the model (Yes) or not (No). [5]Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.4. (continued) Average partial effects of models with farm robustness as dependent variable across different regions and farm types.

	Northern Europe			Eastern Europe		
	ACP	Livestock	Mixed	ACP	Livestock	Mixed
ROA	1.979***	0.281**	2.936***	-1.354***	0.045	-1.177***
	(0.159)	(0.131)	(0.350)	(0.174)	(0.117)	(0.162)
ATO	-0.358***	-0.339***	0.488***	1.585***	-0.141***	1.657***
	(0.118)	(0.045)	(0.132)	(0.111)	(0.040)	(0.096)
Log(land)	0.056**	0.030	-0.083	0.019	0.064***	-0.039**
	(0.025)	(0.020)	(0.052)	(0.016)	(0.014)	(0.016)
Age	0.005*	0.002	-0.005	0.001	0.004***	0.003***
	(0.003)	(0.002)	(0.004)	(0.001)	(0.001)	(0.001)
Decoupled payments	-0.473*** (0.135)	-1.191*** (0.184)	0.454 (0.382)	-0.682*** (0.177)	-2.215*** (0.120)	-1.222*** (0.087)
Rural development payments	0.510*** (0.162)	0.087 (0.140)	-0.404 (0.483)	0.563*** (0.091)	0.811*** (0.062)	1.036*** (0.052)
Country[1]	No	No	No	No	No	No
Farm type[2]	Yes	Yes	No	Yes	Yes	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes
CRE[4]	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	None	ROA, ATO	None	ROA	ROA, ATO	ROA
N	1,132	3,601	437	15,898	19,543	21,459

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE indicates if the correlated random effects parameters are included in the model (Yes) or not (No). [5]Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.5 Average partial effects of models with farm adaptation as dependent variable across different regions and farm types.

	Western Europe			Southern Europe		
	ACP	Livestock	Mixed	ACP	Livestock	Mixed
ROA	-0.023***	-0.046***	-0.021	-0.030***	0.002	-0.049*
	(0.005)	(0.014)	(0.018)	(0.006)	(0.011)	(0.028)
ATO	0.003	0.008	-0.007	0.017***	0.011	0.014
	(0.002)	(0.007)	(0.009)	(0.004)	(0.007)	(0.015)
Log(land)	-0.001	0.010***	0.001	0.002	0.000	0.002
	(0.001)	(0.003)	(0.004)	(0.001)	(0.002)	(0.004)
Age	-0.000***	-0.001***	-0.001***	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled	0.005	0.019	0.028	-0.002	0.012	-0.018
payments	(0.016)	(0.016)	(0.033)	(0.005)	(0.008)	(0.019)
Rural	-0.015	-0.000	0.017	0.011	0.001	0.027
development	(0.026)	(0.001)	(0.038)	(0.008)	(0.012)	(0.036)
payments						
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	No	Yes	Yes	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes
CRE[4]	Yes	Yes	Yes	Yes	Yes	Yes
N	38,888	42,969	14,162	54,105	23,369	3,920

	Northern Europe			Eastern Europe		
	ACP	Livestock	Mixed	ACP	Livestock	Mixed
ROA	-0.036	-0.088*	-0.230**	-0.080***	0.005	0.005
	(0.067)	(0.053)	(0.111)	(0.020)	(0.024)	(0.021)
ATO	-0.038	0.028	0.013	0.059***	0.012	-0.000
	(0.040)	(0.033)	(0.123)	(0.015)	(0.016)	(0.016)
Log(land)	-0.039***	-0.005	0.017	0.004	0.009	0.006*
	(0.015)	(0.010)	(0.021)	(0.003)	(0.006)	(0.003)
Age	-0.005***	-0.001	-0.003*	-0.001***	-0.001***	-0.001***
	(0.002)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)
Decoupled	0.066	0.249***	0.259	0.007	0.087***	0.117***
payments	(0.066)	(0.086)	(0.203)	(0.023)	(0.032)	(0.027)
Rural	-0.053	-0.076	0.124	0.025	-0.033*	0.012
development	(0.092)	(0.069)	(0.308)	(0.016)	(0.017)	(0.013)
payments						
Country[1]	No	No	No	No	No	No
Farm type[2]	Yes	Yes	No	Yes	Yes	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes
CRE[4]	Yes	Yes	Yes	Yes	Yes	Yes
N	1,132	3,601	437	15,898	19,543	21,459

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE indicates if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4.6 Average partial effects of models with farm transformation as dependent variable across different regions and farm types.

	Western Europe			Southern Europe		
	ACP	Livestock	Mixed	ACP	Livestock	Mixed
ROA	0.013	-0.051	-0.127	-0.020	0.025	-0.090
	(0.017)	(0.032)	(0.079)	(0.018)	(0.039)	(0.171)
ATO	-0.013	-0.010	-0.015	-0.008	-0.019	-0.156
	(0.008)	(0.017)	(0.037)	(0.011)	(0.027)	(0.111)
Log(land)	-0.007*	-0.000	0.004	0.018***	0.002	-0.007
	(0.004)	(0.007)	(0.017)	(0.003)	(0.004)	(0.021)
Age	-0.000	-0.000	-0.000	-0.001**	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.002)
Decoupled	0.273***	0.026	-0.032	-0.005	-0.004	0.134
payments	(0.045)	(0.036)	(0.140)	(0.013)	(0.024)	(0.107)
Rural	-0.064	0.049***	-0.103	0.065***	0.067**	0.002
development	(0.056)	(0.017)	(0.183)	(0.025)	(0.033)	(0.208)
payments						
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	No	Yes	Yes	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes
CRE[4]	Yes	Yes	Yes	Yes	Yes	Yes
N	38,888	42,969	14,162	54,105	23,369	3,920

	Northern Europe			Eastern Europe		
	ACP	Livestock	Mixed	ACP	Livestock	Mixed
ROA	0.031	-0.049	-0.388	0.090	0.044	-0.068
	(0.194)	(0.143)	(0.608)	(0.072)	(0.069)	(0.084)
ATO	-0.060	-0.244**	-0.002	-0.134**	-0.136***	0.054
	(0.105)	(0.107)	(0.361)	(0.057)	(0.051)	(0.065)
Log(land)	-0.052*	-0.030	0.026	-0.008	-0.015	0.025**
	(0.027)	(0.028)	(0.105)	(0.010)	(0.014)	(0.012)
Age	-0.003	-0.004	0.003	0.000	-0.000	-0.001
	(0.004)	(0.002)	(0.004)	(0.001)	(0.001)	(0.001)
Decoupled	0.060	0.393*	1.248*	0.006	0.110	-0.033
payments	(0.207)	(0.211)	(0.734)	(0.071)	(0.086)	(0.114)
Rural	-0.090	-0.138	0.113	-0.097	-0.059	0.010
development	(0.226)	(0.194)	(0.975)	(0.060)	(0.050)	(0.054)
payments						
Country[1]	No	No	No	No	No	No
Farm type[2]	Yes	Yes	No	Yes	Yes	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes
CRE[4]	Yes	Yes	Yes	Yes	Yes	Yes
N	1,132	3,601	437	15,898	19,543	21,459

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE indicates if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Our results reveal that the effect of ROA on farm robustness is mixed and differs across regions. For all Northern European farms and Western European livestock farms, profitability positively affects robustness. This positive effect suggests that more profitable farms are better able to absorb, withstand, and recover from adverse events. These findings are consistent with Cabell and Oelofse (2012), who describe that being reasonably profitable improves the capacity to recover and contributes to creating buffers. However, we find evidence that ROA negatively affects robustness for all Southern European farms, Eastern European ACP and mixed farms, and Western ACP farms. A possible explanation for this relationship is that more profitable years compared to the average farm profitability do not necessarily help to obtain a more stable profitability, which could lead to less robust farms. In most regions, we find no significant effect of profitability on adaptation and transformation.

We find that ATO decreases robustness for livestock farms in most regions, while having a positive effect on the robustness of mixed farms. There are mixed results for ACP farms. For livestock farms, higher operational efficiency is related to lower buffer capacities and reserves, which comes at the cost of farm robustness (Darnhofer 2014). A possible explanation for this could be that farms with higher ATO use their assets more efficiently, keeping their asset buffers low. An explanation for the positive effect of ATO on mixed farm robustness is that these farms are already diverse as they combine livestock and arable farming practices, giving them sufficient redundancy and buffers (Altieri et al. 2015). Hence, an increased operational efficiency would make them more robust. We find no effect of ATO on adaptation or transformation in most models. Only for Southern and Eastern European ACP farms, we find only a positive effect of ATO on adaptation. This effect reveals that a higher operational efficiency facilitates small adaptations that do not require investments in new assets.

Furthermore, we find that land has mixed effects on robustness, while land has no significant effect on adaptation and transformation in most models. Age has a positive effect on robustness for ACP and mixed farms in most regions. An explanation for this is that older farmers are more experienced in dealing with risk and more willing to remain the status quo, which makes them more robust (Peerlings, Polman and Dries 2014). Age negatively affects adaptation for all Western and Eastern European farms and ACP and mixed farms in Northern Europe. This implies that younger farmers are more open to change, resulting in more adaptable farms. We find that age has no significant effect on farm transformation, except for ACP farms in Southern Europe.

Except for mixed Northern European farms, the results indicate a negative effect of decoupled payments on robustness. A possible explanation for this could be that income support offered by decoupled payments does not prevent exposure to risk (Kleinhanß et al. 2007, Zheng and Gohin 2020) and potentially creates a dependency on subsidies (de Mey et al. 2016). This suggests that farms receiving more decoupled payments have a reduced ability to adequately respond to risk, resulting in less robust farms. Furthermore, we find that decoupled payments have no effect on adaptation and transformation in most regions. Only for Northern European livestock farms and Eastern European livestock and mixed farms, we find that decoupled payments increase farm adaptation. An explanation for this could be that livestock and mixed farm adaptation requires more capital (e.g. purchasing a new breed of dairy cows) compared to adaptation of arable farms (Peerlings, Polman and Dries 2014). Farm transformation is only supported by decoupled payments for ACP farms in Western Europe and livestock and mixed farms in Northern Europe. A possible explanation for this positive effect could be that decoupled payments are used to invest (Moro and Sckokai 2013) and that these investments could be used to stimulate farm transformation.

One of the aims of the rural development policy is to promote a resilient agricultural sector (European Commission 2020b). In general, our results reveal that rural development payments contribute to robustness, while these payments have no effect on adaptation and transformation. On the one hand, the positive effect of rural development payments on robustness indicates that payments aiming to support innovation and environmental friendly practices help farms to absorb shocks and maintain current production practices. On the other hand, the mostly non-significant effect of rural development payments on adaptation and transformation suggests that alternative policy instruments, such as payments for providing public goods, may be more effective to enhance adaptation and transformation. Only in some regions and farm types—i.e. Western European livestock farms and Southern European ACP and livestock farms—rural development payments successfully promote innovations that stimulate farm transformation (Dwyer 2013). One of the statistical robustness checks (see Table A.88-90) revealed that rural development payments could have a positive effect on both adaptation and transformation of Western European ACP farms. Although this contradicts the presented results in Table 4.5-4.6, our main finding still holds, which describes that rural development payments have in general no effect on adaptation and transformation.

4.5 Discussion and conclusions

This chapter quantified European farm resilience in terms of robustness, adaptation, and transformation. We investigated general patterns that reflect how farms deal with change, risk, and uncertainty. This approach allows for a comparison of farms from different regions and farm types. We developed a novel indicator framework that captures dynamics by investigating changes in inputs and outputs over time. Composite indicators were used to aggregate the resilience capacity indicators into a measure that is easy to interpret for policy makers. Our empirical application used FADN data from nine European countries to explore which farm and farmer characteristics affect the resilience capacities.

The characteristics that have a positive effect on the resilience capacities help agricultural policy makers to create future pathways towards more resilient farms. Importantly, we found that our findings are heterogeneous across regions and farm types. Furthermore, the direction of effects often differs between resilience capacities, implying that there were trade-offs between robustness, adaptation, and transformation. This calls for a holistic view on resilience, invariably considering all three resilience capacities. We found that decoupled payments have a negative effect on farm robustness in almost all regions and farm types. This suggests that decoupled payments do not stimulate farmers to obtain a more stable farm income, resulting in less robust farms. In most regions, decoupled payments had no effect on adaptation and transformation. Finally, our results revealed that the rural development measures of the CAP in general support farm robustness but are less effective in facilitating adaptation and transformation.

As we contribute to the call for empirical resilience assessments, our results are of interest to European agricultural policy makers (European Commission 2020a). However, the proposed method has two limitations: (i) the underrepresentation of environmental and social dimensions and (ii) limitations related to the design of the FADN dataset. Below, we discuss these limitations.

First, the environmental and social dimensions of farm resilience are somewhat underrepresented. Additional insights into environmental aspects (e.g. by collecting data on nitrogen and phosphorus balances or biodiversity indicators) would improve resilience assessments by an increased understanding of a farm's natural capital (Reidsma et al. 2020). In line with Dardonville, Bockstaller and Therond (2021), we find that capturing dynamics in social dimensions are constrained by what can be quantified and are hence hard to include in econometric models. Additional insights into social aspects could increase our understanding on how farms respond and deal with change (Cinner and Barnes 2019). To better capture the social dimension, researchers could investigate a farmer's network and ability to learn (Urquhart et al. 2019), self-assessed resilience capacities (Jones and d'Errico 2019, Slijper et al. 2020), and futures literacy—i.e. the ability to anticipate to future risk (Miller 2015, Mathijs and Wauters 2020). These examples illustrate that future resilience assessments benefit from interdisciplinary research using sequential mixed methods, in which qualitative and quantitative research data are combined from researchers with different scientific backgrounds.

Second, we illustrate that quantifying farm resilience is data-demanding, ideally involving repetitive measures over time. The FADN dataset has some limitations for quantifying farm resilience. For instance, FADN does not report the reason why farms dropped out. Some farmers might not be willing to cooperate to data collection anymore, while others may have stopped farming. Another explanation could be the rotating panel schemes applied in several countries. Knowing which farms dropped out due to farm exit helps researchers to investigate if less resilient farms are more likely to quit farming. Additionally, FADN is limited to yearly observations and does not capture monthly or quarterly changes. Adaptation processes such as changes in the timing of sowing or harvesting activities cannot be observed. Collecting data at a higher frequency (e.g. via precision agricultural equipment) will allow researchers to capture more detailed dynamics, resulting in more accurate resilience assessments. However, this would surely bring additional data collection costs.

The findings have important implications for European policy makers who aim to enhance farm resilience. We show that some of the most important policy instruments from the CAP Pillar I (decoupled payments) and Pillar II (rural development payments) only affect robustness but have, in general, no effect on adaptation and transformation. This implies that stimulating farm adaptation and transformation requires alternative policy instruments. For instance, those that support business models that incorporate payments for public good provision (e.g. landscape and biodiversity services). While our resilience assessment helps designing optimal resilience-enhancing policies in future CAP reforms, it also calls for a broadening of FADN data collection to be fully able to strengthen agricultural resilience in the face of a broadening risk landscape.

5 Assessing the effectiveness of income support to ensure European farm viability

This chapter is based on the paper: Slijper, T., de Mey, Y., Poortvliet, P.M., Meuwissen, M.P.M. (2021). Assessing the effectiveness of income support to ensure European farm viability. Submitted to a journal.

Abstract

One of the key objectives of the EU Common Agricultural Policy (CAP) is to secure a fair and viable farm income. To this end, the largest part of the CAP budget is spent on income support in terms of decoupled direct payments. Between 2014 and 2020, the EU has spent about €290 billion on direct payments to support farmers. This chapter investigates the effect of decoupled direct payments on both short and long-term farm viability. We use the rich FADN panel dataset that contains farm-level data from eleven European countries over the period 2004–2013 to estimate several dynamic correlated random effects probit models. By employing control functions, our econometric approach accounts for endogeneity caused by the non-random assignment of decoupled direct payments and rural development payments. We show that 74.5% of the farms in our sample displays short-term viability, while only 42.5% of the farms is long-term viable. Receiving more decoupled direct payments increases the probability to be short-term viable in the Southern and Eastern European countries in our sample. However, in Western and Northern European countries, decoupled direct payments have no significant effect or even have a negative effect on the probability of being short-term viable. Moreover, our results reveal that decoupled direct payments decrease the probability of being long-term viable in most countries. Findings suggest that policy makers and agricultural interest groups should envision alternative measures to stimulate farm viability, such as biodiversity programs or programs to design more fair and balanced supply chains.

Keywords

Farm viability; Common Agricultural Policy (CAP); direct payments; dynamic correlated random effects probit model.

5.1 Introduction

Supporting a fair and viable farm income has been a key objective of the EU's Common Agricultural Policy (CAP) and remains a focal policy point in the CAP 2021-2027 (European Commission 2020a). To support a viable farm income, the CAP provides decoupled direct payments[12] to farmers as income support (Offermann, Nieberg and Zander 2009). A viable farm has the ability to fulfil short-term operating objectives and long-term missions (Barnes et al. 2015). Accomplishing short-term objectives requires a revenue that covers operating expenses, while fulfilling long-term goals requires a consideration of the opportunity costs of farm capital and own capital (Barnes et al. 2015, O'Donoghue et al. 2016). A viable farm income enhances resilience as it enables farms to continue investing and adds to financial buffers to better cope with agricultural risk, uncertainty, and challenges (Cabell and Oelofse 2012, Meuwissen et al. 2019, Slijper et al. 2020). Understanding the effectiveness of decoupled direct payments to ensure farm viability is important for agricultural policy makers to evaluate existing policies. The aim of this chapter is to assess the effect of decoupled direct payments on short and long-term farm viability.

The CAP consists of two pillars; the first pillar contains market measures and direct payments, which makes up about 75 per cent of the CAP-budget, while the remaining quarter is spent on the second pillar for rural development measures. Decoupled direct payments are the main source of income support provided by the first pillar (European Commission 2020a). These decoupled direct payments were gradually introduced during the MacSharry reform in 1992 and were further implemented by the Fischler reform (2003), which introduced major changes in the CAP by decoupling payments from production and introducing area-based payments (Moro and Sckokai 2013, Bozzola and Finger 2021). Furthermore, cross-compliance was introduced to set minimum environmental standards that are required to receive decoupled direct payments (Ciaian, Kancs and Swinnen 2014). The second pillar aims to enhance sustainability and the agricultural-environmental relationship by incorporating rural development payments to support sustainable investments, providing agri-environmental schemes, and supporting regional development (European Commission 2020a). We focus on decoupled direct payments as this policy instrument receives by far the largest part of the budget (€290 billion in the period 2014-2020 (European Commission 2018)) to support farm viability.

Previous studies have shown that farm viability is heterogeneous across European countries (Vrolijk et al. 2010, O'Donoghue et al. 2016), farm types (Barnes, Foreman and Bevan 2018), and over time (Barnes et al. 2015, Ojo et al. 2020). To investigate how decoupled direct payments affect farm viability, several studies compared a regime with decoupled direct payments to a situation under the abolishment of these payments. For instance, Vrolijk et al.

[12] Decoupled direct payments are area-based payments that are uncoupled from production. In order to receive these payments, farmers have to comply with several regulations (i.e. the so-called cross-compliance).

(2010) investigated the short-term effects of abolishing all CAP payments on farm viability in Europe. They found that farms receiving less decoupled direct payments are more viable than farms that relied more on decoupled direct payments. Ojo et al. (2020) analysed the long-term effects of decoupled direct payments on farm viability in the context of a post-Brexit agricultural policy in the UK. They found that abolishing decoupled direct payments results in less viable farms by lowering farm income. We expand these approaches by distinguishing between the effects of decoupled direct payments on short and long-term farm viability. Previous studies that distinguished between short and long-term viability investigated the role of diversification in enhancing farm viability (Barnes et al. 2015) but did not focus on decoupled direct payments.

Barnes, Foreman and Bevan (2018) demonstrated that viable farms were likely to remain permanently viable over time, while non-viable farms were less likely to transform into a viable state. This implies the presence of state dependence, as being viable in the past may increase the probability of being viable in the future (Cappellari and Jenkins 2004). Therefore, approaches accounting for past viability states to control for state dependence are required to fully understand the dynamics of farm viability. A considerable amount of agricultural and development economic studies have been published on state dependence in the context of low farm income persistence (Phimister, Roberts and Gilbert 2004), poverty traps in developing countries (Thomas and Gaspart 2014, Barrett, Garg and McBride 2016) or the resilience of rural economies (Tonts, Plummer and Argent 2014). However, existing farm viability studies are limited to static approaches that have not considered state dependence.

This chapter goes beyond this limitation and has a twofold contribution to the literature. First, we differentiate between the effects of decoupled direct payments on short and long-term farm viability. Second, we investigate the dynamics of farm viability in terms of state dependence and acknowledge the endogenous nature of decoupled direct payments and other CAP subsidies in explaining farm viability. Previous econometric studies on farm viability treated decoupled direct payments as exogenous variables (e.g. Barnes et al. 2015, Barnes, Thomson and Ferreira 2020, Coppola et al. 2020), not acknowledging that decoupled direct payments are non-randomly assigned to farms and, therefore, are potentially correlated with the error term in econometric models (Biagini, Antonioli and Severini 2020). To this end, we estimate a dynamic correlated random effects probit model that accounts for endogeneity by employing the control function approach proposed by Giles and Murtazashvili (2013). The empirical analysis compares farm viability across eleven European countries using the rich Farm Accountancy Data Network (FADN) panel dataset over the timespan 2007–2013. Our findings are relevant for agricultural policy makers as we investigate the effectiveness of decoupled direct payments to support a viable farm income. Our results reveal that decoupled direct payments support short-term farm viability in Southern and Eastern European countries, while it constrains short-term farm viability in Western and Northern Europe. However, decoupled direct payments constrain or have no effect on long-term farm viability in most countries, indicating that the long-term policy goal of supporting viable farm incomes is not met.

5.2 Background on farm viability and decoupled direct payments

To investigate if decoupled direct payments support farm viability, section 5.2.1 operationalises farm viability and section 5.2.2 discusses the relationship between decoupled direct payments and farm viability.

5.2.1 Operationalising farm viability

Farm viability studies if farmers are able to make a living from farming by comparing the obtained farm income to an external standard of living (Barnes et al. 2015, O'Donoghue et al. 2016). This external standard of living is used as a threshold to determine if a farmer is better off working on-farm compared to off-farm labour. The national hourly minimum wage is used to benchmark the hourly return on unpaid labour to working an hour off-farm (Ojo et al. 2020). Short-term viability only considers operating expenses, while long-term viability also accounts for opportunity costs of capital. We operationalise both short and long-term viability below.

Short-term viability is sensitive to yearly fluctuations in farm income and reflects the ability to meet financial obligations by cash expenditures (Barnes et al. 2015). From a short-term perspective, there is no need to account for investments in technology, buildings or other fixed assets. Therefore, we use the earnings before interest, taxation, depreciation, and amortization (EBITDA) as indicator for operational return on unpaid labour. EBITDA is defined as net farm income from operations[13] plus interest paid, depreciation and amortization[14] (Barry and Ellinger 2011). A farm is short-term viable if EBITDA is larger than or equal to the national hourly minimum wage multiplied by the unpaid on-farm labour hours:

$$EBITDA_t \geq (wage_{it} \times unpaid\ labour\ hours_t) \tag{1a}$$

[13] Barnes et al. (2015) and O'Donoghue et al. (2016) argue that farm viability is a concept that should be applied at farm level and not at farm household level. We do not account for off-farm income as this would have resulted in studying farm households as a decision-making unit rather than farms.

[14] Following Barry and Ellinger (2011), we define NFIO as: NFIO = gross revenue – purchase costs of feed and feeder livestock – cash operating expenses – changes in account payables – depreciation – interest expenses. For the sake of reproducibility, we add the FADN variables (FADN 2018). FADN reports net farm income before taxation (NFI) instead of NFIO. We calculated NFIO as NFI (SE420) – change in capital gains and losses (change in SE510). EBITDA is computed as: EBITDA = NFI (SE420) – change in capital gains and losses (change in SE510) + interest paid (SE380) + depreciation (SE360). Amortization is assumed to be zero.

where $wage_{it}$ is the national hourly minimum wage of country i at year t. We define short-term viability (STV) as a dummy variable that takes 1 if a farm is short-term viable and 0 if not.

In the long run, farm viability considers the costs of capital to ensure investments or replacement of depreciated machinery and/or buildings. Hence, long-term viability requires an hourly return on unpaid labour and capital. We use the average net farm income before taxation (NFI) over a 3-year period as income measure (Barnes et al. 2015), reflecting the return on unpaid labour and management after paid rent and labour. Furthermore, we account for the opportunity costs of capital (OCC) to consider the return on land and capital (Barnes, Thomson and Ferreira 2020, Ojo et al. 2020). We define OCC as total assets multiplied by the annual returns on 10-year government bonds (Vrolijk et al. 2010). A farm is long-term viable if the 3-year average of NFI[15] minus OCC is larger than or equal to the national hourly minimum wage multiplied by the unpaid on-farm labour hours (Barnes et al. 2015):

$$\sum_{t-2}^{t}(NFI_t - OCC_t) \geq \sum_{t-2}^{t}(wage_{it} \times unpaid\ labour\ hours_t) \qquad (1b)$$

We define long-term viability (LTV) as a dummy variable that takes 1 if a farm is long-term viable and 0 if not. Being long-term non-viable, makes it less attractive to continue farming or for potential successors to take over the farm because the benefits of working off-farm are structurally higher than from working on-farm (Happe, Kellermann and Balmann 2006, Breustedt and Glauben 2007, Pitson et al. 2020).

5.2.2 The relationship between decoupled direct payments and farm viability

We distinguish between the effects of decoupled direct payments on short and long-term farm viability. In the short term, decoupled direct payments are considered to be payments that directly contribute to farm income if they exceed cross-compliance costs. In the rare case that the cross-compliance costs exceed the amount of decoupled direct payments, farmers will decide not to receive any subsidies. Previous studies have confirmed the income transfer efficiency of decoupled direct payments, arguing that decoupled direct payments contribute to higher farm incomes (Dewbre, Antón and Thompton 2001, Biagini, Antonioli and Severini 2020) or how decoupled direct payments contribute to farm viability (Ojo et al. 2020). Hence, we expect that higher (lower) decoupled direct payments increase (decrease) the probability of being short-term viable.

[15] Note that we compare NFI before taxations to gross national minimum wages. Hence, NFI is not deflated as inflation is already captured by changes in national minimum wages over time.

From a long-term perspective, the longer farms receive decoupled direct payments and the higher the levels of these payments are, the more these payments are absorbed in the cost structure of a farm (Harvey 2004, Offermann, Nieberg and Zander 2009). This implies that decoupled direct payments create a dependency on subsidies, lowering the responsiveness of farms to change (Kazukauskas et al. 2013, Brady et al. 2017, Buitenhuis et al. 2020b). Ultimately, this dependency on subsidies hinders the probability of being long-term viable (Barnes et al. 2015). In line with this, Goetz and Debertin (2001) found that farms depending more on government payments are more likely to exit farming, indicating lower farm viability.

Based on this background, we construct two hypotheses:

Hypothesis 1: *Receiving more decoupled direct payments increases the probability of being short-term viable.*

Hypothesis 2: *Receiving more decoupled direct payments decreases the probability of being long-term viable.*

5.3 Econometric model

We estimate two dynamic correlated random effects probit models. The first model estimates the effects of decoupled direct payments on short-term viability, while the second model focusses on long-term viability. We introduce the basic dynamic random effects probit model and discuss limitations of pure random effects below.

5.3.1 Dynamic random effects probit model

The dynamic random effects probit model investigates which variables increase or decrease the probability of a farm being short- or long-term viable. It can be specified as:

$$y_{1it} = \begin{cases} 1 \text{ if } y_{1it}^{*} > 0 \\ 0 \text{ if } y_{1it}^{*} \leq 0 \end{cases} \tag{2a}$$

where, y_{1it} is a binary variable that takes the value 1 if farm i is short or long-term viable in year t and 0 if not. y_{1it}^{*} is the latent propensity to short or long-term viability:

$$y_{1it}^{*} = \boldsymbol{x}_{it}\boldsymbol{\beta} + y_{1it-1}\gamma + \boldsymbol{y}_{\boldsymbol{2it}}\boldsymbol{\delta} + \varepsilon_{it} = \boldsymbol{x}_{it}\boldsymbol{\beta} + y_{1it-1}\gamma + \boldsymbol{y}_{\boldsymbol{2it}}\boldsymbol{\delta} + c_i + u_{it} \tag{2b}$$

where $\boldsymbol{x}_{it}$ represents a vector of exogenous explanatory variables, y_{1it-1} is the lagged dependent variable, $\boldsymbol{y}_{\boldsymbol{2it}}$ is a vector of endogenous variables, and ε_{it} is the error term that can be decomposed into time-invariant unobserved farm heterogeneity (c_i) and a random error (u_{it}). The coefficient γ captures the potential presence of state dependence—i.e. the impact of lagged viability states on current farm viability. The selected explanatory variables—

decoupled direct payments, rural development payments, land tenure, unpaid labour, size, age, price volatility, price shock, agricultural diversification, less favoured areas, farm type, and year—will be detailed in section 5.4.2.

The dynamic random effects probit model assumes that $u_{it} \sim N(0,1)$. Additionally, it assumes that the time-invariant unobserved farm-specific effects, exogenous variables, and lagged dependent variables are uncorrelated. This assumption is likely to be too restrictive as unobserved heterogeneity is often not independent of the exogenous variables and their initial conditions (Giles and Murtazashvili 2013). Therefore, we relax the "pure" random effects assumption by estimating correlated random effects (see section 5.3.2).

Additionally, the presented model set-up potentially suffers from two sources of endogeneity: (i) the initial condition problem and unobserved time-invariant heterogeneity and (ii) endogenous explanatory variables caused by the non-random assignment of decoupled direct payments and rural development payments. Section 5.3.2 explains how correlated random effects address the initial condition problem and deal with unobserved time-invariant heterogeneity. Section 5.3.3 introduces a control function approach to address the remaining endogenous explanatory variables.

5.3.2 Initial condition problem and correlated random effects

Including a lagged dependent variable as explanatory variable introduces the incidental parameter problem, which occurs if unobserved heterogeneity is estimated in relatively short panels—i.e. small *T*. The incidental parameter problem results in inconsistent estimators (Heckman 1981) and can be solved by integrating out unobserved heterogeneity (Wooldridge 2010). While this solves for the incidental parameter problem, it raises the initial conditions problem that appears if the first available observation of the dependent variable (y_{i0}) does not represent the true start of the process (Wooldridge 2010). This results in overestimating the correlation between the unobserved time-invariant farm heterogeneity (c_i) and state dependence (Heckman 1981).

Wooldridge (2005b) proposes a solution to deal with the initial conditions problem using correlated random effects (CRE). CRE flexibly extends the random effects estimators by accounting for time-invariant unobserved heterogeneity. Hence, it mimics fixed effects and addresses the unobserved and omitted variables problem in a similar way as fixed effects do. CRE defines c_i as the mean of all time-variant exogenous variables and the initial observation of the dependent variable (Wooldridge 2005b). However, this approach requires balanced panel data. As our panel dataset is unbalanced, we use the adjustment proposed by Rabe-Hesketh and Skrondal (2013) that is applicable to unbalanced panel datasets. They model the unobserved time-invariant heterogeneity as the initial values of the dependent variable, the initial values of the time-varying exogenous variables, and the mean of the time-varying exogenous variables:

$$c_i = \alpha_0 + y_{i0}\alpha_1 + \bar{\boldsymbol{x}}_i\boldsymbol{\alpha_2} + \boldsymbol{x}_{i0}\boldsymbol{\alpha_3} + \varepsilon_i \tag{3}$$

Where y_{i0} and $\boldsymbol{x}_{i0}$ are the initial conditions of, respectively, the dependent variable and the time-varying exogenous variables, $\overline{\boldsymbol{x}}_i = \frac{1}{T}\sum_{i=0}^{T}\boldsymbol{x}_{it}$ represents the within-unit averages of the time-varying exogeneous variables over the period $t = 0, \ldots, T$, and ε_i is a farm-specific error term that is normally distributed with mean 0 and variance σ_α^2. The inclusion of the initial conditions and averages in c_i absorbs correlations with the unobserved heterogeneity (Wooldridge 2005b, O'Brien et al. 2010). The dynamic CRE probit model is estimated using quasi-maximum likelihood (QMLE).

5.3.3 Endogenous explanatory variables

Two of the considered explanatory variables are potentially endogenous—decoupled direct payments and rural development payments—as they are non-randomly assigned to farms. The assignment of these payments depends on the average productivity of a country, a farmer's decision regarding cross-compliance or the willingness to participate in rural development programs (Mary 2012, Biagini, Antonioli and Severini 2020). This introduces a correlation between the variables and the error term, ultimately resulting in endogeneity. We expect that this is not captured by CRE, which accounts for time-invariant unobserved heterogeneity, as the characteristics that shape farmers cross-compliance decisions may vary over time.

We apply a control function approach to account for this source of endogeneity. Control function approaches are especially suitable to address endogeneity in non-linear models with binary dependent variables (Papke and Wooldridge 2008, Wooldridge 2015). Giles and Murtazashvili (2013) provide a two-stage control function specification for dynamic CRE probit models. In the first stage, a reduced form equation is estimated using pooled OLS. Contrary to two-stage least squares approaches, a control function approach adds the residuals of the first-stage regression as an additional explanatory variable to the second-stage regression. Our two-stage model is estimated based on procedure 2.2 of Giles and Murtazashvili (2013):

(i) Estimate the reduced form equation for each endogenous variable using pooled OLS: $y_{2it} = \boldsymbol{z_{it}\eta} + \boldsymbol{x}_{it}\boldsymbol{\beta} + c_i + v_{it}$, where $\boldsymbol{z_{it}}$ is a vector of instrumental variables and c_i is defined in equation (3). Obtain the residuals of the reduced form equations ($\widehat{\boldsymbol{v}}_{\boldsymbol{it}}$) for all (*i, t*) pairs.

(ii) Add $\widehat{\boldsymbol{v}}_{\boldsymbol{it}}$ to equation (2b) and estimate the dynamic CRE probit model using QMLE.

We use lagged variables of the endogenous variables as instrumental variables.

Following the recommendations of Wooldridge (2010), we present average partial effects instead of parameter estimates in order to ensure a straightforward interpretation of the results. Giles and Murtazashvili (2013) show that the obtained standard errors of the second-stage model should be corrected for the inclusion of the first-stage residuals. We use bootstrapping to correct the second-stage standard errors (Wooldridge 2015).

5.4 Data and descriptive statistics

Section 5.4.1 introduces the dataset used in our analysis and section 5.4.2 defines the variables that are used in our econometric model.

5.4.1 Data

We use the unbalanced FADN panel dataset (FADN 2018), which contains farm-level data from eleven European countries: Belgium, Bulgaria, France, Germany, Italy, the Netherlands, Poland, Romania, Spain, Sweden, and the United Kingdom. The dataset covers a 10-year period from 2004-2013 for most countries. Bulgaria and Romania joined the EU in 2007, therefore, no data are available from before 2007 and the dataset includes 7 years (2007-2013). Our sample is compiled by selecting observations that (i) are at least 4 consecutive years present in FADN[16], (ii) do not have missing values, and (iii) are not considered as outliers. The following data entries are considered as outliers: the top and bottom 1% of unpaid labour hours and net farm income before taxation. Long-term viability is computed over a three-year period, leading to the omission of data entries from 2004 and 2005. Additionally, testing for state dependence requires the consideration of a lagged dependent variable in our model, resulting in the exclusion of data entries from 2006. Our final dataset contains data from 2007-2013. For Bulgaria and Romania, we use data from 2010-2013. The final sample contains 243,234 observations representing 61,661 farms. Farms are on average 3.94 years in the sample.

Additionally, we use 10-year government bond data from ECB (2020) and national minimum wage data from Eurostat (2020a, 2020b) and SCB (2020) to compute the viability states. For countries without minimum wages (Italy and Sweden), we used the 10th percentile income or wage as proxy for minimum wage. Farmgate prices from FAO (2020) are used to generate price risk variables (5.4.2). An overview of the datasets is available in Appendix 4.

5.4.2 Variable definition and descriptive statistics

Table 5.1 presents the definitions and expected signs of the variables considered in our econometric model. The dependent variable, *farm viability*, has been formally defined in section 5.2.1. Unless stated otherwise, we expect the same effects of the control variables on both short and long-term viability.

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[16] 3 years are required to compute the viability state and 1 additional year is needed to investigate state dependence. Hence, only farms that are for at least 4 consecutive years present in FADN are selected.

Four groups of independent variables are considered that reflect key elements of farm viability: (i) policy instruments, (ii) farm and farmer characteristics, (iii) risk and risk management variables, and (iv) other variables. The descriptive statistics (Table 5.2) show that most European farms are short-term viable (74.5%), while only 42.5% is long-term viable. In all eleven countries, more farms are short-term viable than long-term variable.

Table 5.1 Definition of the selected variables and expected coefficient signs for short-term viability (STV) and long-term viability (LTV).

Variable	Definition	Expected coefficient sign	
		STV	LTV
Dependent variables			
Short-term viability (STV)	Dummy variable that takes 1 if a farm is short-term viable and 0 if not		
Long-term viability (LTV)	Dummy variable that takes 1 if a farm is long-term viable and 0 if not		
Policy instruments			
Decoupled direct payments (DDP)	Decoupled direct payments / total revenue	+	–
Rural development payments (RDP)	RDP / total revenue	+/–	+/–
Farm(er) characteristics			
Land tenure	Owned land (ha) / total land (ha)	–	–
Unpaid labour	Unpaid labour expressed in annual working units (AWU) / total labour (AWU)	+	+
Size	Farm size expressed in 100s of Economic Size Units (ESU)	+	+
Age	Age of the farm operator	+	+
Risk and risk management variables			
Price volatility	3-year coefficient variation (CV) of farmgate prices	–	–
Price shock	Percentage decrease in farmgate prices with respect to the previous year, ranging from 0 (no price shock) to 1 (highest possible price shock)	–	–
Diversification	Herfindahl–Hirschman index (HHI), ranging from 0 (perfectly specialised) to 1 (perfectly diversified)	+	+
Others			
Less favoured area (LFA)	Dummy that takes 1 if the majority of land is located in a LFA and 0 if not	–	–
Farm type	Farm type dummy: 1 = field crops, 2 = horticulture, 3 = wine, 4 = other permanent crops, 5 = dairy, 6 = other grazing livestock, 7 = granivores, 8 = mixed	+/–	+/–
Year	Year dummy for each year in the period 2007-2013	+/–	+/–

Notes: A positive (negative) expected sign means that a higher value of a variable relates to a higher (lower) probability of being viable. +/– indicates either a positive or negative effect.

Table 5.2 Descriptive statistics. Standard deviations are presented in parentheses.

	Belgium	Bulgaria	France	Germany	Italy	The Netherlands
N	6,209	3,062	35,411	33,582	40,684	5,692
STV	0.818	0.708	0.854	0.788	0.614	0.768
LTV	0.467	0.641	0.542	0.339	0.414	0.214
DDP (ST)	0.091	0.118	0.121	0.120	0.101	0.056
	(0.070)	(0.110)	(0.089)	(0.093)	(0.117)	(0.061)
DDP (LT)	0.090	0.105	0.117	0.121	0.099	0.051
	(0.066)	(0.090)	(0.083)	(0.091)	(0.109)	(0.056)
RDP (ST)	0.021	0.035	0.029	0.028	0.026	0.008
	(0.050)	(0.101)	(0.067)	(0.067)	(0.066)	(0.029)
RDP (LT)	0.020	0.028	0.030	0.029	0.026	0.008
	(0.044)	(0.079)	(0.065)	(0.066)	(0.058)	(0.026)
Land tenure	0.349	0.344	0.185	0.442	0.650	0.679
	(0.294)	(0.411)	(0.293)	(0.306)	(0.407)	(0.323)
Unpaid labour	0.901	0.381	0.811	0.812	0.850	0.791
	(0.215)	(0.380)	(0.262)	(0.264)	(0.247)	(0.272)
Size	2.651	1.285	1.909	2.422	0.993	4.298
(100 ESU)	(2.323)	(2.174)	(1.951)	(3.322)	(4.507)	(4.399)
Age	47.737	51.596	48.933	50.820	56.231	50.644
	(8.620)	(12.616)	(8.577)	(9.226)	(13.641)	(9.289)
Price volatility	0.106	0.136	0.103	0.138	0.102	0.129
	(0.073)	(0.065)	(0.086)	(0.081)	(0.073)	(0.076)
Price shock	0.043	0.048	0.037	0.051	0.036	0.054
	(0.076)	(0.079)	(0.073)	(0.100)	(0.075)	(0.093)
Diversification	0.395	0.372	0.363	0.420	0.349	0.226
	(0.263)	(0.245)	(0.247)	(0.229)	(0.254)	(0.223)
LFA	0.186	0.185	0.402	0.366	0.542	0.055

Notes: Farm type omitted for the sake of brevity; the descriptive statistics including farm types can be consulted in Appendix 4. STV = short-term viability; LTV = long-term viability; DDP (ST) = short-term decoupled direct payments; DDP (LT) = long-term decoupled direct payments; RDP (ST) = short-term rural development payments; RDP (LT) = long-term rural development payments; LFA = less favoured area. STV, LTV, and LFA are dummy variables; therefore, only means are presented.

Table 5.2 (continued) Descriptive statistics. Standard deviations are presented in parentheses.

	Poland	Romania	Spain	Sweden	United Kingdom	Total
N	58,923	3,781	40,142	4,928	10,820	243,234
STV	0.780	0.746	0.714	0.467	0.756	0.745
LTV	0.361	0.637	0.568	0.126	0.261	0.425
DDP (ST)	0.105	0.102	0.131	0.143	0.185	0.116
	(0.072)	(0.070)	(0.132)	(0.086)	(0.118)	(0.102)
DDP (LT)	0.093	0.090	0.121	0.140	0.193	0.110
	(0.060)	(0.061)	(0.115)	(0.080)	(0.119)	(0.094)
RDP (ST)	0.046	0.011	0.024	0.090	0.068	0.034
	(0.078)	(0.043)	(0.061)	(0.098)	(0.101)	(0.072)
RDP (LT)	0.048	0.010	0.023	0.090	0.071	0.034
	(0.070)	(0.034)	(0.050)	(0.094)	(0.100)	(0.066)
Land tenure	0.780	0.623	0.697	0.552	0.671	0.581
	(0.242)	(0.430)	(0.381)	(0.334)	(0.378)	(0.388)
Unpaid labour	0.915	0.692	0.834	0.888	0.777	0.841
	(0.183)	(0.398)	(0.234)	(0.214)	(0.268)	(0.252)
Size	0.490	0.769	0.879	1.683	1.933	1.359
(100 ESU)	(0.719)	(1.597)	(1.706)	(2.089)	(2.435)	(2.799)
Age	44.938	50.084	53.882	54.448	56.106	50.755
	(9.008)	(11.258)	(11.524)	(9.462)	(10.669)	(11.271)
Price volatility	0.143	0.097	0.098	0.102	0.124	0.118
	(0.094)	(0.072)	(0.063)	(0.083)	(0.080)	(0.083)
Price shock	0.038	0.043	0.040	0.037	0.019	0.040
	(0.075)	(0.053)	(0.074)	(0.073)	(0.050)	(0.078)
Diversification	0.531	0.489	0.283	0.459	0.457	0.402
	(0.204)	(0.248)	(0.229)	(0.179)	(0.202)	(0.247)
LFA	0.560	0.290	0.680	0.581	0.460	0.493

Notes: Farm type omitted for the sake of brevity; the descriptive statistics including farm types can be consulted in Appendix 4. STV = short-term viability; LTV = long-term viability; DDP (ST) = short-term decoupled direct payments; DDP (LT) = long-term decoupled direct payments; RDP (ST) = short-term rural development payments; RDP (LT) = long-term rural development payments; LFA = less favoured area. STV, LTV, and LFA are dummy variables; therefore, only means are presented.

5.4.2.1 Policy instruments

Our analysis considers decoupled direct payments and rural development payments as policy instruments. *Decoupled direct payments* is the variable of interest in our analysis. It represents the dependency on decoupled direct payments and is defined as the amount of decoupled direct payments over total revenue including all received subsidies (Kazukauskas et al. 2013). This is computed as a single-year indicator for short-term viability, while for long-term viability the dependency on decoupled direct payments is calculated over a three-year period. As explained in section 5.2.2, we expect a positive relationship between decoupled direct payments and short-term viability, while decoupled direct payments are expected to negatively affect long-term viability.

Rural development payments are the amount of rural development payments over total revenue including subsidies. A single-year period is used for short-term viability, while a three-year period is used for long-term viability. Rural development payments could either increase or decrease the probability of being viable.

5.4.2.2 Farm and farmer characteristics

We consider the following farm and farmer characteristics: land tenure, unpaid labour, farm size, and age. *Land tenure* is the ratio owned land to total land. A larger proportion of owned land comes at the cost of more restrictive access to capital due to higher liabilities and less income mobility (Barnes, Thomson and Ferreira 2020). Barnes et al. (2015) found that tenanted farms—farms with a high proportion of rented land—are more likely to be viable than owner-occupied farms because tenanted farms tend to be more innovative and flexible to achieve the optimal farm size (Ezcurra et al. 2011). Therefore, we expect that farms with a higher percentage of owned land are less likely to be viable.

Unpaid labour is the ratio unpaid labour to total labour. Family farms typically obtain higher levels of unpaid labour than corporate farms (Argilés 2001). For family farms, using more unpaid labour reduces labour costs (Biagini, Antonioli and Severini 2020). Hence, we expect higher unpaid labour ratios to be positively related to the probability of being viable.

Size is the farm size expressed in 100s of economic size units (ESU)[17]. Economies of scale enable larger farms to apply more cost-efficient management practices, which is positively associated with higher farm viability (Argilés 2001, Coppola et al. 2020). In line with these findings, we expect that larger farms are more likely to be viable.

[17] An ESU is a metric used to compare farm sizes across different farm types. It expresses farm size based on standardised gross margin.

Age is the age of the farm operator. Age reflects the life cycle of a farm, where older farmers are expected to have paid off more debts than younger farmers (de Mey et al. 2014). This reduces financial risk and increases flexibility, which is expected to increase the probability of being viable (Argilés 2001, Barnes, Foreman and Bevan 2018).

5.4.2.3 Risk and risk management variables

We consider price risk in terms of price volatility and price shocks. Additionally, we control for agricultural diversification as a risk management strategy that aims to mitigate the effects of price risk (Hardaker et al. 2015).

Price volatility is the 3-year coefficient of variation (CV) of the farmgate price of the output generating most revenue. Higher levels of price volatility result in more fluctuating farm incomes (Schulte, Musshoff and Meuwissen 2018). This lowers the probability of being viable.

We capture downside price risk by accounting for price shocks. A *price shock* is the percentage decrease in farmgate prices. This yields a continuous variable, ranging from 0 (no price shock at all) to 1 (largest possible price shock). More severe price shocks result in lower farm income, decreasing the probability to be viable.

Diversification reflects a farm's variety in crops and/or livestock. It helps mitigating price and production risk (Argilés 2001, McNamara and Weiss 2005). Barnes et al. (2015) showed that more diversified farms were more likely to be viable. We expect a similar relationship between agricultural diversification and the probability of being viable. The Herfindahl–Hirschman index (HHI) is used as agricultural diversification indicator (Rhoades 1993). Following Park, Mishra and Wozniak (2014), we define HHI as:

$$HHI = 1 - \sum_{i=1}^{n} s_i^2 \tag{4}$$

where s_i is the share of revenue from output i. HHI is a continuous variable, ranging from 0 (perfect specialisation) to 1 (perfect diversification).

5.4.2.4 Other variables

Additionally, we control for less favoured ares, farm types, and years. Less favoured areas (*LFA*) are remote rural areas limited by biophysical constraints (e.g. mountain areas). The restricted access to public services and narrow production possibilities negatively affect yield and income, ultimately constraining farm viability (Argilés 2001, Barnes et al. 2015, Barnes, Thomson and Ferreira 2020). Hence, we expect that farms with a majority of their land classified as LFA to be less likely to be viable. To control for heterogeneity across farm types and over time, we include dummies for, respectively, farm *type*, and *year*.

5.5 Results

We discuss the validity of our instrumental variables in section 5.5.1. Section 5.5.2 discusses the results of the econometric model and section 5.5.3 presents some robustness checks.

5.5.1 Instrumental variables

The reduced form equation is exactly identified. We consider our proposed instruments valid because of (i) the significance of the proposed instruments in the first-stage regression, (ii) the large increase in R^2 of the first-stage regression after including the instruments and the Kleibergen-Paap F-statistics that are larger than 10 and exceed the critical values of Stock and Yogo (2002), and (iii) the significance of the Kleibergen-Paap rk LM-statistics[18]. More details are available in Appendix 4.

Furthermore, we test if decoupled direct payments and rural development payments should be as endogenous using a Hausman test (Papke and Wooldridge 2008). This test inspects if the residuals of the first-stage regressions are significant in the second-stage equation. If one of the residuals has a significant effect on farm viability, we reject exogeneity and treat the corresponding variable as endogenous. A non-significant effect implies that we cannot reject exogeneity and should treat the corresponding variable as exogenous. In this case, the residuals are omitted from the second-stage regression. The results of the Hausman test can be consulted in Appendix 4.

5.5.2 Econometric results

Tables 5.3 and 5.4 present the average partial effects of the dynamic CRE probit models. It shows that both short and long-term viability are subject to state dependence as the lagged variables of short and long-term viability are positive and significant in all countries. Furthermore, the magnitude of state dependence for long-term viability is larger than short-term viability. Especially long-term viable farms are more likely to remain viable in the future, while non-viable farms are less likely to transform into future long-term viable states and are persistently non-viable[19]. These findings are in line with Barnes et al. (2015), who found that most non-viable farms will remain non-viable over a long-term period. Additionally, Phimister, Roberts and Gilbert (2004) found evidence that low-income farms experienced longer spells of low income compared to farms with higher income.

[18] As the first-stage regression is based on pooled OLS, which uses clustered standard errors at farm level, we consulted the Kleibergen-Paap F-statistics instead of the Cragg-Donald F-statistics.

[19] These results are further supported by Markov transition matrices (see Appendix 4), which show that long-term (non-) viable farms have a larger probability of remaining long-term (non-)viable over time, while the probability of transitioning to another viability state is small. For short-term viability, this pattern is less obvious.

Decoupled direct payments are moderately effective policy instruments to enhance short-term viability, while the long-term effectiveness of decoupled direct payments is low as decoupled direct payments constrain long-term farm viability in most countries. For short-term viability, our results reveal that the effect of decoupled direct payments is heterogeneous across two groups of countries: (i) Southern and Eastern European countries (Bulgaria, Italy, Poland, Romania, and Spain) and (ii) Western and Northern European countries (Belgium, France, Germany, the Netherlands, Sweden, and the United Kingdom). In Southern and Eastern European countries, our results confirm that decoupled direct payments increase the probability of being short-term viable. Hence, hypothesis 1 is supported in these countries. These findings are in line with previous studies that confirm the high income transfer efficiency from decoupled direct payments to farm income (Ciaian, Kancs and Paloma 2015, Biagini, Antonioli and Severini 2020). Ultimately, obtaining a higher farm income increases the probability of being short-term viable (Ojo et al. 2020). In Western and Northern Europe, decoupled direct payments reduce the probability of being short-term viable or have a non-significant effect. This implies that increasing the amount of decoupled direct payments does not contribute to a short-term viable farm income. Alternative policy interventions might be more promising to support farm viability in Western and Northern European countries—e.g. market-based measures to secure fair prices for farmers.

In the majority of the countries, hypothesis 2 is supported, indicating that receiving more decoupled direct payments decreases the probability of being long-term viable. Kazukauskas et al. (2013) found that receiving more decoupled direct payments over a long period of time potentially creates a dependency on subsidies, lowering the ability to change. This dependency on subsidies ultimately hinders or has no effect on long-term farm viability, making decoupled direct payments a questionable policy instrument to ensure a long-term viable farm income. We find that only in Romania decoupled direct payments increase the probability of being long-term viable. A possible explanation for this is that Romania is a relatively new EU member state in which the introduction of decoupled direct payments schemes could positively contribute to structural farm changes, resulting in a contribution to long-term viability.

For most other explanatory variables, the effects are heterogeneous across countries or mostly non-significant. We briefly discuss three variables with more consistent results. First, land tenure has a non-significant effect on short-term viability in most countries. However, land tenure has a negative effect on long-term viability in most countries. This indicates that having a higher proportion owned land relative to rented land decreases the probability of long-term being viable. Higher levels of land tenure result in more restrictive access to capital due to higher liabilities, reducing the probability of being long-term viability (Barnes et al. 2015). Restrictive access to capital is less important for short-term viability as this is an operational farm income measure; hence, the mostly non-significant effects.

Second, more volatile farmgate prices increase the probability to be short-term viable in Belgium, France, Italy, Poland, Spain, and Sweden. A possible explanation for this surprising finding could be that price volatility reflects both upwards and downward price fluctuations.

Apparently, short-term upwards price fluctuations outweigh downwards price volatility, resulting in higher prices and increasing farm incomes. This increases the probability of being short-term viable. The effect of price volatility on long-term viability is mixed. More volatile prices increase the probability of being long-term viable in the United Kingdom, while it has a negative effect on France, Germany, Italy, and the Netherlands.

Third, we find that price shocks decrease the probability of being short-term viable in all countries except Romania and Bulgaria. The long-term effects obtain a similar pattern, although it is worth noting that non-significant effects occur in more countries. In general, this indicates that severe price shocks decrease farm income (Schulte, Musshoff and Meuwissen 2018), ultimately reducing the probability of being both short and long-term viable.

Table 5.3 Average partial effects of the dynamic correlated random effects probit model for short-term viability.

	Belgium	Bulgaria	France	Germany	Italy	The Netherlands
STV at *t-1*	0.249***	0.122***	0.197***	0.204***	0.105***	0.269***
	(0.022)	(0.028)	(0.010)	(0.009)	(0.005)	(0.019)
DDP	-0.104	1.030***	0.003	-0.152***	0.189***	-0.850***
	(0.143)	(0.209)	(0.043)	(0.054)	(0.030)	(0.272)
RDP	0.150	-1.208***	-0.357***	0.091*	0.009	-0.607*
	(0.233)	(0.259)	(0.096)	(0.055)	(0.066)	(0.350)
Land tenure	0.154**	0.088	-0.039	-0.064**	-0.016	0.106**
	(0.075)	(0.079)	(0.039)	(0.026)	(0.025)	(0.054)
Unpaid labour	0.025	-0.154**	0.097***	0.087**	0.051*	0.020
	(0.118)	(0.065)	(0.026)	(0.035)	(0.027)	(0.091)
Size	-0.005	-0.008	0.010***	-0.002	-0.001	0.008
	(0.005)	(0.024)	(0.004)	(0.002)	(0.001)	(0.005)
Age	-0.001	-0.000	-0.001*	-0.001	0.001	-0.001
	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Price volatility	0.180*	0.334	0.088**	0.053	0.165***	-0.086
	(0.108)	(0.257)	(0.038)	(0.041)	(0.051)	(0.107)
Price shock	-0.442***	-0.066	-0.377***	-0.173***	-0.119***	-0.147**
	(0.076)	(0.144)	(0.032)	(0.034)	(0.043)	(0.068)
Diversification	-0.002	0.116	0.058**	-0.057	-0.104***	-0.140
	(0.073)	(0.099)	(0.028)	(0.035)	(0.026)	(0.086)
LFA	-0.007	0.108***	-0.010**	-0.014**	-0.003	0.048**
	(0.018)	(0.023)	(0.005)	(0.006)	(0.005)	(0.021)
Farm type	Included, for all countries					
Year	Included, for all countries					
c_i	Included, for all countries					
Endogenous variables	DDP	DDP, RDP	DDP	DDP, RDP	DDP	
N	6,209	3,062	35,411	33,582	40,684	5,692

Notes: STV = short-term viability; DDP = decoupled direct payments; RDP = rural development payments; LFA = less favoured area. c_i refers to unobserved heterogeneity. Endogenous variables are the variables that rejected the Hausman test (Null hypothesis: exogeneity). Lagged variables of endogenous variables are used as instruments. Fully robust bootstrapped standard errors (500 replications) are presented in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Table 5.3 (continued) Average partial effects of the dynamic correlated random effects probit model for short-term viability.

	Poland	Romania	Spain	Sweden	United Kingdom
STV at *t-1*	0.171***	0.333***	0.237***	0.148***	0.112***
	(0.006)	(0.043)	(0.006)	(0.021)	(0.028)
DDP	0.652***	0.425***	0.381***	-0.552***	0.280
	(0.070)	(0.153)	(0.033)	(0.208)	(0.176)
RDP	-0.669***	-0.265	-0.299***	-0.015	0.237
	(0.059)	(0.277)	(0.056)	(0.247)	(0.467)
Land tenure	-0.038	-0.115	0.014	-0.052	0.159
	(0.025)	(0.086)	(0.023)	(0.085)	(0.118)
Unpaid labour	-0.022	0.363***	0.082***	0.149	0.068
	(0.034)	(0.136)	(0.021)	(0.113)	(0.066)
Size	0.001	-0.057***	0.020***	-0.010	0.011
	(0.017)	(0.022)	(0.006)	(0.011)	(0.014)
Age	0.002***	0.006	0.004***	-0.007	-0.001
	(0.000)	(0.004)	(0.001)	(0.005)	(0.002)
Price volatility	0.140***	-0.134	0.424***	0.382**	-0.031
	(0.024)	(0.158)	(0.058)	(0.168)	(0.091)
Price shock	-0.403***	0.035	-0.386***	-0.607***	-0.748***
	(0.025)	(0.180)	(0.034)	(0.150)	(0.208)
Diversification	0.039*	-0.076	-0.081***	-0.073	0.216**
	(0.021)	(0.106)	(0.020)	(0.091)	(0.109)
LFA	-0.006	-0.019	0.000	-0.006	-0.021**
	(0.004)	(0.014)	(0.005)	(0.017)	(0.010)
Farm type			Included, for all countries		
Year			Included, for all countries		
c_i			Included, for all countries		
Endogenous variables	DDP, RDP	DDP	DDP	DDP	DDP, RDP
N	58,923	3,781	40,142	4,928	10,820

Notes: STV = short-term viability; DDP = decoupled direct payments; RDP = rural development payments; LFA = less favoured area. c_i refers to unobserved heterogeneity. Endogenous variables are the variables that rejected the Hausman test (Null hypothesis: exogeneity). Lagged variables of endogenous variables are used as instruments. Fully robust bootstrapped standard errors (500 replications) are presented in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Table 5.4 Average partial effects of the dynamic correlated random effects probit model for long-term viability.

	Belgium	Bulgaria	France	Germany	Italy	The Netherlands
LTV at *t-1*	0.551***	0.491***	0.465***	0.515***	0.635***	0.377***
	(0.031)	(0.047)	(0.012)	(0.016)	(0.015)	(0.030)
DDP	-0.003	-0.045	-0.209***	-0.225***	-0.086***	-0.237
	(0.142)	(0.117)	(0.045)	(0.046)	(0.017)	(0.196)
RDP	-0.027	0.021	-0.457***	-0.041	0.033	-1.254***
	(0.346)	(0.117)	(0.161)	(0.046)	(0.061)	(0.389)
Land tenure	-0.161**	-0.079	-0.074*	-0.084***	-0.108***	-0.077*
	(0.068)	(0.052)	(0.039)	(0.020)	(0.013)	(0.043)
Unpaid labour	-0.123	-0.008	0.021	0.000	-0.003	-0.102**
	(0.101)	(0.046)	(0.027)	(0.026)	(0.015)	(0.048)
Size	-0.001	0.009	0.009**	0.001	0.000	0.001
	(0.005)	(0.020)	(0.004)	(0.001)	(0.002)	(0.003)
Age	-0.003	-0.001	-0.000	-0.001*	0.001**	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
Price volatility	-0.048	0.269	-0.118***	-0.100***	-0.106***	-0.185***
	(0.088)	(0.172)	(0.036)	(0.033)	(0.032)	(0.064)
Price shock	-0.223***	-0.173	-0.109***	-0.088***	0.006	0.001
	(0.068)	(0.106)	(0.032)	(0.028)	(0.028)	(0.048)
Diversification	-0.069	-0.039	0.025	-0.004	-0.069***	-0.127**
	(0.071)	(0.063)	(0.030)	(0.029)	(0.016)	(0.062)
LFA	-0.048***	0.003	-0.027***	-0.034***	0.007***	-0.001
	(0.018)	(0.019)	(0.004)	(0.005)	(0.003)	(0.018)
Farm type			Included, for all countries			
Year			Included, for all countries			
c_i			Included, for all countries			
Endogenous variables	DDP	DDP, RDP	DDP	DDP, RDP	DDP	
N	6,209	3,062	35,411	33,582	40,684	5,692

Notes: LTV = long-term viability; DDP = decoupled direct payments; RDP = rural development payments; LFA = less favoured area. c_i refers to unobserved heterogeneity. Endogenous variables are the variables that rejected the Hausman test (Null hypothesis: exogeneity). Lagged variables of endogenous variables are used as instruments. Fully robust bootstrapped standard errors (500 replications) are presented in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Table 5.4 (continued) Average partial effects of the dynamic correlated random effects probit model for long-term viability.

	Poland	Romania	Spain	Sweden	United Kingdom
LTV at *t-1*	0.463***	0.637***	0.627***	0.313***	0.522***
	(0.010)	(0.072)	(0.051)	(0.040)	(0.042)
DDP	-0.650***	0.269**	0.176	-0.311***	-0.186***
	(0.048)	(0.105)	(0.186)	(0.053)	(0.060)
RDP	0.209***	0.987***	0.011	0.144***	0.143
	(0.035)	(0.324)	(0.095)	(0.031)	(0.309)
Land tenure	-0.193***	-0.089	-0.080***	-0.085***	-0.007
	(0.020)	(0.058)	(0.025)	(0.023)	(0.038)
Unpaid labour	-0.092***	0.238**	0.066	-0.030	0.051
	(0.024)	(0.093)	(0.044)	(0.032)	(0.032)
Size	0.020***	0.055***	0.004	0.000	0.004
	(0.005)	(0.017)	(0.007)	(0.002)	(0.005)
Age	-0.001	-0.005*	-0.001	-0.002	-0.002
	(0.000)	(0.003)	(0.001)	(0.002)	(0.075)
Price volatility	-0.005	0.072	0.142	0.021	0.217**
	(0.021)	(0.108)	(0.128)	(0.033)	(0.106)
Price shock	-0.050**	-0.058	0.029	-0.019	-0.168*
	(0.021)	(0.124)	(0.038)	(0.039)	(0.089)
Diversification	0.024	-0.079	0.030	-0.088***	-0.010
	(0.017)	(0.068)	(0.056)	(0.022)	(0.023)
LFA	-0.001	-0.024**	0.008**	-0.014***	0.012
	(0.004)	(0.010)	(0.004)	(0.005)	(0.009)
Farm type	Included, for all countries				
Year	Included, for all countries				
c_i	Included, for all countries				
Endogenous variables	DDP, RDP	DDP	DDP	DDP, RDP	DDP, RDP
N	58,923	3,781	40,142	4,928	10,820

Notes: LTV = long-term viability; DDP = decoupled direct payments; RDP = rural development payments; LFA = less favoured area. c_i refers to unobserved heterogeneity. Endogenous variables are the variables that rejected the Hausman test (Null hypothesis: exogeneity). Lagged variables of endogenous variables are used as instruments. Fully robust bootstrapped standard errors (500 replications) are presented in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

5.5.3 Robustness checks

To investigate how robust our results are to alternative model specifications, we estimate models that specify long-term viability over a 4 or 5-year period as well. This provides additional insights in the robustness of our results. However, this comes at the cost of losing additional observations as more years are required to compute a long-term viability state. For the sake of brevity, we only report the signs and significance of the two key variables—i.e. state dependence and decoupled direct payments—for the alternative model specifications in Table 5.5. It shows that the results are robust in all countries except Bulgaria, Romania[20], and Spain.

5.6 Discussion and conclusions

A key objective of the CAP is to support viable farm incomes. In this chapter, we assess the effect of decoupled direct payments on short and long-term farm viability in eleven European countries. We estimate dynamic correlated random effects probit models to identify causal effects, using a control function approach to account for endogeneity.

We find that 74.5 per cent of the farms in our sample is short-term viable, while only 42.5 per cent of the farms is long-term viable. Our results suggest that state dependence exists for both short and long-term viability, implying that viable farms are more likely to remain viable over time, while non-viable farms are less likely to become viable. This indicates that it is challenging to facilitate a transition from non-viable to viable farms. The effectiveness of decoupled direct payments in supporting viable farms is low in most countries and depends on the considered time horizon. Decoupled direct payments have a heterogeneous effect on short-term viability that differs across countries and regions. In Western and Northern European countries, decoupled direct payments do not enhance short-term farm viability and even decrease the probability of being short-term viable in most countries. Short-term farm viability is positively affected by decoupled direct payment in Southern and Eastern Europe, making it an effective policy instrument to ensure viable farm incomes in these countries. However, we also find that decoupled direct payments constrain or have no significant effect on long-term farm viability in 10 out of 11 countries. Only in Romania, receiving more decoupled direct payments increases the probability of being long-term viable.

[20] In the 5-year model of Romania, the maximum likelihood function did not converge due to a severe reduction in number of observations. Note that for Romania, only seven years (2007–2013) of data entries are available. Dropping four years to define long-term viability and one year to include a lagged dependent variable, results in a remaining dataset of 2 years.

Table 5.5 Comparison of signs and significance of the average partial effects under several model specification for long-term viability.

	Belgium	Bulgaria	France	Germany	Italy	The Netherlands
			Long term viability at *t-1*			
3 years	+	+	+	+	+	+
4 years	+	+	+	+	+	+
5 years	+	+	+	+	+	+
			Decoupled direct payments			
3 years	n.s.	n.s.	–	–	–	n.s.
4 years	n.s.	n.s.	–	–	–	n.s.
5 years	n.s.	–	–	–	–	n.s.

	Poland	Romania	Spain	Sweden	United Kingdom
			Long term viability at *t-1*		
3 years	+	+	+	+	+
4 years	+	+	+	+	+
5 years	+	n.c.	+	+	+
			Decoupled direct payments		
3 years	–	+	n.s.	–	–
4 years	–	n.s.	+	–	–
5 years	–	n.c.	+	–	–

Notes: 3 years refers to the original model where long-term viability is defined over a 3-year period. 4 and 5 years refer to the alternative model specification where long-term viability is defined over, respectively, a 4 and 5-year period. n.s. indicates no significant effect on farm viability, n.c. indicates no convergence due to limited sample size, + indicates a positive effect on farm viability, and – indicates a negative effect on farm viability.

We discuss three limitations of this study. First, economic theory suggests that farmers of long-term non-viable farms are better off working off-farm. Therefore, these farmers are more likely to quit farming in the long run. However, most of the farms in our sample remains long-term non-viable over time, suggesting farm continuation despite being non-viable. It could be that the considered time-horizon in our analysis—i.e. 7 years— is not sufficient to observe farm exits, which most often occurs if no successor is available. As farm exits or transfer decisions are typically a multi-generational process (Coopmans et al. 2020), these patterns are not captured in our data and model. Second, the dynamic correlated random effects probit model estimates the average effect of decoupled direct payments on farm viability, indicating that the effect is restricted to be the same for both viable and non-viable farms. However, the effect of decoupled direct payments on farm viability might differ between non-viable and viable farms due to large differences in structural farm characteristics. These differential effects could be estimated using an endogenous switching probit model (e.g. Thomas and Gaspart 2014), at the expense of being limited to pooled estimations that do not account for unobserved heterogeneity. Third, our study does not account for heterogeneity in farm type or size due to the broad European scale of the analysis. The unequal distribution of decoupled direct payments in favour of farms with more land could indicate that the effect of decoupled direct payments on farm viability is heterogeneous across farm size. Future research could further explore these heterogeneous farm size effects.

We make two policy recommendations to European agricultural policy makers. First, agricultural policy makers should be aware of the low effectiveness of decoupled direct payments in supporting long-term viability. Despite substantial income support, the majority of the European farms in our sample is non-viable in the long term and most of these farms remain structurally non-viable over time. We recommend that policy makers design policies to support long-term viability instead of short-term viability. Second, we recommend policy makers to investigate alternative policy instruments to support viable farm incomes. Examples of policy instruments that could be more effective then direct income support are measures to facilitate fair farmgate prices in collaboration with supply chain partners (European Commission 2020a), the design of alternative business models that pay farmers for landscape and biodiversity services (Bullock et al. 2011), and risk management solutions for extreme weather circumstances (Vroege and Finger 2020).

6 General discussion and conclusions

6.1 Introduction

Understanding farm resilience has developed into a focal point for European agricultural policy makers. This resulted in a call for assessing farm resilience and an increased interest in better understanding what attributes enhance farm resilience (European Commission 2020a). The overall objective of this thesis is to assess the resilience of European farms.

The specific research objectives (RO) were:

RO1. To explore how farmers' risk behaviour is related to perceived resilience in terms of robustness, adaptability, and transformability.

RO2. To explore how farmers' social networks and learning contribute to perceived resilience in terms of robustness, adaptation, and transformation.

RO3. To quantify farm resilience in terms of robustness, adaptation, and transformation.

RO4. To investigate the effect of decoupled direct payments on short and long-term farm viability.

Note that RO1 investigates the perceived ability to be robust, to adapt or to transform—i.e. it refers to robustness, adaptability, and transformability—while RO2 and RO3 studied how changes in the past have revealed robustness, adaptation and transformation. Hence, these ROs refer to robustness, adaptation, and transformation. Addressing these four research objectives has contributed to a better understanding of the resilience of European farms in terms of shocks and stresses, resilience capacities, and the delivery of private and public goods.

All chapters understood resilience as a latent concept (Meuwissen et al. 2021) that was investigated using multiple indicators that together shape resilience. For instance, by combining psychometric items to elicit perceived resilience (Chapter 2), inferring indicators for revealed past resilience (Chapter 3), or conceptualising multiple indicators based on data from the Farm Accountancy Data Network (FADN) (Chapters 4 and 5). Furthermore, the resilience capacities were assessed in Chapters 2-4 using a combination of perceived and indicator-based approaches. The perceived resilience assessments showed how portfolios of risk management strategies, social networks, and learning contributed to improved decision-making under risk and uncertainty that enhances resilience. The indicator-based assessments reflected on the effectiveness of CAP instruments to enhance farm resilience and viability.

The remainder of this chapter is structured as follows: section 6.2 synthesises the results of Chapters 2-5; the scientific contribution of this thesis is discussed in section 6.3. Section 6.4 provides policy recommendations to enhance European farm resilience. Section 6.5 presents the business recommendations of this thesis. Section 6.6 presents some limitations of this thesis and provides pathways for future studies. Finally, the main conclusions are presented in section 6.7.

6.2 Synthesis of the results

Three common themes across chapters stand out to improve the overall understanding of farm resilience: (i) moving from risk theory to resilience thinking, (ii) assessing the contribution of risk management portfolios to the resilience capacities, and (iii) assessing the role of income in measuring farm resilience. The first and second themes coincide with how dealing with shocks and stresses is related to the resilience capacities. The third theme discusses how farm income can be studied from three different angles in the context of resilience.

Moving from risk theory to resilience thinking

Recently, policy makers and scientists have called for a shift from analysing risk to studying resilience (Aven 2019). Chapter 2 demonstrated how resilience thinking benefits from a better understanding of risk by studying the relationship between risk behaviour—risk perceptions, preferences, and management—and perceived farm resilience. Furthermore, Chapter 3 has shown how learning about risk is important for enhancing the resilience capacities. Some of the similarities and differences between risk analysis and resilience are detailed below, followed by a discussion on how resilience benefits from analysing risk.

A recent literature review of Komarek, De Pinto and Smith (2020) on risk analysis in agriculture revealed that 85% of the studies focused exclusively on one single risk—e.g. production risk (Vollmer, Hermann and Mußhoff 2017), income risk (Finger and El Benni 2014b), or financial risk (de Mey et al. 2016)—while the remaining 15% of studies applied a more holistic approach that addresses multiple risks (Meuwissen, Huirne and Hardaker 2001, Flaten et al. 2005). Such a holistic approach to risk analysis was adopted in Chapters 2 and 3, in which farmers' risk perceptions to multiple sources of risk were elicited. Risk analyses that solely focus on one type of risk have a lot of similarities with specified resilience—i.e. the resilience of what to what (Carpenter et al. 2012)—as both streams of literature consider strategies to successfully deal with one specific risk. This approach was adopted in Chapter 5, which investigated the effect of price risk on short and long-term farm viability. Inherent to studying a selected risk is that a fair amount of knowledge regarding the probabilities and/or outcomes is present. Hence, risk analysis and specified resilience often follow a Knightian understanding of risk—i.e. events with known probabilities and outcomes. Figure 6.1 illustrates that general resilience expands these views by considering ignorance, which refers to events that were unknown until they occurred, implying unknown probabilities and unknown outcomes (Bond et al. 2015). This makes studying general resilience more complex than studying risk or specified resilience. Chapters 2–4 illustrated how general resilience can be investigated by considering farmers' resilience capacities to all kinds of shocks and stresses (Chapters 2 and 3) or by following farms over time to investigate general responses reflecting the revealed robustness, adaptation, and transformation to a whole range of shocks and stresses (Chapter 4). These chapters revealed how general resilience is a suitable lens to study *ex-ante* if farms are prepared for unknown events, like previously unimaginable crises such as COVID-19 (Darnhofer 2020, Meuwissen et al. 2021).

Risk analysis and specified resilience can only be applied to *ex-post* evaluations, as some knowledge about probabilities and outcomes is needed. The added value of analysing risk and specified resilience is that it helps farmers to be better prepared for recurring risks.

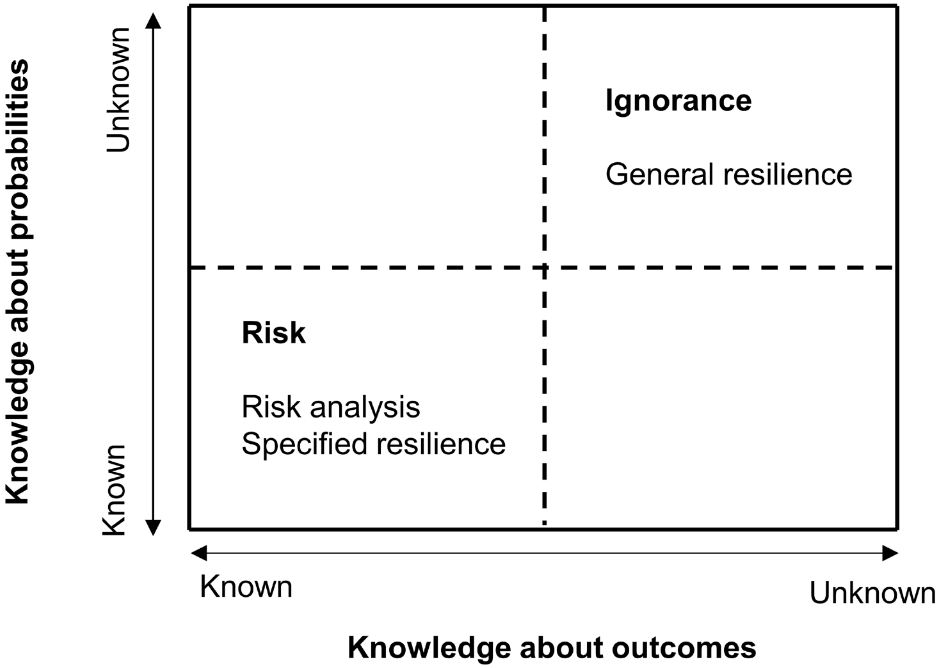

Figure 6.1 Uncertainty matrix to position how risk analysis, specified resilience, and general resilience were analysed in this thesis. Adapted from Stirling (2010) and Bond et al. (2015).

Note that the cells with unknown probabilities and known outcomes or known probabilities and unknown outcomes in Figure 6.1 remained empty as these were not investigated in this thesis. Events with unknown probabilities and known outcomes were defined as uncertainty by Knight (1921), who understood risk as events with known *objective* probabilities and outcomes. Although this conceptualisation between risk and uncertainty is theoretically clear, it is generally accepted in agricultural risk analysis and agricultural economics to replace missing objective probabilities with subjective beliefs about probabilities, making the distinction between risk and uncertainty less clear and probably even ignorable (Moschini and Hennessy 2001, Hardaker and Lien 2010, Bougherara et al. 2017). These subjective beliefs about probabilities of events were studied in Chapters 2 and 3 by eliciting farmers' risk perceptions. Events with known probabilities and unknown outcomes could be analysed using scenario analysis (Stirling 2010), although these tend to be studied less often within risk analysis.

Despite these differences between risk theory and resilience thinking, resilience cannot be assessed without analysing risk (Aven 2017). To move from analysing risk to assessing general resilience, Chapters 2 and 3 started with a risk analysis through the lens of risk behaviour, which was succeeded by an assessment of general resilience in terms of the resilience capacities. Both chapters revealed associations that demonstrated how concepts of risk behaviour may improve our understanding of general resilience. For instance, that less risk-averse farmers perceived themselves as being better able to adapt or transform. There were mixed results on the relationship between risk preferences and perceived robustness. Chapter 3 indicated that more risk-averse farmers were more robust, while Chapter 2 found only in specific cases a significant relationship between higher risk-aversion and robustness. Another important concept from risk analysis that contributes to the assessment of resilience is risk management (Park et al. 2013, Aven 2019). The contribution of risk management to resilience will be discussed in the next paragraphs.

Assessing the contribution of risk management portfolios to the resilience capacities

Chapter 3 has shown that managing and learning about risk is needed to obtain more complete information (Cundill et al. 2015), helping farmers to deal with the unknown. Hence, the role of risk management in enhancing farm resilience was studied by investigating single risk management strategies (agricultural diversification in Chapter 5), portfolios of risk management strategies (Chapter 2), and understanding how farmers learn about risk (Chapter 3). A common misunderstanding about the relationship between risk management and resilience is that risk management primarily contributes to farm robustness and has limited potential for enhancing adaptability and transformability. Chapter 2 showed that a shift from studying risk management strategies in isolation towards an integrated approach that considers farmers' portfolios of risk management strategies is needed. It showed that more diverse risk management portfolios were positively associated with the adaptability and transformability of Dutch farms.

However, the dominant view on risk management within agricultural economics is an economic understanding of costs and benefits for separate risk management strategies. It assumes that risk management strategies will be adopted if the costs are considered to be lower than the benefits (Schmit and Roth 1990). This understanding of risk management can be successful to enhance farm robustness, as the main focus is on creating buffers and absorbing shocks (OECD 2020). For instance, buying insurance or having financial buffers as risk management strategies are likely to enhance farm robustness. Chapter 5 adopted an approach that studied a single risk management strategy and demonstrated the mixed, and mostly non-significant, effects of agricultural diversification on short- and long-term farm viability, providing an example of the low effectiveness of single risk management strategies to enhance farm viability.

To overcome this narrow view on risk management, Chapter 2 showed that the impact on environmental and social functions, such as biodiversity or citizens' trust in agriculture, should also be considered when discussing the contribution of risk management to resilience. This chapter defined risk management as the portfolio of strategies that farmers adopt to minimise the impact and potential costs of risk on economic, environmental, and social farm functions. Supporting this view on risk management, recent developments in agricultural economics and risk theory have started to explore the adoption of combinations of risk management strategies (Coffey and Schroeder 2019, Meraner and Finger 2019, Vigani and Kathage 2019). This portfolio view on risk management is embedded in resilience theory as response diversity and is one of the key resilience-enhancing attributes (Resilience Alliance 2010, Cabell and Oelofse 2012). Chapter 2 confirmed that the diversity of risk management strategies adopted by Dutch farmers was positively associated with adaptability and, in most cases, related to transformability, while no correlations were found between the diversity of risk management portfolios and robustness. This result may be explained by the fact that optimising single (often financial) risk management strategies is sufficient to support farm robustness and improve stability. Furthermore, an increased focus on *ex-ante* risk management strategies rather than *ex-post* strategies is needed to enhance resilience, as *ex-ante* strategies help farmers to prepare for the unknown (OECD 2020). This can be facilitated by diverse portfolios of risk management strategies that help to respond to and be better prepared for the unknown.

Assessing the role of income in measuring farm resilience

The relationship between farm income and resilience was investigated from three perspectives (Chapters 2, 4, and 5): (i) farm income as a function, which performance can be investigated over time to assess resilience, (ii) the usage of indicators derived from farm income and/or profitability to operationalise robustness, and (iii) farm income and/or profitability as a potential resilience-enhancing strategy. First, farm income was understood as a farm function that was studied over time to assess farm resilience (Meuwissen et al. 2019). Chapter 5 adopted this approach and operationalised a viable farm income in terms of a rate-of-return on unpaid labour. Understanding whether farms obtain a viable income over time is of importance to resilience as it enables farms to continue investing and adds to financial buffers (Cabell and Oelofse 2012, Meuwissen et al. 2019) or the financial room to manoeuvre for investments concerning adaptation or transformation.

Second, Chapter 4 demonstrated how changes in profitability over time can be used to study farm robustness by investigating resistance (Urruty, Tailliez-Lefebvre and Huyghe 2016, Dardonville, Bockstaller and Therond 2021), recovery rates (Dardonville, Bockstaller and Therond 2021), and the number of severe income shocks (Sabatier et al. 2015, Sneessens et al. 2019). This view on profitability explains how farms that obtained a stable income over time were considered to be more resilient in terms of robustness.

Third, maintaining a decent farm income could be understood as a resilience-enhancing strategy (Cabell and Oelofse 2012). This view on farm income has been adopted in Chapters 2 and 4. Chapter 2 investigated differences across farmers' perceived resilience capacities by comparing a group of farmers that perceived farm income as less important to farmers that prioritised income over other farm functions. The findings demonstrated that farmers who prioritised farm income less perceived themselves as better able to transform compared to farms that perceived farm income as more important. Note that the perceived importance of farm income does not represent farmers' actual farm income, as it could be that farms with low income prioritised income over providing other farm functions, such as creating biodiversity or maintaining natural resources. Chapter 4 has shown that profitability harms robustness in most European regions while having no significant effect on adaptation and transformation. These findings contradict Cabell and Oelofse (2012), who explain that reasonably profitable farms are better able to create buffers and recover from shocks and stresses. The negative effect of profitability on robustness is in line with previous studies that suggest that being highly profitable does not necessarily ensure stable profitability (Eeswaran, Pouyan Nejadhashemi and Miller 2021). The findings of Chapters 4 and 5 may imply that there are trade-offs between the delivery of farm functions and the resilience capacities. While Chapter 4 revealed that more profitable farms are in general less robust, Chapter 5 indicated that obtaining a viable farm income implies a better performance of farm functions. Although both farm viability and profitability are income-based measures, it is important to bear in mind that Chapter 4 investigated the rate-of-return on assets, while Chapter 5 used a rate-of-return on unpaid labour. Hence, cautious interpretation of these findings is required.

6.3 Scientific contribution

This thesis assessed the resilience of farms from different scientific angles using a combination of qualitative and quantitative methods. The overall scientific contribution of this thesis is an integrated approach to assess the resilience of farms in terms of shock and stresses, the resilience capacities, and farm functions by combining perceived and indicator-based approaches. More specific contributions regarding the operationalisation of and assessment of farm resilience are discussed below.

First, Chapters 2 and 4 have contributed to the operationalisation of farm resilience by considering how robustness, adaptability, and transformability can be jointly measured, while most previous studies that operationalised farm resilience considered one resilience capacity in isolation. Chapter 2 is one of the first studies that has operationalised perceived robustness, adaptability, and transformability based on several self-assessment questions. This perception-based approach to operationalising the resilience capacities has been used as a starting point for further studies on perceived farm resilience (see e.g. Spiegel et al. 2021b). Chapter 4 presented a new method to operationalise the resilience capacities by studying changes in farm inputs and outputs over time. It is the first study that operationalised all three resilience capacities in a large number of European countries using the FADN dataset. An advantage of this approach is that it obtains general indicators that are applicable in a wide context and can be used to compare the resilience capacities across several European countries.

Second, Chapters 2, 3, and 5 contributed to improved farm resilience assessments and a better understanding of the strategies that constrain or enhance farm resilience. Chapter 2 contributed to improved insights into the relationships between risk behaviour—in terms of risk preferences, perceptions, and management—and the perceived resilience capacities. The idea of integrating risk behaviour into resilience thinking is not new but has only been partially captured in previous studies. For instance, by considering the relationship between risk perception and one of the resilience capacities—e.g. adaptability (Grothmann and Patt 2005) or transformability (Marshall et al. 2014)—or investigating how risk management could foster farm adaptability (Sutherland et al. 2017, Deines et al. 2019). Chapter 3 empirically investigated how social networks and learning foster farm robustness, adaptation, and transformation and was among the first applications of the conceptual framework of De Kraker (2017) to farm resilience. Finally, Chapter 5 contributed to a better understanding of farm functions by studying European farm viability over time. This chapter considered a dynamic approach of farm viability that accounts for state dependence, while previous studies were limited to static approaches that did not consider state dependence.

6.4 Policy recommendations

This thesis provides several recommendations to redesign existing policies to enhance farm resilience. Agricultural policy makers should consider fostering the diversity of policy instruments to enhance farm resilience. Chapters 2-4 have shown that it is important to identify specific strategies to enhance robustness, adaptability, and transformability instead of focussing on instruments that target resilience without specifying a resilience capacity. Furthermore, the recommendations in this section suggest how policy makers can improve their resilience assessments.

The starting point of the policy recommendations is an evaluation of the effectiveness of income support provided by the CAP. The findings of this thesis suggest that the main source of income support provided by the CAP—decoupled direct payments—had heterogeneous effects on the resilience capacities (Chapter 4) and farm viability (Chapter 5) across European countries and farm types. Chapter 4 revealed that decoupled direct payments had a positive effect on the robustness of Northern European farms, while it mostly harmed the robustness of all farm types from Western, Southern, and Eastern Europe. Decoupled direct payments had a negative or non-significant effect on farm adaptation and transformation in most European countries. These findings contradict OECD (2020), who hypothesised that transformations can be enhanced by income support. Furthermore, Chapter 5 indicated that decoupled direct payments increased the probability to be short-term viable in Southern and Eastern European countries while having a negative or non-significant effect on farms from Northern and Western European countries. Decoupled direct payments reduced the probability to be long-term viable in almost all countries in our sample. This suggests that the effectiveness of decoupled direct payments to enhance farm resilience and viability is in general low. In line with Pe'er et al. (2020) and Feindt et al. (2021), we recommend policy makers to introduce alternative policy instruments that are not based on direct income support. Instead of focussing on income support, we recommend policy makers to embrace a diversity of instruments to enhance farm resilience in terms of robustness, adaptability, and transformability. The following paragraphs present several of these alternative policy instruments for each of the resilience capacities.

Robustness-enhancing instruments help farmers to maintain the status quo and improve stability (Manevska-Tasevska et al. 2021). For instance, policy makers could stimulate the adoption of financial risk management strategies (e.g. insurance or financial savings) to create buffers or a financial safety net. The CAP already supports current developments for improved risk management solutions to extreme weather, which includes designing improved insurances (Vroege and Finger 2020). Moreover, Chapter 3 demonstrated that robustness can be enhanced by building bonding social capital to facilitate farmers to learn from peers about optimising agricultural practices. Policy makers could facilitate an improved flow of informal knowledge. For instance, by stimulating collaboration with local initiatives (e.g. study clubs) to improve information exchange (Šūmane et al. 2018).

Adaptability-enhancing instruments improve the ability to be flexible by changing the farm inputs and/or outputs composition (Meuwissen et al. 2019). To enhance adaptability, agricultural policy makers should stimulate farmers to adopt a portfolio view on risk management instead of focussing on optimising single risk management strategies (Chapter 2). Additionally, Chapter 3 revealed that combining bonding and bridging social capital based on informal and formal networks has the potential to enhance adaptability by learning about new agricultural practices and innovations. The current CAP already welcomes these initiatives by embedding them within Agricultural Knowledge and Innovation Systems (AKIS). For instance, through the European Innovation Partnership on Agricultural Productivity and Sustainability (EIP-Agri) and the leader programmes that connect farmers with other stakeholders to facilitate learning, innovations, and networking.

Transformability-enhancing instruments support radical changes, often resulting in severe redistributions of farm inputs and/or outputs (Vermeulen et al. 2018). Similar to adaptation, Chapter 2 has shown that diverse risk management portfolios have the potential to facilitate farm transformation by enhancing response diversity (Cabell and Oelofse 2012). Furthermore, Chapter 3 indicated that transformations can be supported by building linking social capital from formal networks and facilitating learning about radically new ideas. Agricultural policy makers could stimulate leader programmes that connect farmers to formal institutes. Finally, policy recommendations from Chapters 4 and 5 suggested that the CAP could enhance farmers' ability to transform by compensating them for providing public goods. This could be done by shifting more resources from decoupled direct payments towards payments for public goods and eco-schemes (Pe'er et al. 2020).

Assessing farm resilience remains one of the focal policy points of the CAP (European Commission 2020a). However, how resilience is best assessed is still being debated. Policy makers are recommended to assess both the resilience capacities (Chapters 2-4) and farm functions over time (Chapter 5) to fully understand resilience. Insights from resilience capacities should be combined with the delivery of farm functions as they provide complementary insights into how farmers cope with shocks and stresses by maintaining the status quo or by changing, and how the provision of private and public goods in agriculture can be ensured.

6.5 Business recommendations

This thesis has implications for farmers, other supply chain actors, innovation platforms, and banks and other credit suppliers. Farmers are recommended to adopt a view on resource allocation that does not just consider optimisation or efficiency but also focuses on having buffers to enhance robustness and/or being flexible (e.g. labour or input flexibility) to foster adaptability or transformability (Darnhofer 2014). Adaptability and transformability could be enhanced by having diverse risk management portfolios that consist of strategies contributing to most of the following attributes: flexibility, cooperation with others, financial risk management, measures to deal with environmental risk, diversification or specialisation, and learning (Chapter 2). Furthermore, learning from both formal and informal networks should be stimulated to increase openness to new ideas (Chapter 3). This helps farmers to be better prepared for change and surprise and enhances specifically adaptability and transformability.

Food supply chains rely on resilient farms to secure a stable and sufficient provision of food. However, Chapter 3 illustrated that the relationships between supply chain actors, such as cooperatives or processors, and farmers were perceived as formal. This was confirmed by Chapter 2, which showed that farmers perceived a low bargaining power towards processors as one of the most severe challenges. These formal relationships imply large power differences between farmers and other supply chain actors that hamper learning and information exchange, potentially constraining the adaptability and transformability of farms and supply chains. Supply chain actors are recommended to foster cooperation and learning with farmers. This could be done by creating joint innovation programmes.

Regional innovation and learning platforms play a key role in building AKIS and knowledge exchange. Chapter 3 underlined the importance of learning from others to facilitate farm adaptation and transformation by building bridging and linking social capital. To build bridging and linking social capital, farmers should learn from a diverse group of stakeholders including peers, technology providers, banks, supply chain actors, and policy makers. Regional innovation and learning platforms could host these events to facilitate social learning about developments in precision agriculture, digitalisation, innovation or even radical non-agricultural ideas, such as farm tourism.

Finally, implications arise for banks and other credit suppliers that grant farmers access to capital for investments. For instance, banks need to comply with Basel III regulations to adhere to standards regarding capital buffers and sufficient liquidity. To determine which farms should be granted loans, banks and other credit suppliers need to understand which farms are future-proof and can be safely provided access to capital while minimising the probability of default. Two of these indicators for future-proof farms are farm resilience, as resilient farms can better cope with shocks and stresses, and farm viability. Chapters 2-4 provide several examples of how resilience can be assessed and Chapter 5 has shown how such a viable farm income can be assessed. Farms that are resilient and viable have a low probability of defaulting loans and are, therefore, the least risky clients for credit providers.

6.6 Limitations and further research

This section discusses four limitations of this thesis: (i) different farm types and countries across chapters are studied, (ii) data limitations and other limitations of quantitative methods, (iii) limitations of qualitative methods, and (iv) the resilience capacities were not aggregated into one resilience indicator. Finally, it presents some avenues for future research.

First, this thesis assessed the resilience of farms in different geographical regions and/or farm types. Chapter 2 focussed on Dutch farmers, without specifying a farm type. Chapter 3 described the resilience of Dutch arable farmers from the Veenkoloniën and Oldambt. Chapters 4 and 5 were based on FADN and considered several farm types from, respectively, nine or eleven European countries. As resilience assessments are often context-specific, these assignments may require different indicators to assess resilience across geographical regions or farm types (Spiegel et al. 2021b). While a general comparison is made across chapters that are based on different methods and cover different regions and/or farm types, an in-depth comparison of what enhances resilience in a specific case study is not possible due to the differences in geographic scales and/or farm type.

Second, the quantitative methods used in this thesis were based on multivariate statistics (Chapter 2) or econometrics (Chapters 4 and 5), which have the advantage that sufficiently large random samples allow for the generalisation of results. However, the quantitative methods applied in this thesis are restricted by their limited ability to quantify social dynamics and the availability of variables in FADN. Some social dynamics, such as understanding the interactions between how farmers learn and their social networks, are less likely to be quantified and are, therefore, harder to include in econometric models (Dardonville, Bockstaller and Therond 2021). Furthermore, Chapters 4 and 5 revealed that quantitative assessments of resilience are data-demanding and require panel data to analyse dynamics. These chapters heavily relied on the FADN panel dataset that contains a combination of accountancy data and socio-economic farm(er) characteristics, resulting in a slight underrepresentation of social and environmental dimensions. Environmental aspects are of importance for assessing farm resilience and viability as it increases our understanding of a farm's natural capital (Reidsma et al. 2020). Additional insights into a farm's natural capital can be obtained by collecting data on nitrogen and phosphorus balances or biodiversity indicators. Social aspects that could be considered when assessing farm resilience and viability are farmers' capacity to learn (De Kraker 2017) or their engagement in social networks (Barnes et al. 2020). Additionally, several dynamics are relevant for assessing the resilience capacities that cannot be captured by yearly FADN-data and require data collection at a higher frequency (e.g. weekly, monthly, or quarterly data).

Third, a limitation of the adopted qualitative methods in Chapter 3 is that data collection requires more resources and is more time-consuming compared to quantitative methods. This has resulted in the adoption of purposive sampling, resulting in small and non-random samples. Hence, it is not possible to generalise the findings based on samples that were analysed using qualitative methods. Some of the limitations of qualitative methods can be masked by quantitative methods, which allow for generalisation based on sufficiently large random samples. Additionally, the limitations of quantitative methods can be complemented by qualitative methods, especially to improve the understanding of social dynamics on a farm. This calls for mixed methods that combine qualitative and quantitative research when assessing farm resilience. Such a combination of qualitative and quantitative methods enables a deeper understanding of the economic, environmental, and social dimensions of farm resilience. A limitation of this thesis is that no mixed methods approaches were adopted. Although Chapter 3 combined qualitative and quantitative methods, it compared methods after data collection, implying that no mixed method design was adopted before data collection.

Fourth, Chapters 2, 3, and 4 assessed farm resilience in terms of robustness, adaptability, and transformability but did not aggregate the three resilience capacities into one generic resilience indicator. While the advantage of using one generic resilience indicator is that it is easy to interpret by policy makers, it comes at the cost of losing information as a result of aggregation. One of the challenges related to aggregating the three resilience capacities is that it requires a profound understanding of the relationship between the resilience capacities and resilience in general (Walker et al. 2004, Folke 2016). The relationship between resilience and the resilience capacities can be conceptualised as $\text{resilience} = f(\text{robustness}, \text{adaptation}, \text{transformation}, \text{control variables})$ with an unknown functional form that strongly depends on the context in which farms operate. For instance, the weights of the resilience capacities may be different in a stable period—where robustness may be sufficient to be resilient—compared to a period of radical change that likely requires adaptation and transformation. The weight of each resilience capacity should therefore be obtained per specific case study in a local context—e.g. Dutch arable farmers from the Veenkoloniën and Oldambt (Chapter 3)—using expert elicitation. However, obtaining weights becomes complicated when studying resilience on a larger geographical scale—e.g. assessing resilience in several European countries and farm types (Chapters 4 and 5). Another complicating factor is the potential existence of trade-offs between the resilience capacities (Spiegel et al. 2020) and that policy instruments or farm(er) characteristics that support robustness may come at the cost of constraining adaptability and transformability (Fath, Dean and Katzmair 2015). Policy makers and researchers should be aware that aggregating the three resilience capacities into one generic resilience indicator masks these trade-offs.

Some of the presented limitations of this thesis and recent developments in the field of farm resilience could be addressed in further research. The first topic for future research relates to the application of mixed methods to understand the social, economic, and environmental dimensions of farm resilience. As discussed in the limitations, some of the dynamics cannot be quantified and therefore require qualitative methods. To improve resilience assessments, researchers should combine insights from shocks and stresses, resilience capacities, and the performance of farm functions over time. It is important that this combination of qualitative and quantitative research targets a specific case study to secure that findings can be compared across methods.

A second topic for future research relates to the aggregation of the resilience capacities into one resilience score. This could be done by studying past developments in a specific case study to determine the relative importance of each resilience capacity, eventually combined with insights from experts that assign weights to the resilience capacities. A promising method for obtaining and validating the weights of each resilience capacity in a specific case study is Structured Expert Judgement (Cooke 1991), in which experts are asked to assess multiple indicators for each resilience capacity. Another possible method could be multi-criteria analysis to obtain indicator weights (Pashaei Kamali et al. 2017).

The third topic for future research relates to recent developments in the availability of big data in agriculture. The availability of precision agriculture data and/or satellites and remote sensing data are promising examples of big data developments (Sebestyén, Czvetkó and Abonyi 2021). The added value of these developments for farm resilience assessments is the availability of high(er) frequency data, which allows researchers to capture dynamics more accurately compared to yearly data that were used in Chapters 4 and 5. This contributes to an improved assessment of the resilience capacities or farm functions. For example, high-frequency data on crop rotations of arable farms will improve adaptation assessments. To improve the assessments of farm functions, data on pesticide management and satellite data provide more accurate insights into developments in yields, soil quality, and biodiversity over time.

6.7 Main conclusions

The objective of this thesis is to assess the resilience of European farms. The main conclusions are:

- The multi-dimensional character of resilience can be assessed by investigating shocks and stresses, resilience capacities, and farm functions based on perceived and indicator-based assessments (Chapters 2-5).
- Each of the resilience capacities—i.e. robustness, adaptability and transformability—can be expressed using a single indicator by aggregating multiple measurements into latent constructs (Chapters 2 and 3) or composite indicators (Chapter 4).
- More diverse risk management portfolios are positively related to the perceived adaptability and, in some cases, to the perceived transformability of Dutch farmers but do not affect perceived robustness (Chapter 2).
- Arable farmers from the Veenkoloniën and Oldambt can enhance robustness by building bonding social capital, acquiring knowledge about agriculture, and

developing financial skills. Farmers' adaptation can be enhanced through bonding and bridging social capital, early adoption of innovations, and high self-efficacy. Transformation can be stimulated by linking social capital to learn radical new ideas and by critically reflecting on current farm business models (Chapter 3).

- Less risk-averse farmers perceive themselves as better able to adapt and transform. The relationship between risk-aversion and perceived robustness is less visible (Chapters 2 and 3).
- Combinations of qualitative and quantitative methods have an added value for resilience assessments, especially regarding social dynamics (Chapter 3).
- Decoupled direct payments have a negative effect on farm robustness in most European regions and have no significant effect on adaptation and transformation (Chapter 4).
- Although rural development payments enhance robustness, these payments do not facilitate adaptation or transformation for most European farms. Rural development payments only contribute to transformations of Western European livestock farms and Southern European livestock and arable, crop, and perennial farms (Chapter 4).
- The majority of the farms in eleven European countries is short-term viable (74.5%), while only 42.5% of the farms is long-term viable (Chapter 5).
- Decoupled direct payments increase the probability of being short-term viable for Southern and Eastern European farms while having no significant effect on the short-term viability of Western and Northern European farms. In most European countries, decoupled direct payments reduce the probability of being long-term viable (Chapter 5).

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English summary

European farms face numerous complex and interrelated economic, environmental, social, and institutional shocks and stresses. In addition, farms face unanticipated crises, such as the COVID-19 pandemic. The impact of these shocks and stresses may limit farmers' access to credit, constrain opportunities to invest, and reduce their willingness to continue farming. This may threaten the delivery of several farm functions, including food production, biodiversity, and the maintenance of natural resources. Resilient farms successfully cope with shocks and stresses and secure the delivery of desired farm functions. This likely requires adaptation and transformation. To this end, the European Commission calls for a better operationalisation and assessment of farm resilience.

The general objective of this thesis is to assess the resilience of European farms. Three building blocks are used to assess farm resilience: (i) understanding shocks and stresses, (ii) assessing the resilience capacities of robustness, adaptability, and transformability, and (iii) evaluating the performance of farm functions over time. These building blocks are investigated by perceived and indicator-based resilience assessments, which provide complementary insights. Perceived resilience assessments contribute to a better understanding of decision-making under risk and uncertainty. Indicator-based resilience assessments have a more objective character, allowing researchers to assess farm resilience using secondary datasets.

Chapter 2 connects risk theory and resilience thinking using survey data from 916 Dutch farmers. This chapter explores how risk perceptions, risk preferences, and risk management strategies are related to perceived robustness, adaptability, and transformability. The results of the Partial Least Squares Structural Equation Model (PLS-SEM) reveal the importance of a diverse portfolio of risk management strategies. More diverse risk management portfolios are associated with higher perceived adaptability and, in some cases, with higher perceived transformability. This underlines the importance of studying combinations of risk management strategies instead of optimising single strategies. Less risk-averse farmers perceive themselves as better able to adapt and transform while the relationship between risk-aversion and perceived robustness is heterogeneous across farms. Furthermore, higher perceived robustness, adaptability, and transformability are related to farmers who perceive themselves as more resilient.

Chapter 3 explores how learning and social networks contribute to farm resilience in terms of robustness, adaptation, and transformation. A combination of qualitative (semi-structured interviews, focus groups, expert interviews) and quantitative methods (farmer survey) is used to study the resilience of Dutch arable farmers from the Veenkoloniën and Oldambt. The results indicate that social networks and learning primarily enable farmers to adapt and, in some cases, contribute to robustness and transformation. Several strategies that enhance each of the resilience capacities are identified. Robustness-enhancing strategies are to build bonding social capital, strengthen financial management skills, and acquire agricultural knowledge. Adaptation-enhancing strategies include building bonding and bridging social

capital and being an early adopter of innovation. Transformations are enhanced by the following strategies: building linking social capital from formal networks, learning radically new ideas, and critically reflecting on the status quo.

Chapter 4 assesses farm resilience in nine European countries. This chapter quantifies the resilience capacities of robustness, adaptation, and transformation. It uses the Farm Accountancy Data Network (FADN) panel dataset to study changes in inputs and outputs over time. Several indicators for each resilience capacity are aggregated into composite indicators. This chapter investigates which farm(er) characteristics and policy instruments affect the resilience capacities by estimating a correlated random effects fractional probit model combined with a control function approach. The results reveal that resilience-enhancing strategies are heterogeneous across regions and farm types. In most European regions, decoupled direct payments constrain robustness, while rural development payments enhance robustness. Both decoupled direct payments and rural development payments do not affect adaptation and transformation in most European regions.

Chapter 5 investigates if decoupled direct payments are an effective policy instrument to ensure short and long-term farm viability. The FADN panel dataset that contains farm-level data from eleven European countries is used. Dynamic correlated random effects probit models are estimated. A control function is employed to account for endogeneity caused by the non-random assignment of decoupled direct payments. The results indicate that 74.5% of the European farms is short-term viable, while less than half of the farms are long-term viable (42.5%). Decoupled direct payments increase the probability to be short-term viable in Southern and Eastern European countries while having no effect or even decrease the probability to be short-term viable for farms from Western and Northern European countries. Additionally, decoupled direct payments decrease the probability of being long-term viable in almost all countries.

Chapter 6 synthesises the results and identifies three common themes: (i) moving from risk analysis to resilience thinking deepens the understanding of farmer behaviour under shocks and stresses, (ii) assessing the contribution of risk management by adopting a portfolio view on risk management rather than focussing on single risk management strategies enhances the understanding of resilience, and (iii) reiterating the need to assess farm income as it contributes to multiple facets of farm resilience. Furthermore, Chapter 6 introduces policy and business implications. Policy instruments are suggested to foster a shift towards diverse risk management portfolios, build social capital through social networks and learning, facilitate the adoption of innovations, and focus on paying farmers for public good provision and eco-schemes. Business implications arise for farmers, other supply chain actors, innovation platforms, and banks and other credit suppliers. Farmers are recommended to adopt diverse risk management portfolios and be open to learn from their formal and informal networks. Food supply chain actors are recommended to foster cooperation and learning with farmers by creating joint innovation programmes. To enhance resilience, innovation platforms could host network events to facilitate social learning between farmers and their social network actors; for instance, concerning developments in precision agriculture and other innovations. For banks and other credit suppliers, being able to identify resilient and viable farms is important to grant loans to the least risky farms.

The main conclusions of this thesis are:

- The multi-dimensional character of resilience can be assessed by investigating shocks and stresses, resilience capacities, and farm functions based on perceived and indicator-based assessments (Chapters 2-5).
- Each of the resilience capacities—i.e. robustness, adaptability and transformability—can be expressed using a single indicator by aggregating multiple measurements into latent constructs (Chapters 2 and 3) or composite indicators (Chapter 4).
- More diverse risk management portfolios are positively related to the perceived adaptability and, in some cases, to the perceived transformability of Dutch farmers but do not affect perceived robustness (Chapter 2).
- Arable farmers from the Veenkoloniën and Oldambt can enhance robustness by building bonding social capital, acquiring knowledge about agriculture, and developing financial skills. Farmers' adaptation can be enhanced through bonding and bridging social capital, early adoption of innovations, and high self-efficacy. Transformation can be stimulated by linking social capital to learn radical new ideas and by critically reflecting on current farm business models (Chapter 3).
- Less risk-averse farmers perceive themselves as better able to adapt and transform. The relationship between risk-aversion and perceived robustness is less visible (Chapters 2 and 3).
- Combinations of qualitative and quantitative methods have an added value for resilience assessments, especially regarding social dynamics (Chapter 3).
- Decoupled direct payments have a negative effect on farm robustness in most European regions and have no significant effect on adaptation and transformation (Chapter 4).
- Although rural development payments enhance robustness, these payments do not facilitate adaptation or transformation for most European farms. Rural development payments only contribute to transformations of Western European livestock farms and Southern European livestock and arable, crop, and perennial farms (Chapter 4).
- The majority of the farms in eleven European countries is short-term viable (74.5%), while only 42.5% of the farms is long-term viable (Chapter 5).
- Decoupled direct payments increase the probability of being short-term viable for Southern and Eastern European farms while having no significant effect on the short-term viability of Western and Northern European farms. In most European countries, decoupled direct payments reduce the probability of being long-term viable (Chapter 5).

About the author

Thomas Slijper was born on May 1, 1993 in Ede, the Netherlands. He obtained a bachelor degree in Economics and Governance at Wageningen University in 2014 and a master degree in Agricultural Economics at Wageningen University in 2017. During his master programme, he was an intern at the Dutch Agricultural and Horticultural Association (LTO Nederland) in the Hague and the RaboResearch Food & Agribusiness department of Rabobank in Utrecht.

In September 2017, he started as a PhD candidate at the Business Economics and Strategic Communication group of Wageningen University under supervision of Prof. Dr. M.P.M. Meuwissen, Dr. Ir. Y. de Mey, and Dr. P.M. Poortvliet. He studies how European farmers deal with several interrelated risks and under which conditions risk management decisions have the potential to contribute to farm resilience and help farmers to obtain a viable income. In October 2021, he started a Postdoc position at the Business Economics group.

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Book chapters

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Datasets

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Education certificate

Thomas Slijper

Wageningen School of Social Sciences (WASS)

Completed Training and Supervision Plan

Name of the learning activity	Department/Institute	Year	ECTS*
A) Project related competences			
A1) Managing a research project			
WASS Introduction Course	WASS	2017	1
Scientific Writing	WGS	2019	1.8
Writing PhD Research Proposal	WUR	2018	3
"*Bridging the gap between risk behaviour and perceived resilience: A case study in Dutch agriculture*"	173th EAAE Seminar, Bucharest	2019	1
BEC PhD Meetings	WUR	2017-2021	2
A2) Integrating research in the corresponding discipline			
Theories for Business Decisions (BEC-54806)	WUR	2017	6
Means-End Chains & Laddering Course	WASS	2017	1
Theory and Practice on Questionnaire Construction and Analysis	FLAMES (KU Leuven)	2018	1
Risk Analysis and Risk Management in Agriculture: Updates on Modelling and Applications	WASS	2018	3
Mixed Linear Models	PE&RC	2019	0.6
The Foundations of Info-Metrics Information-Theoretic Methods of inference	WASS	2019	3
B) General research related competences			
B1) Placing research in a broader scientific			
Data Analysis for Social Scientists	Edx.org (MIT)	2018	5
Community of Practice: Tuesdays with Resilience	WUR	2017-2019	2
Economics Seminar	WASS	2019-2021	2
B2) Placing research in a societal context			
Supervising BSc and MSc thesis students	Education Support, WUR	2018	1
Presenting with Impact	WGS	2019	1
C) Career related competences/personal development			
Various teaching activities: - Introduction to Business Economics (BEC-10306) - Accounting (BEC-22806) - Advanced Business Economics (BEC-30306) - Risk Management in Food Supply Chains (BEC-31806) - Risk Communication (CPT-24306) - Veterinary Epidemiology and Economics (QVE-20306) - Advanced Supply Chain Management (YSS-32806) - Supervision BSc thesis (YSS-81812)	WUR	2017-2021	4
Total			**38.4**

*One credit according to ECTS is on average equivalent to 28 hours of study load

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Appendix 1

Table A1.1 Overview of risk management strategies included in the survey

Flexibility of farm activities	**Cooperation with others**	**Financial risk management**	**Measures to control environmental risks**	**Specialization**	**Diversification**	**Learning**
Improved cost flexibility	Had access to a variety of input suppliers	Bought any type of agricultural insurance	Invested in technologies	Specialization	Diversified in production	Opened up my farm to the public
Improved flexibility in the timing of my production	Member of an (inter)branch organization	Used production or marketing contracts to sell (part of) my production	Implemented measures to prevent pests or diseases		Diversified in other activities on my farm	Used market information to plan my farm activities for the next season
Worked harder to secure production in hard times	Member of a producer organization, cooperative or credit union	Hedged (part of) my production with futures contracts			Had an off-farm job	Learned about challenges in agriculture
	Cooperated with other farmers to secure inputs or production	Maintained financial savings for hard times				Experimenting with precision agriculture, smart farming or drones.
		Had low debts or no debts at all to prevent financial risks				

Table A1.2 Item reliability, internal validity reliability, convergent validity and VIFs of the reflective indicators (full model)

	Outer loadings			Cronbach's alpha			Composite reliability			AVE			VIF		
	All	Low	High	All	Low	High	All	Low	High	All	Low	High	All	Low	High
ADAP				0.760	0.782	0.746	0.848	0.859	0.840	0.589	0.610	0.575	1.758	2.010	1.640
adap_1	0.715	0.711	0.718												
adap_2	0.875	0.881	0.874												
adap_3	0.870	0.894	0.856												
adap_4	0.566	0.600	0.538												
INNO				0.856	0.851	0.858	0.932	0.930	0.933	0.873	0.869	0.875	1.620	1.652	1.586
inno_1	0.944	0.948	0.941												
inno_2	0.925	0.916	0.930												
NET INF				0.774	0.792	0.765	0.869	0.877	0.862	0.689	0.706	0.675	1.527	1.391	1.636
net_1	0.808	0.846	0.788												
net_2	0.891	0.933	0.858												
net_3	0.786	0.731	0.818												
NET FOR				0.813	0.768	0.831	0.888	0.866	0.897	0.726	0.684	0.744	1.777	1.646	1.879
net_4	0.838	0.853	0.833												
net_5	0.864	0.852	0.870												
net_6	0.854	0.774	0.884												
PBC				0.646	0.648	0.643	0.792	0.794	0.789	0.495	0.506	0.488	1.406	1.415	1.404
pbc_1	0.827	0.837	0.829												
pbc_2	0.695	0.746	0.658												
pbc_3	0.743	0.780	0.722												
pbc_4	0.510	0.398	0.557												
ROB				0.576	0.520	0.599	0.762	0.717	0.775	0.484	0.476	0.487	1.323	1.340	1.309
rob_1	0.792	0.796	0.779												
rob_2	0.180	-0.083	0.294												
rob_3	0.771	0.797	0.752												
rob_4	0.827	0.792	0.831												
TRANS				0.715	0.725	0.703	0.828	0.830	0.823	0.582	0.593	0.572	1.705	2.071	1.554
trans_1	0.840	0.881	0.811												
trans_2	0.227	0.173	0.240												
trans_3	0.880	0.867	0.886												
trans_4	0.894	0.903	0.886												

Table A1.3. HTMT confidence intervals (reduced model)

		ADAP	*INNO*	*NET FOR*	*NET INF*	*PBC*	*RM*	*ROB*
INNO	All	[0.387; 0.535]						
	Low	[0.300; 0.536]						
	High	[0.383; 0.568]						
NET FOR	All	[0.303; 0.479]	[0.358; 0.505]					
	Low	[0.326; 0.595]	[0.241; 0.503]					
	High	[0.241; 0.462]	[0.366; 0.539]					
NET INF	All	[0.185; 0.366]	[0.154; 0.328]	[0.663; 0.786]				
	Low	[0.174; 0.421]	[0.062; 0.312]	[0.549; 0.767]				
	High	[0.151; 0.368]	[0.179; 0.379]	[0.691; 0.837]				
PBC	All	[0.572; 0.717]	[0.405; 0.577]	[0.355; 0.527]	[0.260; 0.447]			
	Low	[0.514; 0.764]	[0.330; 0.604]	[0.343; 0.605]	[0.168; 0.470]			
	High	[0.545; 0.735]	[0.387; 0.605]	[0.310; 0.534]	[0.254; 0.489]			
RM	All	[0.127; 0.274]	[0.197; 0.326]	[0.239; 0.371]	[0.114; 0.259]	[0.061; 0.194]		
	Low	[0.112; 0.349]	[0.168; 0.382]	[0.241; 0.461]	[0.084; 0.300]	[0.074; 0.314]		
	High	[0.092; 0.280]	[0.172; 0.333]	[0.206; 0.368]	[0.102; 0.278]	[0.038; 0.152]		
ROB	All	[0.490; 0.642]	[0.132; 0.306]	[0.190; 0.373]	[0.091; 0.256]	[0.455; 0.629]	[0.011; 0.095]	
	Low	[0.438; 0.713]	[0.096; 0.342]	[0.098; 0.367]	[0.088; 0.337]	[0.377; 0.684]	[0.008; 0.096]	
	High	[0.458; 0.649]	[0.103; 0.322]	[0.176; 0.408]	[0.076; 0.247]	[0.443; 0.657]	[0.006; 0.090]	
TRANS	All	[0.693; 0.807]	[0.268; 0.429]	[0.215; 0.383]	[0.093; 0.266]	[0.522; 0.676]	[0.021; 0.154]	[0.453; 0.609]
	Low	[0.766; 0.893]	[0.153; 0.427]	[0.194; 0.472]	[0.113; 0.368]	[0.497; 0.746]	[0.037; 0.242]	[0.468; 0.712]
	High	[0.617; 0.786]	[0.273; 0.461]	[0.167; 0.381]	[0.056; 0.239]	[0.469; 0.673]	[0.011; 0.135]	[0.382; 0.588]

Notes: The numbers in squared brackets present the 95% bias-corrected and accelerated confidence interval of the HTMT statistics. 4,000 bootstrapping samples were used with the no sign changes option.

Table A1.4 Formative item validity assessment (reduced model)

	Outer weight	St dev	Outer weight	St dev	Outer weight	St dev	Outer loadings			VIF		
	All	All	Low	Low	High	High	All	Low	High	All	Low	High
RM										1.140	1.160	1.142
RISK PREF										1.545	1.619	1.514
riskpref_1	-0.021	0.086	-0.035	0.161	-0.024	0.118	0.581	0.609	0.552	1.638	1.742	1.588
riskpref_2	0.561***	0.076	0.537***	0.115	0.609***	0.094	0.845	0.824	0.867	1.349	1.331	1.356
riskpref_3	0.462***	0.090	0.474***	0.152	0.470***	0.116	0.814	0.826	0.799	1.872	1.937	1.832
riskpref_4	0.220**	0.097	0.251*	0.147	0.157	0.116	0.737	0.750	0.701	1.731	1.772	1.715
RISK PERC										1.100	1.121	1.117
RISK PERC_1										1.637	1.449	1.637
riskperc_1	0.460***	0.069	0.422***	0.152	0.462***	0.079	0.865	0.850	0.865	1.650	1.664	1.643
riskperc_2	0.645***	0.063	0.679***	0.136	0.644***	0.072	0.934	0.945	0.933	1.650	1.664	1.643
RISK PERC_2										1.581	1.837	1.581
riskperc_3	0.574***	0.057	0.546***	0.104	0.570***	0.074	0.856	0.856	0.847	1.631	1.769	1.608
riskperc_4	0.589***	0.056	0.603***	0.101	0.599***	0.071	0.864	0.884	0.863	1.683	1.779	1.729
RISK PERC_3										1.743	1.735	1.743
riskperc_5	0.632***	0.045	0.710***	0.079	0.611***	0.057	0.894	0.938	0.877	1.665	1.946	1.719
riskperc_6	0.519***	0.049	0.415***	0.093	0.549***	0.059	0.838	0.806	0.846	1.775	1.838	1.654
RISK PERC_4										1.388	1.367	1.388
riskperc_7	0.708***	0.056	0.787***	0.093	0.690***	0.073	0.900	0.928	0.899	1.411	1.385	1.462
riskperc_8	0.477***	0.066	0.398***	0.125	0.486***	0.085	0.761	0.678	0.782	1.566	1.321	1.419
RISK PERC_5										1.236	1.330	1.236
riskperc_9	0.483***	0.083	0.480***	0.156	0.496***	0.131	0.824	0.810	0.837	1.510	1.539	1.531
riskperc_10	0.661***	0.075	0.673***	0.139	0.645***	0.119	0.910	0.908	0.907	1.566	1.562	1.674
RISK PERC_6										1.256		
riskperc_11	0.710***	0.122					0.873			1.305		
riskperc_12	0.515***	0.135					0.739			1.425		
RISK PERC_7										1.466	1.579	1.466
riskperc_14	0.721***	0.053	0.745***	0.083	0.677***	0.069	0.897	0.919	0.861	1.460	1.710	1.376
riskperc_15	0.476***	0.064	0.430***	0.105	0.540***	0.076	0.742	0.732	0.772	1.456	1.684	1.430

RISK PERC_8										1.402	1.348	1.402
riskperc_16	0.622***	0.126	0.597***	0.212	0.626***	0.175	0.979	0.969	0.983	4.308	3.630	4.941
riskperc_17	0.411***	0.129	0.446**	0.219	0.402**	0.179	0.952	0.944	0.958	4.265	3.560	4.885
RES												
res_1	0.591***	0.079	0.442***	0.149	0.670***	0.096	0.935	0.898	0.953	1.938	2.080	1.873
res_2	0.495***	0.080	0.634***	0.137	0.415***	0.105	0.906	0.952	0.872	1.938	2.080	1.873

Notes: outer weights and outer loadings of the risk perceptions items loading on the second order construct *RISK PERC* have been omitted for brevity. * $p \leq 0.10$; ** $p \leq 0.05$; *** $p \leq 0.01$

Table A1.5 R^2 and Q^2 values of the structural model

	R^2			Q^2		
	All	Low	High	All	Low	High
ADAP	0.334	0.365	0.327	0.219	0.230	0.210
PBC	0.012	0.030	0.006	0.006	0.016	0.002
RES	0.250	0.288	0.233	0.198	0.226	0.178
RISK PERC	1.000	1.000	1.000	0.292	0.330	0.312
RISK PREF	0.056	0.051	0.064	0.026	0.024	0.027
ROB	0.186	0.193	0.194	0.110	0.098	0.113
TRANS	0.282	0.300	0.271	0.202	0.197	0.188

Table A1.6. f^2 statistics of the structural model

		ADAP	*PBC*	*RES*	*RISK PREF*	*ROB*	*TRANS*
ADAP	All			0.041			
ADAP	Low			0.056			
ADAP	High			0.032			
INNO	All	0.010				0.001	0.000
INNO	Low	0.003				0.005	0.002
INNO	High	0.016				0.001	0.002
NET FOR	All	0.004				0.006	0.003
NET FOR	Low	0.018				0.000	0.003
NET FOR	High	0.001				0.015	0.004
NET INF	All	0.001				0.000	0.000
NET INF	Low	0.004				0.004	0.003
NET INF	High	0.000				0.002	0.004
PBC	All	0.152				0.112	0.152
PBC	Low	0.169				0.113	0.183
PBC	High	0.140				0.112	0.136
RISK PERC	All	0.001				0.011	0.003
RISK PERC	Low	0.000				0.000	0.004
RISK PERC	High	0.005				0.022	0.002
RISK PREF	All	0.024				0.007	0.041
RISK PREF	Low	0.019				0.032	0.036
RISK PREF	High	0.026				0.001	0.041
RM	All	0.004	0.012		0.060	0.000	0.001
RM	Low	0.003	0.031		0.053	0.002	0.000
RM	High	0.004	0.006		0.068	0.000	0.002
ROB	All			0.073			
ROB	Low			0.063			
ROB	High			0.085			
TRANS	All			0.010			
TRANS	Low			0.009			
TRANS	High			0.010			

Table A1.7. q^2 statistics of the structural model

		ADAP	***RES***	***ROB***	***TRANS***
ADAP	All		0.030		
ADAP	Low		0.005		
ADAP	High		0.005		
INNO	All	0.005		0.000	-0.001
INNO	Low	-0.015		0.015	-0.007
INNO	High	0.020		-0.005	0.017
NET FOR	All	0.001		0.002	0.002
NET FOR	Low	-0.010		0.012	0.006
NET FOR	High	0.012		0.003	0.019
NET INF	All	0.000		-0.001	0.000
NET INF	Low	-0.013		0.013	0.005
NET INF	High	0.012		-0.004	0.018
PBC	All	0.085		0.062	0.099
PBC	Low	0.086		0.079	0.130
PBC	High	0.092		0.058	0.106
RISK PERC	All	0.000		0.006	0.002
RISK PERC	Low	-0.022		0.004	0.003
RISK PERC	High	0.014		0.008	0.019
RISK PREF	All	0.013		0.003	0.026
RISK PREF	Low	-0.007		0.029	0.022
RISK PREF	High	0.025		-0.006	0.043
RM	All	0.003		0.000	0.000
RM	Low	-0.015		0.011	0.001
RM	High	0.014		-0.005	0.017
ROB	All		0.052		
ROB	Low		0.008		
ROB	High		0.081		
TRANS	All		0.007		
TRANS	Low		-0.032		
TRANS	High		0.033		

Table A1.8. Compositional invariance assessment

	Original Correlation	5.0%	Permutation p-Values
ADAP	0.999	0.998	0.309
INNO	1.000	0.998	0.487
NET FOR	0.997	0.994	0.182
NET INF	0.986	0.968	0.209
PBC	1.000	0.996	0.787
RES	0.985	0.967	0.180
RISK PERC	0.990	0.990	0.067
RISK PERC_1	0.999	0.973	0.710
RISK PERC_2	1.000	0.973	0.966
RISK PERC_3	0.985	0.984	0.062
RISK PERC_4	0.994	0.963	0.437
RISK PERC_5	1.000	0.951	0.886
RISK PERC_6	0.801	0.820	0.040**
RISK PERC_7	0.987	0.963	0.241
RISK PERC_8	1.000	0.964	0.847
RISK PREF	0.994	0.917	0.910
RM	1.000	1.000	0.405
ROB	0.998	0.994	0.314
TRANS	0.999	0.999	0.060

Notes:* p≤0.10; ** p≤0.05; *** p≤0.01.

Table A1.9. Equal means and variance assessments

	Mean - Original Difference	Mean - Permutation Mean Difference	Permutation p-Values	Variance - Original Difference	Variance - Permutation Mean Difference	Permutation p-Values
ADAP	0.079	0.000	0.257	0.076	-0.001	0.413
INNO	0.189	0.002	0.004***	-0.008	-0.001	0.925
NET FOR	0.146	0.000	0.032**	-0.277	-0.003	0.003***
NET INF	0.021	0.000	0.757	0.089	-0.005	0.382
PBC	0.169	0.001	0.011**	0.052	-0.002	0.590
RES	0.092	0.000	0.179	-0.004	-0.001	0.968
RISK PERC	-0.166	0.001	0.017**	0.010	-0.001	0.938
RISK PERC_1	-0.029	0.001	0.665	-0.099	-0.001	0.297
RISK PERC_2	-0.134	0.000	0.051*	0.015	-0.002	0.872
RISK PERC_3	-0.130	0.001	0.059*	0.012	-0.003	0.902
RISK PERC_4	-0.076	0.001	0.260	-0.129	-0.001	0.108
RISK PERC_5	-0.019	0.003	0.787	-0.049	-0.001	0.589
RISK PERC_7	-0.236	-0.001	0.001***	0.130	-0.003	0.207
RISK PERC_8	-0.121	0.000	0.084	-0.088	-0.002	0.314
RISK PREF	0.225	0.002	0.001***	-0.110	-0.004	0.266
RM	-0.056	0.000	0.416	0.017	-0.002	0.834
ROB	0.185	0.001	0.009***	-0.204	-0.006	0.039**
TRANS	0.260	0.002	0.001***	0.088	-0.004	0.293

Notes:* p≤0.10; ** p≤0.05; *** p≤0.01.

Table A1.11. Summary statistics all farmers, *Low*, and *High*.

	All (*N* = 916)		Low (*N* = 329)		High (*N* = 587)	
	Mean	St dev	Mean	St dev	Mean	St dev
Risk behavior						
RM	3.98	1.35	3.94	1.36	4.01	1.35
RISK PERC						
RISK PERC_1						
riskperc_1	4.44	1.53	4.41	1.47	4.46	1.56
riskperc_2	4.16	1.47	4.14	1.43	4.17	1.49
RISK PERC_2						
riskperc_3	4.91	1.62	4.69	1.61	5.04***	1.62
riskperc_4	4.78	1.45	4.77	1.44	4.78	1.46
RISK PERC_3						
riskperc_5	4.93	1.70	4.70	1.73	5.06***	1.67
riskperc_6	4.02	1.54	4.03	1.46	4.02	1.59
RISK PERC_4						
riskperc_7	4.17	1.74	4.02	1.73	4.26**	1.75
riskperc_8	3.42	1.75	3.49	1.63	3.39	1.81
RISK PERC_5						
riskperc_9	4.50	1.61	4.52	1.61	4.49	1.61
riskperc_10	4.38	1.56	4.33	1.53	4.41	1.57
RISK PERC_6						
riskperc_11	3.71	1.95	3.77	1.99	3.67	1.92
riskperc_12	3.20	1.67	3.17	1.62	3.22	1.70
riskperc_13	3.68	1.99	3.62	1.97	3.72	2.00
RISK PERC_7						
riskperc_14	5.51	1.50	5.27	1.57	5.65***	1.45
riskperc_15	4.36	1.92	4.21	1.91	4.44*	1.93
RISK PERC_8						
riskperc_16	4.87	1.62	4.76	1.59	4.94	1.64
riskperc_17	4.84	1.69	4.71	1.66	4.92*	1.71
RISK PREF						
riskpref_1	4.08	1.49	4.18	1.43	4.03	1.53
riskpref_2	4.39	1.50	4.64	1.42	4.26***	1.52
riskpref_3	4.15	1.40	4.27	1.36	4.08**	1.42
riskpref_4	4.35	1.35	4.42	1.34	4.32	1.36
Resilience						
ROB						
rob_1	4.21	1.43	4.36	1.32	4.13**	1.48
rob_2	3.90	1.54	3.90	1.48	3.90	1.57
rob_3	4.44	1.47	4.55	1.42	4.38*	1.50
rob_4	4.02	1.53	4.18	1.43	3.94**	1.58
ADAP						
adap_1	3.97	1.71	4.05	1.78	3.93	1.66
adap_2	4.58	1.42	4.64	1.40	4.54	1.42
adap_3	4.65	1.37	4.71	1.40	4.61	1.36

adap_4	4.57	1.59	4.76	1.54	4.45***	1.61
TRANS						
trans_1	3.84	1.58	4.00	1.57	3.75**	1.57
trans_2	4.08	1.56	4.23	1.50	4.00**	1.58
trans_3	3.98	1.46	4.23	1.48	3.84***	1.44
trans_4	3.72	1.57	3.98	1.60	3.58***	1.53
RES						
res_1	4.87	1.47	4.98	1.43	4.81*	1.49
res_2	4.38	1.59	4.43	1.62	4.35	1.58
Control variables						
INNO						
inno_1	4.15	1.58	4.37	1.59	4.02***	1.56
inno_2	4.12	1.58	4.25	1.56	4.04*	1.59
NET INF						
net_1	5.62	1.31	5.60	1.33	5.63	1.30
net_2	4.98	1.47	4.93	1.48	5.01	1.46
net_3	4.28	1.52	4.39	1.57	4.21*	1.49
NET FOR						
net_4	5.09	1.35	5.14	1.26	5.07	1.39
net_5	4.56	1.49	4.69	1.40	4.48**	1.53
net_6	4.66	1.50	4.82	1.42	4.57**	1.54
PBC						
pbc_1	4.64	1.30	4.79	1.28	4.56**	1.30
pbc_2	4.78	1.43	4.87	1.39	4.73	1.45
pbc_3	3.96	1.45	4.07	1.49	3.90*	1.43
pbc_4	4.43	1.46	4.51	1.50	4.38	1.43

Notes: All items are measured on a 7-point Likert scale, except the diversity of risk management strategies (RM). This item is the count of different types of risk management strategies, ranging from 0 to 7. Significant differences between *Low* and *High* were tested using a t-test. * $p \leq 0.10$; ** $p \leq 0.05$; *** $p \leq 0.01$.

Appendix 2

Table A 1 Item wordings and summary statistics to compare farmers who have actively learned to farmers that have not actively learned. Averages are presented if multiple items were used to measure a construct. All items were measured on a 7-point Likert scale.

Item		Mean		
		All (*N*=71)	Not learned (*N*=35)	Learned (*N*=36)
Size informal network				
net_1	I know a lot of other farmers in my region.	5.70	5.54	5.86
Ties informal network (average)		4.87	4.70	5.03
net_2	Concerning farming, I often interact with neighbouring farmers.	5.34	5.26	5.42
net_3	Farmers in my region tend to support each other when there is a problem.	4.39	4.14	4.64
Size formal network				
net_4	I know a lot of agricultural professionals, experts, or value chain actors.	5.35	5.06	5.64
Ties formal network (average)		4.79	4.47	5.10
net_5	When I attend agricultural events and meetings, I interact a lot with professionals, experts, or value chain actors.	4.66	4.23	5.08
net_6	I feel I can receive support from agricultural professionals, experts, or value chain actors in my network.	4.92	4.71	5.11
Knowledge				
	I know a lot about agricultural challenges on my farm	5.00	4.77	5.22
Openness to innovation (average)		4.16	3.81	4.50
inno_1	Compared with other farmers, I am among the first to try out a new practice on my farm	4.06	3.69	4.42
inno_2	I like to try out all kinds of new technologies or varieties	4.27	3.94	4.58
Perceived behavioural control (average)		4.54	4.34	4.72
pbc_1	If I wanted to, it would be easy for me to deal with agricultural challenges on my farm	4.73	4.71	4.75
pbc_2	It is mostly up to me whether or not I can deal with the challenges on my farm	4.69	4.71	4.67
pbc_3	I have a lot of control about agricultural challenges affecting my farm	4.21	3.77	4.64
pbc_4	For me, it is difficult to deal with the challenges that affect my farm[1]	4.51	4.17	4.83
Willingness to take risk (average)		4.35	4.19	4.51
	I am willing to take more risks than other farmers in terms of...			
riskpref_1	Production	4.45	4.23	4.67
riskpref_2	Marketing and prices	4.41	4.23	4.58
riskpref_3	Financial risks	4.17	4.20	4.14
riskpref_4	Innovation	4.28	3.97	4.58
riskpref_5	Farming in general	4.45	4.34	4.56

Robustness (average)		4.44	4.29	4.59
rob_1	After something challenging has happened, it is easy for my farm to bounce back to its current profitability.	4.54	4.43	4.64
rob_2	Personally, I find it easy to get back to normal after a setback.	4.56	4.37	4.75
rob_3	A big shock will not heavily affect me, as I have enough options to deal with this shock on my farm.	4.23	4.06	4.39
Adaptability (average)		4.90	4.60	5.19
adap_1	If needed, my farm can adopt new activities, varieties, or technologies in response to challenging situations.	4.82	4.54	5.08
adap_2	As a farmer, I can easily adapt myself to challenging situations.	4.90	4.66	5.14
adap_3	In times of change, I am good at adapting myself and facing up to agricultural challenges.	4.99	4.60	5.36
Transformability (average)		4.36	4.32	4.39
trans_1	For me, it is easy to make decisions that result in a transformation.	4.46	4.40	4.53
trans_2	After facing a challenging period on my farm, I still have the ability to radically reorganize my farm.	4.37	4.17	4.56
trans_3	If needed, I can easily make major changes that would transform my farm.	4.24	4.40	4.08

Notes: [1] Reversed scores of the negatively worded items are presented. If a construct was measured using more than 1 item, we used averages of multiple items to compute descriptive statistics in the chapter.

Appendix 3

This appendix consists of 5 parts:

1. Summary statistics comparing the initial and final sample across different regions and farm types. (Table A1-A5).

2. Detailed description of the obtained composite indicators, including KMO-statistics, Bartlett test, and an overview of the indicator weights (Table A6-A20).

3. Instrumental variable validity, including F-statistics, Kleibergen-Paap rank statistics, and parameter estimates of the reduced for equations (Table A21-A23).

4. Robustness checks (Table A24-A102)

5. Seemingly unrelated estimation to test if the estimated parameters are statistically equal across regions (Table A103-A111)

1. Summary statistics of the initial and final sample

The initial sample contains all farms in FADN over the period 2006-2012. This includes the farms in the final sample. The farms that are not considered in the analysis (i.e. these farms that are not in the final sample but are in the initial sample) are mostly left out because they are the first, second or last data entry of a farm. These observations are left to be able to generate changes over time, to generate instrumental variables using second lags as instruments, and the forward-looking character of recovery rate.

Table A 1 Overview of the variables used in this Appendix

Variable	Definition
Land (ha)	Utilised agricultural area expressed in hectares (ha)
Owned land (ratio)	Ratio owned land relative to total land
Labour (AWU)	Labour expressed in annual working units (AWU)
Paid labour (ratio)	Ratio paid labour relative to total labour
Total assets (€1000s)	Total assets expressed in €1000s
Total output (€1000s)	Total output expressed in €1000s
ROA	Return on assets, defined as the ratio net farm income before taxation to total assets
ATO	Asset turnover, defined as the ratio total revenue to total assets
Age	Age of the main farm operator in years
Decoupled payments	Ratio decoupled payments to total revenue including subsidies
Rural development payments	Ratio rural development payments to total revenue including subsidies

Table A 2 Summary statistics of the initial sample and final sample for Western European farms. ACP = Arable, crops, and perennials

	ACP initial sample	ACP final sample	Livestock initial sample	Livestock final sample	Mixed initial sample	Mixed final sample
Farm characteristics						
Land (ha)	104.585	101.531	115.792	119.349	228.813	222.499
	(225.366)	(209.965)	(222.556)	(232.361)	(451.580)	(437.971)
Owned land (ratio)	0.396	0.394	0.404	0.407	0.309	0.303
	(0.383)	(0.383)	(0.351)	(0.350)	(0.307)	(0.305)
Labour (AWU)	3.740	3.717	2.296	2.362	4.338	4.262
	(6.092)	(5.648)	(4.393)	(4.879)	(10.026)	(9.936)
Paid labour (ratio)	0.329	0.331	0.126	0.121	0.200	0.190
	(0.322)	(0.320)	(0.224)	(0.219)	(0.309)	(0.300)
Total assets (€1000s)	1,001.930	993.996	951.634	983.066	1,300.117	1,258.355
	(1,785.713)	(1,728.891)	(1,180.769)	(1,227.315)	(2,085.375)	(2,016.248)
Total output (€1000s)	348.410	349.018	259.672	263.030	462.303	447.971
	(666.264)	(643.474)	(472.872)	(485.955)	(1009.819)	(969.173)
Independent variables						
ROA	0.113	0.112	0.062	0.061	0.063	0.064
	(0.144)	(0.138)	(0.070)	(0.067)	(0.077)	(0.075)
ATO	0.521	0.515	0.317	0.308	0.368	0.366
	(0.531)	(0.497)	(0.264)	(0.243)	(0.258)	(0.237)
Age	50.101	50.291	49.343	49.573	49.719	49.750
	(9.691)	(9.377)	(9.715)	(9.509)	(9.584)	(9.359)
Decoupled payments	0.097	0.095	0.141	0.141	0.147	0.146
	(0.102)	(0.100)	(0.103)	(0.099)	(0.076)	(0.074)
Rural development payments	0.011	0.010	0.055	0.055	0.026	0.025
	(0.038)	(0.034)	(0.188)	(0.219)	(0.054)	(0.051)
N	56,473	38,888	64,399	42,969	20,803	14,162

Table A 3 Summary statistics of the initial sample and final sample for Southern European farms. ACP = Arable, crops, and perennials

	ACP initial sample	ACP final sample	Livestock initial sample	Livestock final sample	Mixed initial sample	Mixed final sample
Farm characteristics						
Land (ha)	33.948	36.309	56.975	59.656	64.846	73.827
	(60.425)	(57.100)	(96.418)	(101.407)	(93.467)	(97.740)
Owned land (ratio)	0.732	0.746	0.526	0.534	0.602	0.624
	(0.378)	(0.365)	(0.408)	(0.404)	(0.401)	(0.393)
Labour (AWU)	1.899	1.808	1.969	1.916	1.817	1.761
	(3.061)	(2.472)	(1.801)	(1.445)	(1.631)	(1.426)
Paid labour (ratio)	0.194	0.190	0.102	0.097	0.106	0.104
	(0.265)	(0.257)	(0.216)	(0.208)	(0.213)	(0.208)
Total assets (€1000s)	534.217	494.235	730.428	717.001	663.309	634.364
	(1,355.131)	(1,042.032)	(1,405.776)	(1,310.606)	(1,559.620)	(1,471.996)
Total output (€1000s)	85.355	74.749	165.852	156.839	94.926	90.542
	(283.587)	(199.793)	(399.514)	(329.749)	(190.966)	(176.202)
Independent variables						
ROA	0.118	0.111	0.109	0.105	0.090	0.090
	(0.166)	(0.139)	(0.098)	(0.088)	(0.092)	(0.084)
ATO	0.241	0.216	0.252	0.240	0.191	0.184
	(0.410)	(0.269)	(0.222)	(0.178)	(0.166)	(0.146)
Age	54.844	55.696	50.962	51.503	53.567	54.135
	(13.324)	(12.892)	(12.119)	(11.824)	(13.114)	(12.730)
Decoupled payments	0.113	0.117	0.104	0.105	0.134	0.142
	(0.147)	(0.155)	(0.160)	(0.101)	(0.108)	(0.112)
Rural development payments	0.021	0.022	0.036	0.034	0.027	0.026
	(0.062)	(0.062)	(0.078)	(0.069)	(0.055)	(0.052)
N	87,815	54,105	38,563	23,369	6,388	3,920

Table A 4 Summary statistics of the initial sample and final sample for Northern European farms. ACP = Arable, crops, and perennials

	ACP initial sample	ACP final sample	Livestock initial sample	Livestock final sample	Mixed initial sample	Mixed final sample
Farm characteristics						
Land (ha)	128.163	120.310	114.845	110.939	146.907	148.924
	(170.710)	(143.022)	(112.636)	(108.925)	(151.226)	(154.605)
Owned land (ratio)	0.612	0.629	0.513	0.526	0.553	0.555
	(0.372)	(0.360)	(0.324)	(0.318)	(0.336)	(0.326)
Labour (AWU)	1.595	1.447	1.965	1.917	1.679	1.694
	(2.588)	(1.636)	(1.469)	(1.395)	(1.032)	(1.033)
Paid labour (ratio)	0.145	0.138	0.140	0.126	0.146	0.149
	(0.261)	(0.251)	(0.228)	(0.218)	(0.255)	(0.258)
Total assets (€1000s)	954.604	941.010	891.824	871.538	1,033.112	1,084.124
	(1,036.642)	(912.850)	(917.162)	(843.402)	(1,085.297)	(1,163.213)
Total output	202.560	171.507	245.596	234.564	214.336	216.156
(€1000s)	(400.482)	(224.137)	(321.592)	(288.219)	(239.463)	(250.952)
Independent variables						
ROA	0.041	0.038	0.041	0.040	0.020	0.022
	(0.087)	(0.076)	(0.064)	(0.061)	(0.061)	(0.058)
ATO	0.271	0.241	0.278	0.269	0.236	0.225
	(0.358)	(0.316)	(0.153)	(0.141)	(0.178)	(0.167)
Age	55.449	56.092	52.131	52.700	53.219	53.474
	(9.763)	(9.306)	(9.404)	(9.234)	(9.254)	(9.110)
Decoupled payments	0.183	0.186	0.125	0.125	0.148	0.152
	(0.117)	(0.115)	(0.074)	(0.072)	(0.078)	(0.079)
Rural development	0.041	0.042	0.106	0.105	0.069	0.070
payments	(0.075)	(0.079)	(0.100)	(0.099)	(0.076)	(0.073)
N	1,504	1,132	4,867	3,601	547	437

Table A 5 Summary statistics of the initial sample and final sample for Eastern European farms. ACP = Arable, crops, and perennials

	ACP initial sample	ACP final sample	Livestock initial sample	Livestock final sample	Mixed initial sample	Mixed final sample
Farm characteristics						
Land (ha)	63.985	57.038	32.568	31.620	37.682	32.706
	(163.120)	(129.410)	(49.753)	(37.916)	(128.564)	(82.254)
Owned land (ratio)	0.773	0.777	0.773	0.771	0.793	0.792
	(0.274)	(0.266)	(0.236)	(0.233)	(0.234)	(0.229)
Labour (AWU)	2.648	2.590	2.054	2.022	2.150	1.962
	(3.776)	(3.299)	(1.610)	(1.205)	(4.850)	(2.777)
Paid labour (ratio)	0.194	0.189	0.053	0.051	0.046	0.042
	(0.266)	(0.255)	(0.145)	(0.137)	(0.141)	(0.124)
Total assets (€1000s)	319.387	311.651	245.919	240.520	207.716	192.939
	(531.389)	(461.741)	(293.120)	(254.848)	(456.963)	(329.810)
Total output	78.648	74.420	65.714	63.441	50.840	43.983
(€1000s)	(192.551)	(166.655)	(130.576)	(105.513)	(220.975)	(151.527)
Independent variables						
ROA	0.105	0.105	0.096	0.098	0.081	0.084
	(0.094)	(0.090)	(0.064)	(0.062)	(0.061)	(0.060)
ATO	0.252	0.246	0.257	0.258	0.216	0.219
	(0.191)	(0.173)	(0.156)	(0.145)	(0.112)	(0.108)
Age	44.163	44.673	43.426	43.789	44.138	44.433
	(9.361)	(9.018)	(8.989)	(8.726)	(9.230)	(9.002)
Decoupled payments	0.108	0.108	0.080	0.079	0.100	0.100
	(0.087)	(0.087)	(0.065)	(0.058)	(0.055)	(0.054)
Rural development	0.047	0.045	0.047	0.046	0.057	0.055
payments	(0.097)	(0.094)	(0.081)	(0.074)	(0.081)	(0.077)
N	22,951	15,898	26,301	19,543	29,367	21,459

2. Composite indicators

Section 2.1 presents the output of the KMO-statistics for each farm type within each region. Section 2.2 presents the outcomes of the Bartlett tests. Section 2.3 discusses the weights of the resilience capacity indicators based on principal component analysis.

2.1. KMO-statistics

Table A 6 KMO-statistics for ACP farms

	Western Europe	Southern Europe	Northern Europe	Eastern Europe
Robustness	0.511	0.560	0.530	0.585
Adaptation	0.543	0.569	0.508	0.532

Table A 7 KMO-statistics for livestock farms

	Western Europe	Southern Europe	Northern Europe	Eastern Europe
Robustness	0.513	0.537	0.517	0.570
Adaptation	0.502	0.523	0.507	0.506

Table A 8 KMO-statistics for mixed farms

	Western Europe	Southern Europe	Northern Europe	Eastern Europe
Robustness	0.525	0.579	0.555	0.562
Adaptation	0.567	0.632	0.611	0.563

2.2. Bartlett test

Table A 9 Bartlett test for robustness of ACP farms

	Western Europe	Southern Europe	Northern Europe	Eastern Europe
Chi-square	65,542.058	73,263.652	25,773.161	116,417.029
p-value	0.000	0.000	0.000	0.000
df	3	3	3	3

Table A 10 Bartlett test for robustness of livestock farms

	Western Europe	Southern Europe	Northern Europe	Eastern Europe
Chi-square	47,277.007	8,582.640	2,080.367	5,824.013
p-value	0.000	0.000	0.000	0.000
df	3	3	3	3

Table A 11 Bartlett test for robustness of mixed farms

	Western Europe	Southern Europe	Northern Europe	Eastern Europe
Chi-square	753.261	34,798.488	42,419.818	46,114.292
p-value	0.000	0.000	0.000	0.000
df	3	3	3	3

Table A 12 Bartlett test for adaptation of ACP farms

	Western Europe	Southern Europe	Northern Europe	Eastern Europe
Chi-square	1,346.844	3,969.494	62.075	425.540
p-value	0.000	0.000	0.000	0.000
df	6	6	6	6

Table A 13 Bartlett test for adaptation of livestock farms

	Western Europe	Southern Europe	Northern Europe	Eastern Europe
Chi-square	3,205.275	4,410.761	422.737	2,320.763
p-value	0.000	0.000	0.000	0.000
df	3	3	3	3

Table A 14 Bartlett test for adaptation of mixed farms

	Western Europe	Southern Europe	Northern Europe	Eastern Europe
Chi-square	967.189	752.589	91.577	1,776.847
p-value	0.000	0.000	0.000	0.000
df	15	15	15	15

2.3. Weights of the resilience capacity indicators for principal component analysis

Table A 15 Weights of the resilience capacity indicators for robustness of ACP farms

	Western Europe	Southern Europe	Northern Europe	Eastern Europe
Shock	0.380	0.367	0.371	0.365
Resistance	0.383	0.362	0.372	0.359
Recovery rate	0.237	0.271	0.257	0.276

Table A 16 Weights of the resilience capacity indicators for robustness of livestock farms

	Western Europe	Southern Europe	Northern Europe	Eastern Europe
Shock	0.379	0.371	0.380	0.370
Resistance	0.382	0.372	0.382	0.366
Recovery rate	0.238	0.257	0.238	0.264

Table A 17 Weights of the resilience capacity indicators for robustness of mixed farms

	Western Europe	Southern Europe	Northern Europe	Eastern Europe
Shock	0.377	0.369	0.369	0.370
Resistance	0.376	0.360	0.364	0.366
Recovery rate	0.247	0.272	0.267	0.264

Table A 18 Weights of the resilience capacity indicators for adaptation of ACP farms

	Western Europe	Southern Europe	Northern Europe	Eastern Europe
FCE	0.265	0.255	0.356	0.300
Diversification	0.255	0.243	0.220	0.259
Irrigation	0.163	0.214	0.025	0.107
Labour	0.317	0.288	0.399	0.333

Notes: FCE = Fertiliser, crop protection, and energy costs

Table A 19 Weights of the resilience capacity indicators for adaptation of livestock farms

	Western Europe	Southern Europe	Northern Europe	Eastern Europe
Labour	0.442	0.408	0.436	0.438
Feed	0.108	0.194	0.136	0.120
LU	0.450	0.398	0.428	0.441

Notes: LU = livestock units

Table A 20 Weights of the resilience capacity indicators for adaptation of mixed farms

	Western Europe	Southern Europe	Northern Europe	Eastern Europe
FCE	0.147	0.150	0.102	0.101
Diversification	0.205	0.216	0.146	0.227
Irrigation	0.079	0.121	0.115	0.016
Labour	0.212	0.194	0.215	0.280
Feed	0.106	0.129	0.192	0.106
LU	0.250	0.190	0.229	0.271

Notes: FCE = Fertiliser, crop protection, and energy costs; LU = livestock units.

3. Instrumental variables

We present the output of the reduced form equations in Table A21-A22. The outcomes of the tests for instrumental variable validity is presented in Table A23.

Table A 21 Parameter estimates of the first-stage pooled OLS regression for with return on assets (ROA) as dependent variable. ACP = Arable, crops, and perennials farms. Northern-European ACP and mixed farms are omitted because ROA is not endogenous in this region.

	Western Europe			Southern Europe			Northern Europe	Eastern Europe		
	ACP	Livestock	Mixed	ACP	Livestock	Mixed	Livestock	ACP	Livestock	Mixed
ROA at *t-2*	0.442***	0.475***	0.438***	0.342***	0.374***	0.267***	0.501***	0.225***	0.282***	0.245***
	(0.010)	(0.008)	(0.012)	(0.018)	(0.011)	(0.022)	(0.024)	(0.013)	(0.012)	(0.008)
ATO at *t-2*		0.040***		0.070***	0.072***		-0.021*		0.084***	
		(0.003)		(0.012)	(0.006)		(0.011)		(0.008)	
ATO	0.177***		0.205***			0.399***		0.509***		0.435***
	(0.025)		(0.011)			(0.042)		(0.022)		(0.010)
Log(land)	0.033***	0.010***	-0.005	0.005**	0.004**	-0.003	0.012**	0.001	0.023***	-0.006*
	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)
Age	0.000	0.000	0.000***	0.000	0.000	0.000	0.000	-0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	-0.611***	-0.189***	-0.260***	-0.059*	-0.073**	0.005	-0.390***	-0.128***	-0.533***	-0.162***
	(0.039)	(0.011)	(0.023)	(0.032)	(0.034)	(0.017)	(0.045)	(0.030)	(0.027)	(0.015)
Rural development payments	0.279***	0.006**	0.164***	-0.029**	0.011	0.085***	0.114***	0.139***	0.210***	0.187***
	(0.045)	(0.002)	(0.030)	(0.013)	(0.015)	(0.025)	(0.034)	(0.016)	(0.010)	(0.006)
Constant	-0.049*	0.023***	0.020	0.032***	0.027***	-0.030*	-0.006	-0.057***	0.003	-0.028***
	(0.025)	(0.008)	(0.016)	(0.009)	(0.008)	(0.017)	(0.031)	(0.016)	(0.010)	(0.011)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Farm type[2]	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	ROA	ROA, ATO	ROA	ROA, ATO	ROA, ATO	ROA	ROA, ATO	ROA	ROA, ATO	ROA
N	38,888	42,969	14,162	54,105	23,369	3,920	3,601	15,898	19,543	21,459

ATO at *t-2* is included as regressor if ATO is considered to be endogenous. If this is not the case, then ATO is included as regressor. [1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region. [2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model of a specific farm type (i.e. for mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are clustered at farm level. $p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$.

Table A 22 Parameter estimates of the first-stage pooled OLS regression for with asset turnover (ATO) as dependent variable. ACP = Arable, crops, and perennials farms. The regions and farm types where ATO is not endogenous are omitted for brevity.

	Western Europe	Southern Europe		Northern Europe	Eastern Europe
	Livestock	ACP	Livestock	Livestock	Livestock
ATO at *t-2*	0.921***	0.462***	0.699***	0.680***	0.744***
	(0.012)	(0.061)	(0.022)	(0.034)	(0.036)
ROA at *t-2*	-0.320***	0.042	-0.240***	-0.174***	-0.238***
	(0.019)	(0.083)	(0.025)	(0.044)	(0.036)
Log(land)	0.017***	0.007	0.012***	0.033***	0.019***
	(0.004)	(0.004)	(0.003)	(0.009)	(0.005)
Age	-0.000	-0.001***	0.000	-0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Decoupled payments	-0.395***	-0.154*	-0.173**	-0.560***	-0.544***
	(0.016)	(0.086)	(0.078)	(0.064)	(0.043)
Rural development	0.014***	-0.145***	-0.172***	-0.196***	-0.026**
payments	(0.001)	(0.023)	(0.025)	(0.046)	(0.013)
Constant	0.046**	0.137***	0.019	0.035	0.066***
	(0.020)	(0.020)	(0.016)	(0.051)	(0.019)
Country[1]	Yes	Yes	Yes	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO
N	42,969	54,105	23,369	3,601	19,543

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region.
[2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model of a specific farm type (i.e. for mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are clustered at farm level. p < 0.10, ** p < 0.05, *** p < 0.01.

Table A 23 Validity tests for instruments for the models with robustness as dependent variable. ACP = Arable, crops, and perennials farms. Northern European ACP and mixed farms are omitted because both a Hausman test indicated that both ATO and ROA are not endogenous.

	Western Europe			Southern Europe			Northern Europe	Eastern Europe		
	ACP	Livestock	Mixed	ACP	Livestock	Mixed	Livestock	ACP	Livestock	Mixed
Instrument validity										
F-statistic	1930.894***	2296.524***	1020.765***	76.528***	1063.472***	144.300***	274.779***	273.975***	578.583***	771.054***
Kleibergen-Paap LM-statistic	766.223***	1498.419***	457.949***	265.314***	873.005***	99.832***	179.289***	196.274***	651.839***	489.360***
Endogenous variables	ROA	ROA, ATO	ROA	ROA, ATO	ROA, ATO	ROA	ROA, ATO	ROA	ROA, ATO	ROA
Hausman test for endogeneity										
Residuals ROA	4.600***	9.067***	9.377***	5.943***	9.486***	12.356***	8.419***	12.135***	10.783***	17.245***
	(0.133)	(0.216)	(0.395)	(0.236)	(0.299)	(1.249)	(0.714)	(0.772)	(0.497)	(0.752)
Residuals ATO		0.333***		-0.642***	-0.341**		1.254***		0.359*	
		(0.070)		(0.124)	(0.134)		(0.322)		(0.193)	
Correlation between instrument and farm robustness										
ROA at *t-2*	-0.071	-0.072	-0.087	-0.178	-0.141	-0.077	-0.033	-0.141	-0.095	-0.089
ATO at *t-2*		-0.124		-0.167	-0.137		-0.152		-0.086	

Bootstrapped standard errors are presented in parentheses (1,000 repetitions). The Hausman test tests for endogeneity by including the residuals of the first-stage regressions in the second stage model. If the residuals are significant, we treat the corresponding variable as endogenous. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4. Robustness checks

This section provides an overview of the robustness checks. Five robustness check were conducted: (i) models based on other weighting methods (equal weights) to compute composite indicators for robustness and adaptation (section 4.1), (ii) models based on other threshold values for farm tourism as transformation indicator (section 4.2), (iii) models including additional economic and environmental variables (section 4.3), (iv) models that investigate if decoupled payments and/or rural development payments are exogenous or endogenous explanatory variables (section 4.4), and (v) models including age squared and land squared as additional explanatory variables (section 4.5).

4.1 Robustness checks based on alternative weighting methods

One of the key decisions that we had to make when we constructed the composite indicators was to choose the optimal weighting method. As robustness check, we compare the outcome of the original model, where the Principal Component Analysis (PCA) is used as weighting method, to an equal weights method. This section presents the average partial effects of the correlated random effects fractional probit models.

4.1.1. Robustness checks based on alternative weighting methods for farm robustness

For each farm type (i.e. arable, crops and perennials (ACP), livestock, and mixed farms) within each region (i.e. Western, Southern, Northern, and Eastern Europe), we compare results of using PCA as weighting method with equal weights. The results can be found in Table A24-A27.

As the output of the robustness check is large and consists of 4 tables, we present a short summary of our findings below. The robustness checks shows that the findings are in general robust to alternative weighting methods, except for the significance of ROA in two of the regions for livestock farms. For Western (Table A24) and Northern (Table A26) European livestock farms, the effects of profitability on robustness is positive and significant if we use PCA as weighting method but not significant when applying equal weights.

Table A 24 Robustness check for robustness in Western Europe for alternative composite indicator weighting methods. Average partial effects of the correlated random effects fractional probit model are presented. ACP = arable, crops, and perennials farms.

	ACP		Livestock		Mixed	
	Original model (Principal component analysis)	Equal weights	Original model (Principal component analysis)	Equal weights	Original model (Principal component analysis)	Equal weights
ROA	-0.059**	-0.117***	0.076*	-0.015	-0.027	-0.118
	(0.024)	(0.025)	(0.041)	(0.042)	(0.076)	(0.079)
ATO	0.181***	0.186***	-0.086***	-0.078***	0.384***	0.395***
	(0.027)	(0.028)	(0.009)	(0.009)	(0.034)	(0.036)
Log(land)	0.054***	0.055***	0.025***	0.024***	0.006	0.007
	(0.004)	(0.005)	(0.006)	(0.006)	(0.011)	(0.011)
Age	0.001**	0.001**	0.000	0.000	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Decoupled payments	-0.926***	-0.890***	-0.662***	-0.646***	-0.872***	-0.869***
	(0.054)	(0.056)	(0.051)	(0.052)	(0.084)	(0.088)
Rural development payments	0.481***	0.476***	0.028	0.029	0.425***	0.428***
	(0.091)	(0.094)	(0.074)	(0.077)	(0.110)	(0.115)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	ROA	ROA	ROA, ATO	ROA, ATO	ROA	ROA
N	38,888	38,888	42,969	42,969	14,162	14,162

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region.
[2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5] Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 25 Robustness check for robustness in Southern Europe for alternative composite indicator weighting methods. Average partial effects of the correlated random effects fractional probit model are presented. ACP = arable, crops, and perennials farms.

	ACP		Livestock		Mixed	
	Original model (Principal component analysis)	Equal weights	Original model (Principal component analysis)	Equal weights	Original model (Principal component analysis)	Equal weights
ROA	-0.377***	-0.468***	-0.620***	-0.726***	-0.786***	-0.901***
	(0.047)	(0.049)	(0.064)	(0.066)	(0.241)	(0.245)
ATO	0.007	0.028	0.000	0.021	1.014***	1.039***
	(0.024)	(0.025)	(0.028)	(0.028)	(0.166)	(0.171)
Log(land)	0.021***	0.021***	0.010**	0.011**	-0.026**	-0.027**
	(0.004)	(0.004)	(0.005)	(0.005)	(0.012)	(0.012)
Age	0.001***	0.001***	0.001	0.001	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Decoupled payments	-0.163***	-0.151***	-0.193*	-0.187*	-0.170**	-0.160**
	(0.062)	(0.057)	(0.109)	(0.104)	(0.067)	(0.068)
Rural development payments	-0.029	-0.023	0.171***	0.180***	0.446***	0.447***
	(0.030)	(0.031)	(0.061)	(0.061)	(0.125)	(0.128)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA	ROA
N	54,105	54,105	23,369	23,369	3,920	3,920

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region.
[2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5] Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 26 Robustness check for robustness in Northern Europe for alternative composite indicator weighting methods. Average partial effects of the correlated random effects fractional probit model are presented. ACP = arable, crops, and perennials farms.

	ACP		Livestock		Mixed	
	Original model (Principal component analysis)	Equal weights	Original model (Principal component analysis)	Equal weights	Original model (Principal component analysis)	Equal weights
ROA	1.979***	1.862***	0.281**	0.149	2.936***	2.866***
	(0.159)	(0.163)	(0.131)	(0.142)	(0.350)	(0.363)
ATO	-0.358***	-0.328***	-0.339***	-0.337***	0.488***	0.533***
	(0.118)	(0.120)	(0.045)	(0.047)	(0.132)	(0.143)
Log(land)	0.056**	0.052**	0.030	0.026	-0.083	-0.080
	(0.025)	(0.026)	(0.020)	(0.022)	(0.052)	(0.056)
Age	0.005*	0.006**	0.002	0.002	-0.005	-0.005
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)
Decoupled payments	-0.473***	-0.443***	-1.191***	-1.175***	0.454	0.463
	(0.135)	(0.137)	(0.184)	(0.188)	(0.382)	(0.402)
Rural development payments	0.510***	0.495***	0.087	0.068	-0.404	-0.399
	(0.162)	(0.169)	(0.140)	(0.148)	(0.483)	(0.525)
Country[1]	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	None	None	ROA, ATO	ROA, ATO	None	None
N	1,132	1,132	3,601	3,601	437	437

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region.
[2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5] Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 27 Robustness check for robustness in Eastern Europe for alternative composite indicator weighting methods. Average partial effects of the correlated random effects fractional probit model are presented. ACP = arable, crops, and perennials farms.

	ACP		Livestock		Mixed	
	Original model (Principal component analysis)	Equal weights	Original model (Principal component analysis)	Equal weights	Original model (Principal component analysis)	Equal weights
ROA	-1.354***	-1.437***	0.045	-0.085	-1.177***	-1.364***
	(0.174)	(0.176)	(0.117)	(0.120)	(0.162)	(0.166)
ATO	1.585***	1.588***	-0.141***	-0.141***	1.657***	1.703***
	(0.111)	(0.111)	(0.040)	(0.041)	(0.096)	(0.098)
Log(land)	0.019	0.019	0.064***	0.059***	-0.039**	-0.041**
	(0.016)	(0.016)	(0.014)	(0.015)	(0.016)	(0.016)
Age	0.001	0.001	0.004***	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Decoupled payments	-0.682***	-0.662***	-2.215***	-2.114***	-1.222***	-1.173***
	(0.177)	(0.170)	(0.120)	(0.116)	(0.087)	(0.089)
Rural development payments	0.563***	0.559***	0.811***	0.795***	1.036***	1.046***
	(0.091)	(0.090)	(0.062)	(0.062)	(0.052)	(0.053)
Country[1]	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	ROA	ROA	ROA, ATO	ROA, ATO	ROA	ROA
N	15,898	15,898	19,543	19,543	21,459	21,459

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region.
[2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5] Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.1.2. Robustness checks based on alternative weighting methods for farm adaptation

One of the key decisions that we had to make when we constructed the composite indicators was to choose the optimal weighting method. As a robustness check, we compare the outcome of the original model, where the Principal Component Analysis (PCA) is used as weighting method, to an equal weights method. This section presents the average partial effects of the correlated random effects fractional probit models. For each farm type (i.e. arable, crops and perennials (ACP), livestock, and mixed farms) within each region (i.e. Western, Southern, Northern, and Eastern Europe), we compare results of using PCA as weighting method with equal weights. The results can be found in Table A28-A31.

As the output of the robustness check is large and consists of 4 tables, we present a short summary of our findings below. The robustness checks shows that the findings are robust to alternative weighting methods, except for the significance of decoupled payments for livestock farms in Western Europe (Table A28). For Western European livestock farms, the effect of decoupled direct payments on adaptation is not significant if we use PCA as weighting method but is significant when applying equal weights.

Table A 28 Robustness check for adaptation in Western Europe for alternative composite indicator weighting methods. Average partial effects of the correlated random effects fractional probit model are presented. ACP = arable, crops, and perennials farms.

	ACP		Livestock		Mixed	
	Original model (Principal component analysis)	Equal weights	Original model (Principal component analysis)	Equal weights	Original model (Principal component analysis)	Equal weights
ROA	-0.023***	-0.024***	-0.046***	-0.029*	-0.021	-0.018
	(0.005)	(0.006)	(0.014)	(0.016)	(0.018)	(0.019)
ATO	0.003	0.002	0.008	0.003	-0.007	-0.008
	(0.002)	(0.002)	(0.007)	(0.008)	(0.009)	(0.010)
Log(land)	-0.001	0.000	0.010***	0.004*	0.001	0.000
	(0.001)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
Age	-0.000***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	0.005	0.002	0.019	0.048***	0.028	0.046
	(0.016)	(0.018)	(0.016)	(0.018)	(0.033)	(0.035)
Rural development payments	-0.015	-0.019	-0.000	-0.002	0.017	0.010
	(0.026)	(0.028)	(0.001)	(0.001)	(0.038)	(0.040)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes
N	38,888	38,888	42,969	42,969	14,162	14,162

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region. [2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). $p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A 29 Robustness check for adaptation in Southern Europe for alternative composite indicator weighting methods. Average partial effects of the correlated random effects fractional probit model are presented. ACP = arable, crops, and perennials farms.

	ACP		Livestock		Mixed	
	Original model (Principal component analysis)	Equal weights	Original model (Principal component analysis)	Equal weights	Original model (Principal component analysis)	Equal weights
ROA	-0.030***	-0.030***	0.002	-0.009	-0.049*	-0.049*
	(0.006)	(0.006)	(0.011)	(0.012)	(0.028)	(0.028)
ATO	0.017***	0.018***	0.011	0.015	0.014	0.010
	(0.004)	(0.004)	(0.007)	(0.010)	(0.015)	(0.016)
Log(land)	0.002	0.001	0.000	-0.000	0.002	0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)	(0.004)
Age	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	-0.002	-0.003	0.012	0.010	-0.018	-0.020
	(0.005)	(0.004)	(0.008)	(0.008)	(0.019)	(0.020)
Rural development	0.011	0.013	0.001	0.008	0.027	0.030
payments	(0.008)	(0.008)	(0.012)	(0.013)	(0.036)	(0.038)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes
N	54,105	54,105	23,369	23,369	3,920	3,920

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region. [2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). $p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A 30 Robustness check for adaptation in Northern Europe for alternative composite indicator weighting methods. Average partial effects of the correlated random effects fractional probit model are presented. ACP = arable, crops, and perennials farms.

	ACP		Livestock		Mixed	
	Original model (Principal component analysis)	Equal weights	Original model (Principal component analysis)	Equal weights	Original model (Principal component analysis)	Equal weights
ROA	-0.036	-0.028	-0.088*	-0.089*	-0.230**	-0.257**
	(0.067)	(0.080)	(0.053)	(0.054)	(0.111)	(0.116)
ATO	-0.038	-0.058	0.028	0.019	0.013	0.008
	(0.040)	(0.050)	(0.033)	(0.035)	(0.123)	(0.130)
Log(land)	-0.039***	-0.050***	-0.005	0.004	0.017	0.020
	(0.015)	(0.017)	(0.010)	(0.011)	(0.021)	(0.023)
Age	-0.005***	-0.006***	-0.001	-0.001	-0.003*	-0.003*
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Decoupled payments	0.066	0.104	0.249***	0.256***	0.259	0.311
	(0.066)	(0.086)	(0.086)	(0.090)	(0.203)	(0.215)
Rural development payments	-0.053	-0.061	-0.076	-0.091	0.124	0.103
	(0.092)	(0.113)	(0.069)	(0.076)	(0.308)	(0.322)
Country[1]	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes
N	1,132	1,132	3,601	3,601	437	437

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region.
[2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). $p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A 31 Robustness check for adaptation in Eastern Europe for alternative composite indicator weighting methods. Average partial effects of the correlated random effects fractional probit model are presented. ACP = arable, crops, and perennials farms.

	ACP		Livestock		Mixed	
	Original model (Principal component analysis)	Equal weights	Original model (Principal component analysis)	Equal weights	Original model (Principal component analysis)	Equal weights
ROA	-0.080***	-0.074***	0.005	0.016	0.005	0.025
	(0.020)	(0.021)	(0.024)	(0.025)	(0.021)	(0.022)
ATO	0.059***	0.060***	0.012	0.010	-0.000	-0.007
	(0.015)	(0.017)	(0.016)	(0.016)	(0.016)	(0.017)
Log(land)	0.004	0.005	0.009	0.007	0.006*	0.008**
	(0.003)	(0.003)	(0.006)	(0.006)	(0.003)	(0.004)
Age	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	0.007	0.018	0.087***	0.089***	0.117***	0.144***
	(0.023)	(0.027)	(0.032)	(0.033)	(0.027)	(0.029)
Rural development payments	0.025	0.026	-0.033*	-0.035**	0.012	0.004
	(0.016)	(0.018)	(0.017)	(0.018)	(0.013)	(0.014)
Country[1]	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes
N	15,898	15,898	19,543	19,543	21,459	21,459

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region.
[2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). $p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4.2 Robustness checks for farm transformation using different thresholds for farm tourism

We defined farm transformation as a dichotomous variable that turns 1 if a farm has transformed and 0 if not. Hence, weighting methods have no influence on this indicator.

This section presents the average partial effects of the correlated random effects probit models explaining transformation under different threshold values for farm tourism. For each farm type (i.e. arable, crops and perennials (ACP), livestock, and mixed farms) within each region (i.e. Western, Southern, Northern, and Eastern Europe), a sensitivity analysis has been conducted under different thresholds values for when farm tourism is considered to be a transformation. The original model uses 30% of total revenue as threshold. The sensitivity analysis shift this threshold to 10%, 20%, 40%, and 50%.

As the output of the sensitivity analysis is large and consists of 12 tables, we present a short summary of our findings below. Tables (A32-A43) show that our findings are robust to alternative thresholds for farm tourism, except for the significance of ROA of livestock farms from Western Europe (see Table A33; models using 40% and 50% as threshold) and rural development payments of ACP farms from Eastern Europe (see Table A41; models using 10% and 20% as threshold). However, these statistical difference are caused by a slight increase in the (absolute) value of the corresponding average partial effect, while the direction of the effect and the standard error remained approximately constant across models. This implies similar effect sizes and no large changes in the p-values across the different model specifications (which are all close to 0.10). For this reason, we believe that our findings are robust to alternative thresholds for farm tourism.

Table A 32 Sensitivity analysis for transformation of ACP farms in Western Europe under different thresholds for farm tourism (10%, 20%, 40%, 50%). Average partial effects of the correlated random effects probit model are presented.

	Original model (30%)	Tourism 10%	Tourism 20%	Tourism 40%	Tourism 50%
ROA	0.013	0.013	0.013	0.014	0.014
	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)
ATO	-0.013	-0.012	-0.013	-0.012	-0.013
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Log(land)	-0.007*	-0.009**	-0.007*	-0.007*	-0.007*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	0.273***	0.286***	0.278***	0.275***	0.273***
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Rural development	-0.064	-0.071	-0.063	-0.062	-0.058
payments	(0.056)	(0.058)	(0.056)	(0.056)	(0.056)
Country[1]	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes
N	38,888	38,888	38,888	38,888	38,888

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region. [2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). $p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A 33 Sensitivity analysis for transformation of livestock farms in Western Europe under different thresholds for farm tourism (10%, 20%, 40%, 50%). Average partial effects of the correlated random effects probit model are presented.

	Original model (30%)	Tourism 10%	Tourism 20%	Tourism 40%	Tourism 50%
ROA	-0.051	-0.051	-0.053	-0.055*	-0.056*
	(0.032)	(0.033)	(0.033)	(0.032)	(0.032)
ATO	-0.010	-0.018	-0.011	-0.008	-0.007
	(0.017)	(0.018)	(0.017)	(0.017)	(0.016)
Log(land)	-0.000	0.001	0.000	0.000	0.001
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	0.026	0.013	0.023	0.037	0.036
	(0.036)	(0.037)	(0.036)	(0.037)	(0.037)
Rural development payments	0.049***	0.050***	0.048***	0.047***	0.049***
	(0.017)	(0.018)	(0.017)	(0.017)	(0.017)
Country[1]	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes
N	42,969	42,969	42,969	42,969	42,969

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region. [2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). $p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$.

Table A 34 Sensitivity analysis for transformation of mixed farms in Western Europe under different thresholds for farm tourism (10%, 20%, 40%, 50%). Average partial effects of the correlated random effects probit model are presented.

	Original model (30%)	Tourism 10%	Tourism 20%	Tourism 40%	Tourism 50%
ROA	-0.127	-0.126	-0.129	-0.125	-0.127
	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)
ATO	-0.015	-0.019	-0.014	-0.015	-0.015
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
Log(land)	0.004	0.001	0.003	0.004	0.004
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Age	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Decoupled payments	-0.032	-0.052	-0.035	-0.026	-0.028
	(0.140)	(0.141)	(0.140)	(0.140)	(0.140)
Rural development	-0.103	-0.118	-0.110	-0.110	-0.104
payments	(0.183)	(0.185)	(0.182)	(0.183)	(0.183)
Country[1]	Yes	Yes	Yes	Yes	Yes
Farm type[2]	No	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes
N	14,162	14,162	14,162	14,162	14,162

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region. [2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). $p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$.

Table A 35 Sensitivity analysis for transformation of ACP farms in Southern Europe under different thresholds for farm tourism (10%, 20%, 40%, 50%). Average partial effects of the correlated random effects probit model are presented.

	Original model (30%)	Tourism 10%	Tourism 20%	Tourism 40%	Tourism 50%
ROA	-0.020	-0.023	-0.021	-0.023	-0.021
	(0.018)	(0.019)	(0.019)	(0.018)	(0.018)
ATO	-0.008	-0.006	-0.007	-0.009	-0.008
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Log(land)	0.018***	0.018***	0.018***	0.018***	0.018***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age	-0.001**	-0.001***	-0.001**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	-0.005	-0.007	-0.006	-0.005	-0.005
	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)
Rural development payments	0.065***	0.066***	0.065***	0.067***	0.069***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Country[1]	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes
N	54,100	54,100	54,100	54,100	54,100

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region. [2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). $p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$.

Table A 36 Sensitivity analysis for transformation of livestock farms in Southern Europe under different thresholds for farm tourism (10%, 20%, 40%, 50%). Average partial effects of the correlated random effects probit model are presented.

	Original model (30%)	Tourism 10%	Tourism 20%	Tourism 40%	Tourism 50%
ROA	0.025	0.012	0.021	0.023	0.027
	(0.039)	(0.041)	(0.040)	(0.039)	(0.039)
ATO	-0.019	-0.028	-0.019	-0.023	-0.025
	(0.027)	(0.028)	(0.027)	(0.027)	(0.027)
Log(land)	0.002	0.002	0.002	0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	-0.004	-0.008	-0.007	-0.005	-0.001
	(0.024)	(0.024)	(0.024)	(0.023)	(0.024)
Rural development	0.067**	0.071**	0.073**	0.069**	0.065**
payments	(0.033)	(0.034)	(0.034)	(0.033)	(0.033)
Country[1]	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes
N	23,369	23,369	23,369	23,369	23,369

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region. [2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). $p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$.

Table A 37 Sensitivity analysis for transformation of mixed farms in Southern Europe under different thresholds for farm tourism (10%, 20%, 40%, 50%). Average partial effects of the correlated random effects probit model are presented.

	Original model (30%)	Tourism 10%	Tourism 20%	Tourism 40%	Tourism 50%
ROA	-0.090	-0.081	-0.084	-0.084	-0.089
	(0.171)	(0.171)	(0.171)	(0.171)	(0.171)
ATO	-0.156	-0.167	-0.157	-0.155	-0.145
	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)
Log(land)	-0.007	-0.004	-0.007	-0.006	-0.006
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Age	0.000	0.000	0.000	0.000	0.000
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Decoupled payments	0.134	0.125	0.135	0.136	0.140
	(0.107)	(0.107)	(0.107)	(0.107)	(0.106)
Rural development	0.002	0.011	0.000	0.007	-0.011
payments	(0.208)	(0.208)	(0.208)	(0.207)	(0.207)
Country[1]	Yes	Yes	Yes	Yes	Yes
Farm type[2]	No	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes
N	3,920	3,920	3,920	3,920	3,920

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region. [2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 38 Sensitivity analysis for transformation of ACP farms in Northern Europe under different thresholds for farm tourism (10%, 20%, 40%, 50%). Average partial effects of the correlated random effects probit model are presented.

	Original model (30%)	Tourism 10%	Tourism 20%	Tourism 40%	Tourism 50%
ROA	0.031	0.031	0.031	0.036	0.036
	(0.194)	(0.196)	(0.196)	(0.192)	(0.192)
ATO	-0.060	-0.058	-0.058	-0.061	-0.061
	(0.105)	(0.105)	(0.105)	(0.104)	(0.104)
Log(land)	-0.052*	-0.050*	-0.050*	-0.051*	-0.051*
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Age	-0.003	-0.003	-0.003	-0.003	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Decoupled payments	0.060	0.051	0.051	0.068	0.068
	(0.207)	(0.207)	(0.207)	(0.206)	(0.206)
Rural development payments	-0.090	-0.068	-0.068	-0.089	-0.089
	(0.226)	(0.227)	(0.227)	(0.225)	(0.225)
Country[1]	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes
N	1,132	1,132	1,132	1,132	1,132

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region. [2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). $p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$.

Table A 39 Sensitivity analysis for transformation of livestock farms in Northern Europe under different thresholds for farm tourism (10%, 20%, 40%, 50%). Average partial effects of the correlated random effects probit model are presented.

	Original model (30%)	Tourism 10%	Tourism 20%	Tourism 40%	Tourism 50%
ROA	-0.049	-0.048	-0.048	-0.053	-0.053
	(0.143)	(0.143)	(0.143)	(0.142)	(0.142)
ATO	-0.244**	-0.245**	-0.245**	-0.240**	-0.240**
	(0.107)	(0.108)	(0.108)	(0.107)	(0.107)
Log(land)	-0.030	-0.031	-0.031	-0.033	-0.033
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Age	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Decoupled payments	0.393*	0.402*	0.402*	0.391*	0.391*
	(0.211)	(0.211)	(0.211)	(0.210)	(0.210)
Rural development payments	-0.138	-0.141	-0.141	-0.136	-0.136
	(0.194)	(0.194)	(0.194)	(0.194)	(0.194)
Country[1]	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes
N	3,601	3,601	3,601	3,601	3,601

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region. [2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No)The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). $p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$.

Table A 40 Sensitivity analysis for transformation of mixed farms in Northern Europe under different thresholds for farm tourism (10%, 20%, 40%, 50%). Average partial effects of the correlated random effects probit model are presented.

	Original model (30%)	Tourism 10%	Tourism 20%	Tourism 40%	Tourism 50%
ROA	-0.388	-0.362	-0.388	-0.388	-0.388
	(0.608)	(0.608)	(0.608)	(0.608)	(0.608)
ATO	-0.002	0.021	-0.002	-0.002	-0.002
	(0.361)	(0.359)	(0.361)	(0.361)	(0.361)
Log(land)	0.026	0.036	0.026	0.026	0.026
	(0.105)	(0.105)	(0.105)	(0.105)	(0.105)
Age	0.003	0.003	0.003	0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Decoupled payments	1.248*	1.387*	1.248*	1.248*	1.248*
	(0.734)	(0.731)	(0.734)	(0.734)	(0.734)
Rural development	0.113	-0.001	0.113	0.113	0.113
payments	(0.975)	(0.967)	(0.975)	(0.975)	(0.975)
Country[1]	No	No	No	No	No
Farm type[2]	No	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes
N	437	437	437	437	437

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region. [2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). $p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A 41 Sensitivity analysis for transformation of ACP farms in Eastern Europe under different thresholds for farm tourism (10%, 20%, 40%, 50%). Average partial effects of the correlated random effects probit model are presented.

	Original model (30%)	Tourism 10%	Tourism 20%	Tourism 40%	Tourism 50%
ROA	0.090	0.089	0.091	0.092	0.097
	(0.072)	(0.073)	(0.073)	(0.072)	(0.072)
ATO	-0.134**	-0.138**	-0.135**	-0.136**	-0.139**
	(0.057)	(0.058)	(0.058)	(0.057)	(0.057)
Log(land)	-0.008	-0.010	-0.008	-0.008	-0.008
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Age	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Decoupled payments	0.006	0.005	0.009	0.006	0.010
	(0.071)	(0.071)	(0.071)	(0.070)	(0.070)
Rural development	-0.097	-0.101*	-0.100*	-0.089	-0.093
payments	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
Country[1]	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes
N	15,897	15,897	15,897	15,897	15,897

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region. [2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). $p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$.

Table A 42 Sensitivity analysis for transformation of livestock farms Eastern Europe under different thresholds for farm tourism (10%, 20%, 40%, 50%). Average partial effects of the correlated random effects probit model are presented.

	Original model (30%)	Tourism 10%	Tourism 20%	Tourism 40%	Tourism 50%
ROA	0.044	0.039	0.048	0.051	0.054
	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)
ATO	-0.136***	-0.134***	-0.137***	-0.141***	-0.142***
	(0.051)	(0.050)	(0.050)	(0.050)	(0.050)
Log(land)	-0.015	-0.016	-0.016	-0.016	-0.016
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Age	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Decoupled payments	0.110	0.096	0.108	0.108	0.109
	(0.086)	(0.086)	(0.086)	(0.085)	(0.085)
Rural development	-0.059	-0.060	-0.063	-0.063	-0.065
payments	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)
Country[1]	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes
N	19,543	19,543	19,543	19,543	19,543

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region. [2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). $p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A 43 Sensitivity analysis for transformation of mixed farms in Eastern Europe under different thresholds for farm tourism (10%, 20%, 40%, 50%). Average partial effects of the correlated random effects probit model are presented.

	Original model (30%)	Tourism 10%	Tourism 20%	Tourism 40%	Tourism 50%
ROA	-0.068	-0.078	-0.071	-0.060	-0.053
	(0.084)	(0.085)	(0.084)	(0.083)	(0.083)
ATO	0.054	0.060	0.058	0.044	0.041
	(0.065)	(0.066)	(0.066)	(0.065)	(0.065)
Log(land)	0.025**	0.025**	0.025**	0.026**	0.027**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Age	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Decoupled payments	-0.033	-0.012	-0.013	-0.048	-0.052
	(0.114)	(0.115)	(0.114)	(0.114)	(0.114)
Rural development	0.010	0.020	0.012	0.016	0.019
payments	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)
Country[1]	No	No	No	No	No
Farm type[2]	No	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes
N	21,459	21,459	21,459	21,459	21,459

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region. [2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model. [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). $p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$.

4.3 Robustness checks based on adding economic and environmental variables

Section 4.3.1 presents the robustness checks for farm robustness, section 4.3.2 describes the robustness checks for farm adaptation, and section 4.3.3. presents the findings for farm transformation.

We conducted a series of robustness checks for alternative models that include several economic and environmental variables (Table A.44-80). As economic variables, we included two variables that are based on farmgate price time series: price volatility and market shocks (Vigani and Kathage 2019). These variables account for the volatility of agricultural markets and sudden drops in farmgate prices that may affect the robustness, adaptation, and transformation of farms. Following Bozzola et al. (2018), we included the following environmental variables in our model: seasonal (i.e. winter, spring, summer, autumn) temperature and precipitation data. These environmental variables are often used to investigate climate change and if changes in temperature or precipitation affect the resilience of farms. Note that the most accurate location of farms provided by FADN is at NUTS-3 level. Therefore, we included the environmental variables at NUTS-3 level. Table A.44 presents the variable definitions and the data sources used to these compute additional economic and environmental variables. Including these economic and environmental variables resulted in seven alternative model specifications. The following variables were added to the original model: (i) price volatility, (ii) price shocks, (iii) price volatility and price shocks, (iv) temperature, (v) precipitation, (vi) temperature and precipitation, (vii) price volatility, price shocks, temperature, and precipitation.

As the reduced form equations slightly change under alternative model specifications (see section 3.2.3), it is important to first verify if the instrumental variables remain valid. We did this by inspecting the Kleibergen-Paap F-statistics and Kleibergen-Paap LM-statistic, the signficance of the instruments in the reduced form equations, and checking the outcomes of the Hausman test for each alternative model specification. The instruments remained valid in all cases. To limit the length of this appendix, we decided not to present this output but describe our approach and findings in words.

Table A 44 Overview of the variables used for the robustness checks that include commodity price and climate variables. References to the data source are included if the variables were not based on FADN.

Variable	Definition
Land (ha)	Utilised agricultural area expressed in hectares (ha)
Owned land (ratio)	Ratio owned land relative to total land
Labour (AWU)	Labour expressed in annual working units (AWU)
Paid labour (ratio)	Ratio paid labour relative to total labour
Total assets (€1000s)	Total assets expressed in €1000s
Total output (€1000s)	Total output expressed in €1000s
ROA	Return on assets, defined as the ratio net farm income before taxation to total assets
ATO	Asset turnover, defined as the ratio total revenue to total assets
Age	Age of the main farm operator in years
Decoupled payments	Ratio decoupled payments to total revenue including subsidies
Rural development payments	Ratio rural development payments to total revenue including subsidies
Price volatility	Coefficient of variation of three years of farmgate prices (data from FAO 2020)
Price shock	Percentage decrease in farmgate prices with respect to the previous year (data from FAO 2020). This variable takes a value of 0 if farmgate prices increased.
Precipitation (winter)	Monthly mean of sum of precipitation (mm) in December, January, and February (data from Angelova and Lupio 2020)
Precipitation (spring)	Monthly mean of sum of precipitation (mm) in March, April, and May (data from Angelova and Lupio 2020)
Precipitation (summer)	Monthly mean of sum of precipitation (mm) in June, July, and August (data from Angelova and Lupio 2020)
Precipitation (autumn)	Monthly mean of sum of precipitation (mm) in September, October, November (data from Angelova and Lupio 2020)

Temperature (winter)	Daily average air temperature in degrees Centigrade in December, January, and February (data from Angelova and Lupio 2020)
Temperature (spring)	Daily average air temperature in degrees Centigrade in March, April, and May (data from Angelova and Lupio 2020)
Temperature (summer)	Daily average air temperature in degrees Centigrade in June, July, and August (data from Angelova and Lupio 2020)
Temperature (autumn)	Daily average air temperature in degrees Centigrade in December, January, and February (data from Angelova and Lupio 2020)

4.3.1. Robustness checks based on adding economic and environmental variables for farm robustness

Section 4.3.1 presents the robustness checks that add economic and environmental variables to the model for farm robustness. Including these economic and environmental variables resulted in seven alternative model specifications. The following variables were added to the original model: (i) price volatility, (ii) price shocks, (iii) price volatility and price shocks, (iv) temperature, (v) precipitation, (vi) temperature and precipitation, (vii) price volatility, price shocks, temperature, and precipitation. These findings are presented in Table A.45-56.

Table A 45 Average partial effects (APE) of the robustness check for economic and environmental variables for robustness of arable farms from Western Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.059**	-0.059**	-0.054**	-0.052**	-0.057**	-0.063***	-0.057**	-0.046**
	(0.024)	(0.023)	(0.023)	(0.023)	(0.024)	(0.024)	(0.024)	(0.023)
ATO	0.181***	0.181***	0.179***	0.178***	0.182***	0.181***	0.181***	0.178***
	(0.027)	(0.029)	(0.029)	(0.028)	(0.027)	(0.028)	(0.028)	(0.029)
Log(land)	0.054***	0.054***	0.053***	0.053***	0.054***	0.055***	0.054***	0.052***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age	0.001**	0.001**	0.001**	0.001**	0.001**	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	-0.926***	-0.916***	-0.867***	-0.858***	-0.929***	-0.933***	-0.931***	-0.836***
	(0.054)	(0.057)	(0.057)	(0.057)	(0.054)	(0.055)	(0.054)	(0.056)
Rural development payments	0.481***	0.480***	0.466***	0.466***	0.462***	0.484***	0.463***	0.436***
	(0.091)	(0.090)	(0.089)	(0.089)	(0.091)	(0.092)	(0.091)	(0.089)
Price volatility		0.022		0.045**				0.030
		(0.019)		(0.019)				(0.019)
Price shock			-0.168***	-0.174***				-0.233***
			(0.014)	(0.015)				(0.015)
Temperature (winter)					-0.007***		-0.007***	-0.009***
					(0.002)		(0.002)	(0.002)
Temperature (spring)					0.028***		0.026***	0.035***
					(0.003)		(0.003)	(0.003)
Temperature (summer)					-0.022***		-0.023***	-0.033***
					(0.003)		(0.003)	(0.003)
Temperature (autumn)					-0.002		-0.002	-0.000
					(0.003)		(0.003)	(0.003)
Precipitation (winter)						-0.004	-0.004	-0.007***
						(0.003)	(0.003)	(0.003)
Precipitation (spring)						-0.011***	-0.005*	-0.003
						(0.003)	(0.003)	(0.003)
Precipitation (summer)						0.002	-0.001	-0.000
						(0.003)	(0.003)	(0.003)
Precipitation (autumn)						0.007***	0.006**	0.009***
						(0.003)	(0.003)	(0.003)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	ROA	ROA	ROA	ROA	ROA	ROA	ROA	ROA
N	38,888	38,888	38,888	38,888	38,888	38,888	38,888	38,888

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5]Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 46 Average partial effects (APE) of the robustness check for economic and environmental variables for robustness of livestock farms from Western Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	0.076*	0.080*	0.122***	0.133***	0.071*	0.081**	0.077*	0.135***
	(0.041)	(0.042)	(0.040)	(0.041)	(0.040)	(0.041)	(0.041)	(0.041)
ATO	-0.086***	-0.089***	-0.087***	-0.091***	-0.088***	-0.086***	-0.087***	-0.093***
	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Log(land)	0.025***	0.025***	0.022***	0.023***	0.024***	0.024***	0.023***	0.020***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Age	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	-0.662***	-0.667***	-0.625***	-0.627***	-0.673***	-0.665***	-0.675***	-0.640***
	(0.051)	(0.052)	(0.050)	(0.051)	(0.053)	(0.049)	(0.051)	(0.051)
Rural development payments	0.028	0.028	0.027	0.026	0.029	0.028	0.029	0.026
	(0.074)	(0.076)	(0.070)	(0.072)	(0.078)	(0.070)	(0.074)	(0.071)
Price volatility		0.232***		0.239***				0.249***
		(0.028)		(0.028)				(0.029)
Price shock			-0.263***	-0.278***				-0.286***
			(0.025)	(0.024)				(0.026)
Temperature (winter)					0.004***		0.005***	0.003*
					(0.002)		(0.002)	(0.002)
Temperature (spring)					-0.007**		-0.009***	-0.004
					(0.003)		(0.003)	(0.003)
Temperature (summer)					-0.004		-0.001	-0.010***
					(0.003)		(0.003)	(0.003)
Temperature (autumn)					0.006***		0.004*	0.008***
					(0.002)		(0.002)	(0.002)
Precipitation (winter)						0.019***	0.019***	0.019***
						(0.002)	(0.002)	(0.002)
Precipitation (spring)						-0.002	-0.002	-0.001
						(0.003)	(0.003)	(0.003)
Precipitation (summer)						0.004*	0.004**	0.001
						(0.002)	(0.002)	(0.002)
Precipitation (autumn)						0.003	0.003	0.002
						(0.002)	(0.002)	(0.002)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO
N	42,969	42,969	42,969	42,969	42,969	42,969	42,969	42,969

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5] Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A 47 Average partial effects (APE) of the robustness check for economic and environmental variables for robustness of mixed farms from Western Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.212***	-0.202***	-0.197***	-0.181***	-0.118*	-0.161**	-0.096	-0.059
	(0.068)	(0.068)	(0.068)	(0.067)	(0.062)	(0.068)	(0.072)	(0.071)
ATO	0.409***	0.408***	0.404***	0.403***	0.406***	0.405***	0.403***	0.395***
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.034)
Log(land)	0.007	0.007	0.009	0.008	0.005	0.008	0.005	0.006
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)
Age	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Decoupled payments	-0.896***	-0.913***	-0.873***	-0.885***	-0.876***	-0.891***	-0.871***	-0.840***
	(0.086)	(0.086)	(0.086)	(0.086)	(0.087)	(0.086)	(0.087)	(0.087)
Rural development payments	0.429***	0.443***	0.414***	0.427***	0.458***	0.440***	0.462***	0.449***
	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)
Price volatility		0.166***		0.176***				0.137***
		(0.034)		(0.035)				(0.034)
Price shock			-0.126***	-0.147***				-0.173***
			(0.035)	(0.035)				(0.035)
Temperature (winter)					0.002		0.002	0.001
					(0.003)		(0.003)	(0.003)
Temperature (spring)					0.027***		0.026***	0.029***
					(0.006)		(0.006)	(0.006)
Temperature (summer)					-0.027***		-0.026***	-0.030***
					(0.006)		(0.006)	(0.006)
Temperature (autumn)					-0.014***		-0.016***	-0.015***
					(0.005)		(0.005)	(0.005)
Precipitation (winter)						0.007	0.007	0.008
						(0.006)	(0.006)	(0.006)
Precipitation (spring)						-0.024***	-0.020***	-0.018***
						(0.005)	(0.005)	(0.006)
Precipitation (summer)						0.008*	0.005	0.004
						(0.005)	(0.005)	(0.005)
Precipitation (autumn)						-0.007	-0.010*	-0.008
						(0.005)	(0.005)	(0.005)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	No	No	No	No	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	ROA	ROA	ROA	ROA	ROA	ROA	ROA	ROA
N	14,162	14,162	14,162	14,162	14,162	14,162	14,162	14,162

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5]Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A 48 Average partial effects (APE) of the robustness check for economic and environmental variables for robustness of arable farms from Southern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.377***	-0.385***	-0.374***	-0.377***	-0.399***	-0.378***	-0.396***	-0.394***
	(0.047)	(0.048)	(0.048)	(0.048)	(0.050)	(0.048)	(0.050)	(0.050)
ATO	0.007	0.009	0.004	0.005	0.020	0.010	0.018	0.015
	(0.024)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.026)
Log(land)	0.021***	0.021***	0.021***	0.021***	0.020***	0.022***	0.020***	0.020***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	-0.163***	-0.168***	-0.159***	-0.162***	-0.174***	-0.173***	-0.182***	-0.180***
	(0.062)	(0.062)	(0.061)	(0.061)	(0.065)	(0.066)	(0.069)	(0.068)
Rural development payments	-0.029	-0.027	-0.032	-0.030	-0.035	-0.032	-0.037	-0.038
	(0.030)	(0.030)	(0.030)	(0.030)	(0.031)	(0.030)	(0.031)	(0.031)
Price volatility		-0.073***		-0.020				-0.007
		(0.027)		(0.028)				(0.028)
Price shock			-0.203***	-0.201***				-0.192***
			(0.020)	(0.020)				(0.020)
Temperature (winter)					0.004**		-0.002	-0.003*
					(0.002)		(0.002)	(0.002)
Temperature (spring)					-0.004		-0.002	-0.001
					(0.003)		(0.003)	(0.003)
Temperature (summer)					0.025***		0.027***	0.026***
					(0.003)		(0.003)	(0.003)
Temperature (autumn)					-0.013***		-0.014***	-0.013***
					(0.002)		(0.002)	(0.002)
Precipitation (winter)						0.016***	0.016***	0.015***
						(0.002)	(0.002)	(0.002)
Precipitation (spring)						-0.010***	-0.010***	-0.009***
						(0.003)	(0.003)	(0.003)
Precipitation (summer)						-0.006*	0.001	-0.001
						(0.003)	(0.004)	(0.004)
Precipitation (autumn)						-0.012***	-0.015***	-0.015***
						(0.002)	(0.002)	(0.002)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO
N	54,105	54,105	54,105	54,105	54,105	54,105	54,105	54,105

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5]Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 49 Average partial effects (APE) of the robustness check for economic and environmental variables for robustness of livestock farms from Southern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.620***	-0.614***	-0.619***	-0.619***	-0.640***	-0.621***	-0.627***	-0.629***
	(0.064)	(0.064)	(0.064)	(0.064)	(0.067)	(0.066)	(0.070)	(0.069)
ATO	0.000	-0.001	0.003	0.003	0.017	-0.003	0.013	0.016
	(0.028)	(0.028)	(0.028)	(0.028)	(0.029)	(0.029)	(0.031)	(0.031)
Log(land)	0.010**	0.011**	0.010**	0.010**	0.009*	0.008*	0.008	0.008
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age	0.001	0.001*	0.001	0.001	0.001	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	-0.193*	-0.194*	-0.188*	-0.189*	-0.201*	-0.206*	-0.211*	-0.206*
	(0.109)	(0.109)	(0.107)	(0.107)	(0.115)	(0.116)	(0.118)	(0.116)
Rural development payments	0.171***	0.170***	0.168***	0.169***	0.198***	0.198***	0.202***	0.193***
	(0.061)	(0.060)	(0.060)	(0.060)	(0.062)	(0.062)	(0.062)	(0.062)
Price volatility		-0.122**		-0.013				0.029
		(0.053)		(0.054)				(0.056)
Price shock			-0.414***	-0.411***				-0.422***
			(0.045)	(0.047)				(0.049)
Temperature (winter)					0.017***		0.017***	0.020***
					(0.003)		(0.003)	(0.003)
Temperature (spring)					-0.008*		-0.008*	-0.016***
					(0.004)		(0.005)	(0.005)
Temperature (summer)					0.015***		0.013***	0.014***
					(0.004)		(0.004)	(0.004)
Temperature (autumn)					-0.018***		-0.020***	-0.017***
					(0.004)		(0.004)	(0.004)
Precipitation (winter)						-0.001	-0.002	-0.002
						(0.003)	(0.003)	(0.003)
Precipitation (spring)						-0.006	-0.011***	-0.013***
						(0.003)	(0.004)	(0.004)
Precipitation (summer)						-0.009**	-0.004	-0.002
						(0.004)	(0.005)	(0.005)
Precipitation (autumn)						-0.015***	-0.013***	-0.012***
						(0.003)	(0.003)	(0.003)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO
N	23,369	23,369	23,369	23,369	23,369	23,369	23,369	23,369

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5] Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 50 Average partial effects (APE) of the robustness check for economic and environmental variables for robustness of mixed farms from Southern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.786***	-0.802***	-0.795***	-0.805***	-0.918***	-0.864***	-0.955***	-0.978***
	(0.241)	(0.242)	(0.244)	(0.246)	(0.279)	(0.269)	(0.304)	(0.312)
ATO	1.014***	1.021***	1.022***	1.028***	1.073***	1.054***	1.094***	1.110***
	(0.166)	(0.167)	(0.169)	(0.169)	(0.186)	(0.183)	(0.198)	(0.202)
Log(land)	-0.026**	-0.027**	-0.026**	-0.026**	-0.030**	-0.029**	-0.032**	-0.032**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)
Age	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Decoupled payments	-0.170**	-0.165**	-0.172**	-0.167**	-0.187***	-0.177**	-0.183***	-0.181**
	(0.067)	(0.067)	(0.067)	(0.067)	(0.069)	(0.069)	(0.071)	(0.071)
Rural development payments	0.446***	0.444***	0.449***	0.447***	0.451***	0.437***	0.454***	0.460***
	(0.125)	(0.126)	(0.125)	(0.125)	(0.129)	(0.128)	(0.131)	(0.131)
Price volatility		-0.064		-0.031				-0.008
		(0.080)		(0.083)				(0.084)
Price shock			-0.123	-0.112				-0.144*
			(0.081)	(0.083)				(0.087)
Temperature (winter)					0.001		-0.002	-0.003
					(0.007)		(0.008)	(0.009)
Temperature (spring)					0.020**		0.023**	0.024**
					(0.010)		(0.011)	(0.011)
Temperature (summer)					0.020**		0.013	0.013
					(0.010)		(0.011)	(0.011)
Temperature (autumn)					-0.017**		-0.018**	-0.017**
					(0.008)		(0.009)	(0.009)
Precipitation (winter)						0.008	0.003	0.003
						(0.007)	(0.007)	(0.007)
Precipitation (spring)						-0.007	-0.002	0.001
						(0.010)	(0.011)	(0.011)
Precipitation (summer)						-0.035***	-0.025*	-0.024*
						(0.011)	(0.014)	(0.014)
Precipitation (autumn)						0.009	0.004	0.004
						(0.007)	(0.008)	(0.008)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	No	No	No	No	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	ROA	ROA	ROA	ROA	ROA	ROA	ROA	ROA
N	3,920	3,920	3,920	3,920	3,920	3,920	3,920	3,920

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5] Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 51 Average partial effects (APE) of the robustness check for economic and environmental variables for robustness of arable farms from Northern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	1.979***	2.000***	1.926***	1.925***	1.900***	1.968***	1.925***	1.888***
	(0.159)	(0.159)	(0.157)	(0.155)	(0.157)	(0.159)	(0.155)	(0.154)
ATO	-0.358***	-0.353***	-0.345***	-0.344***	-0.343***	-0.366***	-0.336***	-0.331***
	(0.118)	(0.115)	(0.110)	(0.108)	(0.109)	(0.115)	(0.108)	(0.103)
Log(land)	0.056**	0.057**	0.052**	0.050**	0.033	0.048**	0.032	0.031
	(0.025)	(0.026)	(0.024)	(0.024)	(0.023)	(0.021)	(0.020)	(0.020)
Age	0.005*	0.005*	0.005*	0.005*	0.004**	0.004	0.004**	0.004*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Decoupled payments	-0.473***	-0.365***	-0.354***	-0.313**	-0.431***	-0.412***	-0.413***	-0.278**
	(0.135)	(0.129)	(0.135)	(0.132)	(0.135)	(0.137)	(0.141)	(0.134)
Rural development payments	0.510***	0.436***	0.447***	0.416***	0.467***	0.541***	0.556***	0.478***
	(0.162)	(0.158)	(0.161)	(0.159)	(0.152)	(0.155)	(0.152)	(0.144)
Price volatility		-0.142		0.084				0.119
		(0.114)		(0.145)				(0.141)
Price shock			-0.330***	-0.359***				-0.301***
			(0.079)	(0.099)				(0.097)
Temperature (winter)					-0.004		0.016	0.013
					(0.015)		(0.016)	(0.016)
Temperature (spring)					-0.017		-0.058*	-0.056*
					(0.029)		(0.030)	(0.028)
Temperature (summer)					0.083***		0.114***	0.096***
					(0.028)		(0.031)	(0.030)
Temperature (autumn)					-0.003		0.006	0.009
					(0.020)		(0.021)	(0.020)
Precipitation (winter)						0.011	-0.010	-0.009
						(0.022)	(0.024)	(0.024)
Precipitation (spring)						-0.024	-0.018	-0.030
						(0.038)	(0.038)	(0.038)
Precipitation (summer)						-0.021*	-0.003	-0.000
						(0.013)	(0.015)	(0.015)
Precipitation (autumn)						-0.088***	-0.110***	-0.106***
						(0.027)	(0.028)	(0.028)
Country[1]	No	No	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	None	None	None	None	None	None	None	None
N	1,132	1,132	1,132	1,132	1,132	1,132	1,132	1,132

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5] Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 52 Average partial effects (APE) of the robustness check for economic and environmental variables for robustness of livestock farms from Northern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	0.281**	0.248*	0.279**	0.264**	0.285**	0.266*	0.268*	0.271*
	(0.131)	(0.132)	(0.133)	(0.133)	(0.140)	(0.141)	(0.151)	(0.154)
ATO	-0.339***	-0.324***	-0.331***	-0.319***	-0.334***	-0.339***	-0.340***	-0.325***
	(0.045)	(0.046)	(0.044)	(0.045)	(0.045)	(0.046)	(0.048)	(0.048)
Log(land)	0.030	0.027	0.031	0.028	0.034*	0.032	0.034*	0.032
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Age	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Decoupled payments	-1.191***	-1.262***	-1.076***	-1.136***	-1.209***	-1.207***	-1.231***	-1.168***
	(0.184)	(0.188)	(0.179)	(0.182)	(0.186)	(0.184)	(0.186)	(0.185)
Rural development payments	0.087	0.143	0.001	0.052	0.127	0.083	0.127	0.100
	(0.140)	(0.144)	(0.136)	(0.138)	(0.142)	(0.142)	(0.143)	(0.141)
Price volatility		0.517***		0.477***				0.503***
		(0.172)		(0.162)				(0.161)
Price shock			-0.729***	-0.721***				-0.715***
			(0.122)	(0.122)				(0.124)
Temperature (winter)					0.008		0.007	0.012*
					(0.006)		(0.007)	(0.007)
Temperature (spring)					-0.001		-0.002	-0.007
					(0.013)		(0.014)	(0.014)
Temperature (summer)					0.025		0.023	0.013
					(0.017)		(0.020)	(0.020)
Temperature (autumn)					-0.010		-0.003	0.001
					(0.012)		(0.013)	(0.013)
Precipitation (winter)						0.027**	0.023	0.023*
						(0.013)	(0.014)	(0.013)
Precipitation (spring)						-0.032	-0.024	-0.017
						(0.024)	(0.025)	(0.025)
Precipitation (summer)						-0.006	-0.005	-0.002
						(0.010)	(0.011)	(0.011)
Precipitation (autumn)						-0.008	-0.019	-0.018
						(0.014)	(0.015)	(0.015)
Country[1]	No	No	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO
N	3,601	3,601	3,601	3,601	3,601	3,601	3,601	3,601

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5] Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 53 Average partial effects (APE) of the robustness check for economic and environmental variables for robustness of mixed farms from Northern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	2.936***	3.018***	3.090***	3.025***	3.069***	2.824***	2.963***	2.970***
	(0.350)	(0.388)	(0.368)	(0.378)	(0.376)	(0.358)	(0.370)	(0.358)
ATO	0.488***	0.509***	0.485***	0.475***	0.505***	0.485***	0.462***	0.447***
	(0.132)	(0.137)	(0.131)	(0.133)	(0.145)	(0.137)	(0.146)	(0.146)
Log(land)	-0.083	-0.086	-0.091*	-0.092*	-0.092*	-0.081	-0.074	-0.083
	(0.052)	(0.053)	(0.053)	(0.052)	(0.054)	(0.057)	(0.056)	(0.054)
Age	-0.005	-0.005	-0.005	-0.005	-0.005	-0.004	-0.004	-0.005
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Decoupled payments	0.454	0.539	0.595	0.581	0.639	0.553	0.657	0.693*
	(0.382)	(0.398)	(0.388)	(0.392)	(0.398)	(0.397)	(0.406)	(0.391)
Rural development payments	-0.404	-0.438	-0.397	-0.359	-0.369	-0.559	-0.452	-0.455
	(0.483)	(0.495)	(0.474)	(0.491)	(0.513)	(0.488)	(0.485)	(0.465)
Price volatility		-0.082		-0.046				-0.037
		(0.170)		(0.166)				(0.173)
Price shock			-0.236	-0.227				-0.128
			(0.155)	(0.157)				(0.176)
Temperature (winter)					-0.029		-0.021	-0.014
					(0.024)		(0.027)	(0.027)
Temperature (spring)					0.044		0.062	0.059
					(0.057)		(0.066)	(0.067)
Temperature (summer)					0.028		0.010	0.019
					(0.052)		(0.065)	(0.066)
Temperature (autumn)					0.012		0.003	0.014
					(0.043)		(0.050)	(0.052)
Precipitation (winter)						-0.048	-0.031	-0.023
						(0.038)	(0.040)	(0.040)
Precipitation (spring)						0.119*	0.112	0.099
						(0.067)	(0.069)	(0.069)
Precipitation (summer)						-0.018	-0.011	-0.009
						(0.027)	(0.033)	(0.033)
Precipitation (autumn)						-0.040	-0.026	-0.033
						(0.041)	(0.042)	(0.042)
Country[1]	No	No	No	No	No	No	No	No
Farm type[2]	No	No	No	No	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	None	None	None	None	None	None	None	None
N	437	437	437	437	437	437	437	437

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5]Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 54 Average partial effects (APE) of the robustness check for economic and environmental variables for robustness of arable farms from Eastern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-1.354***	-1.319***	-1.359***	-1.292***	-1.280***	-1.329***	-1.282***	-1.210***
	(0.174)	(0.172)	(0.172)	(0.169)	(0.167)	(0.173)	(0.170)	(0.165)
ATO	1.585***	1.566***	1.575***	1.543***	1.635***	1.607***	1.637***	1.591***
	(0.111)	(0.109)	(0.110)	(0.108)	(0.110)	(0.112)	(0.112)	(0.108)
Log(land)	0.019	0.016	0.018	0.014	0.020	0.017	0.020	0.016
	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.016)	(0.017)	(0.016)
Age	0.001	0.001	0.001	0.001	-0.001	0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Decoupled payments	-0.682***	-0.669***	-0.663***	-0.637***	-0.801***	-0.740***	-0.803***	-0.753***
	(0.177)	(0.177)	(0.172)	(0.169)	(0.200)	(0.189)	(0.202)	(0.192)
Rural development payments	0.563***	0.551***	0.560***	0.541***	0.628***	0.588***	0.624***	0.599***
	(0.091)	(0.092)	(0.091)	(0.090)	(0.089)	(0.091)	(0.089)	(0.088)
Price volatility		0.170***	-0.219***	0.272***				0.258***
		(0.040)	(0.035)	(0.042)				(0.042)
Price shock				-0.290***				-0.263***
				(0.036)				(0.037)
Temperature (winter)					-0.033***		-0.033***	-0.037***
					(0.007)		(0.007)	(0.007)
Temperature (spring)					0.019**		0.018*	0.019*
					(0.009)		(0.011)	(0.010)
Temperature (summer)					-0.058***		-0.066***	-0.065***
					(0.011)		(0.012)	(0.012)
Temperature (autumn)					-0.037***		-0.034***	-0.033***
					(0.011)		(0.012)	(0.012)
Precipitation (winter)						-0.020	0.009	0.005
						(0.013)	(0.015)	(0.014)
Precipitation (spring)						-0.027***	-0.024**	-0.023**
						(0.009)	(0.010)	(0.010)
Precipitation (summer)						0.027***	0.004	0.001
						(0.006)	(0.007)	(0.007)
Precipitation (autumn)						0.004	0.013	0.007
						(0.010)	(0.010)	(0.010)
Country[1]	No	No	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	ROA	ROA	ROA	ROA	ROA	ROA	ROA	ROA
N	15,898	15,898	15,898	15,898	15,898	15,898	15,898	15,898

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5] Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 55 Average partial effects (APE) of the robustness check for economic and environmental variables for robustness of livestock farms from Eastern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	0.045	0.060	0.232**	0.237**	0.024	0.046	0.019	0.229*
	(0.117)	(0.117)	(0.113)	(0.113)	(0.122)	(0.120)	(0.125)	(0.119)
ATO	-0.141***	-0.153***	-0.179***	-0.187***	-0.131***	-0.142***	-0.133***	-0.185***
	(0.040)	(0.040)	(0.039)	(0.039)	(0.041)	(0.041)	(0.042)	(0.041)
Log(land)	0.064***	0.063***	0.059***	0.059***	0.064***	0.061***	0.063***	0.058***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Age	0.004***	0.003***	0.004***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Decoupled payments	-2.215***	-2.299***	-2.064***	-2.138***	-2.342***	-2.274***	-2.350***	-2.217***
	(0.120)	(0.127)	(0.113)	(0.120)	(0.137)	(0.133)	(0.142)	(0.137)
Rural development payments	0.811***	0.824***	0.759***	0.771***	0.853***	0.822***	0.847***	0.788***
	(0.062)	(0.064)	(0.061)	(0.062)	(0.068)	(0.066)	(0.070)	(0.068)
Price volatility		0.364***		0.291***				0.248***
		(0.061)		(0.059)				(0.060)
Price shock			-1.025***	-1.000***				-0.988***
			(0.057)	(0.057)				(0.058)
Temperature (winter)					-0.012*		-0.010	-0.004
					(0.006)		(0.006)	(0.006)
Temperature (spring)					0.028***		0.029***	0.008
					(0.010)		(0.011)	(0.011)
Temperature (summer)					0.016		0.025**	0.022**
					(0.010)		(0.011)	(0.011)
Temperature (autumn)					-0.024**		-0.025**	-0.016
					(0.011)		(0.011)	(0.011)
Precipitation (winter)						0.003	0.005	0.004
						(0.012)	(0.013)	(0.013)
Precipitation (spring)						-0.004	0.012	0.011
						(0.008)	(0.009)	(0.008)
Precipitation (summer)						0.005	0.005	0.008
						(0.005)	(0.006)	(0.006)
Precipitation (autumn)						0.010	0.014	0.011
						(0.009)	(0.009)	(0.009)
Country[1]	No	No	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO
N	19,543	19,543	19,543	19,543	19,543	19,543	19,543	19,543

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5]Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 56 Average partial effects (APE) of the robustness check for economic and environmental variables for robustness of mixed farms from Eastern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-1.177*** (0.162)	-1.172*** (0.161)	-1.143*** (0.161)	-1.125*** (0.159)	-1.061*** (0.159)	-1.108*** (0.160)	-1.055*** (0.158)	-1.021*** (0.157)
ATO	1.657*** (0.096)	1.670*** (0.096)	1.646*** (0.095)	1.655*** (0.095)	1.827*** (0.099)	1.720*** (0.097)	1.857*** (0.100)	1.845*** (0.099)
Log(land)	-0.039** (0.016)	-0.040** (0.016)	-0.038** (0.016)	-0.040** (0.016)	-0.048*** (0.016)	-0.046*** (0.016)	-0.052*** (0.016)	-0.053*** (0.016)
Age	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.001)
Decoupled payments	-1.222*** (0.087)	-1.247*** (0.087)	-1.173*** (0.087)	-1.195*** (0.087)	-1.460*** (0.091)	-1.312*** (0.090)	-1.435*** (0.092)	-1.392*** (0.092)
Rural development payments	1.036*** (0.052)	1.042*** (0.051)	1.034*** (0.052)	1.037*** (0.051)	1.130*** (0.052)	1.050*** (0.051)	1.117*** (0.052)	1.111*** (0.052)
Price volatility		0.108*** (0.032)		0.130*** (0.032)				0.099*** (0.031)
Price shock			-0.218*** (0.032)	-0.233*** (0.032)				-0.192*** (0.032)
Temperature (winter)					-0.053*** (0.005)		-0.049*** (0.006)	-0.047*** (0.006)
Temperature (spring)					0.038*** (0.008)		0.044*** (0.009)	0.040*** (0.009)
Temperature (summer)					-0.020** (0.009)		-0.040*** (0.010)	-0.042*** (0.010)
Temperature (autumn)					-0.058*** (0.010)		-0.050*** (0.010)	-0.045*** (0.010)
Precipitation (winter)						-0.023** (0.011)	0.009 (0.012)	0.010 (0.012)
Precipitation (spring)						-0.032*** (0.007)	-0.021*** (0.008)	-0.021*** (0.008)
Precipitation (summer)						0.007 (0.005)	-0.010* (0.005)	-0.010** (0.005)
Precipitation (autumn)						0.018** (0.008)	0.027*** (0.008)	0.026*** (0.008)
Country[1]	No	No	No	No	No	No	No	No
Farm type[2]	No	No	No	No	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	ROA	ROA	ROA	ROA	ROA	ROA	ROA	ROA
N	21,459	21,459	21,459	21,459	21,459	21,459	21,459	21,459

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5]Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.3.2. Robustness checks based on adding economic and environmental variables for farm adaptation

Section 4.3.2 presents the robustness checks that add economic and environmental variables to the model for farm adaptation. Including these economic and environmental variables resulted in seven alternative model specifications. The following variables were added to the original model: (i) price volatility, (ii) price shocks, (iii) price volatility and price shocks, (iv) temperature, (v) precipitation, (vi) temperature and precipitation, (vii) price volatility, price shocks, temperature, and precipitation. These findings are presented in Table A.57-68.

Table A 57 Average partial effects (APE) of the robustness check for economic and environmental variables for adaptation of arable farms from Western Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.023***	-0.024***	-0.023***	-0.024***	-0.022***	-0.024***	-0.022***	-0.023***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
ATO	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log(land)	-0.001	-0.001	-0.000	-0.001	-0.002	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	0.005	-0.007	-0.008	-0.014	0.010	0.001	0.007	-0.010
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Rural development payments	-0.015	-0.012	-0.011	-0.010	-0.014	-0.016	-0.012	-0.005
	(0.026)	(0.026)	(0.026)	(0.026)	(0.025)	(0.026)	(0.025)	(0.025)
Price volatility		0.021***		0.018***				0.020***
		(0.007)		(0.007)				(0.007)
Price shock			0.021***	0.022***				0.025***
			(0.005)	(0.005)				(0.005)
Temperature (winter)					0.001		0.001**	0.002***
					(0.001)		(0.001)	(0.001)
Temperature (spring)					-0.004***		-0.003**	-0.004***
					(0.001)		(0.001)	(0.001)
Temperature (summer)					0.001		0.001	0.002*
					(0.001)		(0.001)	(0.001)
Temperature (autumn)					0.004***		0.003***	0.003***
					(0.001)		(0.001)	(0.001)
Precipitation (winter)						-0.003***	-0.002***	-0.002**
						(0.001)	(0.001)	(0.001)
Precipitation (spring)						0.002*	0.002	0.001
						(0.001)	(0.001)	(0.001)
Precipitation (summer)						-0.001	-0.000	-0.001
						(0.001)	(0.001)	(0.001)
Precipitation (autumn)						0.001	0.000	0.000
						(0.001)	(0.001)	(0.001)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	38,888	38,888	38,888	38,888	38,888	38,888	38,888	38,888

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A 58 Average partial effects (APE) of the robustness check for economic and environmental variables for adaptation of livestock farms from Western Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.046***	-0.046***	-0.050***	-0.051***	-0.043***	-0.047***	-0.044***	-0.048***
	(0.014)	(0.014)	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)	(0.015)
ATO	0.008	0.007	0.007	0.007	0.006	0.009	0.007	0.006
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Log(land)	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***	0.009***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	0.019	0.018	0.022	0.023	0.021	0.019	0.022	0.027*
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Rural development payments	-0.000	-0.000	-0.000	-0.001	-0.000	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Price volatility		0.009		0.012				0.004
		(0.012)		(0.012)				(0.012)
Price shock			-0.031***	-0.033***				-0.027**
			(0.011)	(0.011)				(0.011)
Temperature (winter)					-0.000		-0.000	-0.000
					(0.001)		(0.001)	(0.001)
Temperature (spring)					-0.002		-0.001	-0.001
					(0.001)		(0.001)	(0.001)
Temperature (summer)					0.004***		0.004***	0.003*
					(0.001)		(0.001)	(0.001)
Temperature (autumn)					-0.001		-0.001	-0.000
					(0.001)		(0.001)	(0.001)
Precipitation (winter)						0.002	0.002*	0.002*
						(0.001)	(0.001)	(0.001)
Precipitation (spring)						-0.002	-0.000	-0.000
						(0.001)	(0.001)	(0.001)
Precipitation (summer)						0.002*	0.002*	0.001
						(0.001)	(0.001)	(0.001)
Precipitation (autumn)						0.002*	0.001	0.001
						(0.001)	(0.001)	(0.001)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	42,969	42,969	42,969	42,969	42,969	42,969	42,969	42,969

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A 59 Average partial effects (APE) of the robustness check for economic and environmental variables for adaptation of mixed farms from Western Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.021	-0.025	-0.021	-0.025	-0.019	-0.020	-0.019	-0.022
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
ATO	-0.007	-0.007	-0.007	-0.006	-0.008	-0.008	-0.009	-0.008
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Log(land)	0.001	0.001	0.001	0.001	0.000	0.001	0.000	0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	0.028	0.022	0.024	0.019	0.035	0.030	0.033	0.026
	(0.033)	(0.032)	(0.033)	(0.033)	(0.033)	(0.032)	(0.032)	(0.032)
Rural development payments	0.017	0.020	0.019	0.021	0.011	0.013	0.009	0.013
	(0.038)	(0.037)	(0.038)	(0.037)	(0.038)	(0.038)	(0.038)	(0.038)
Price volatility		0.041***		0.041***				0.039***
		(0.010)		(0.010)				(0.010)
Price shock			0.014	0.009				0.008
			(0.011)	(0.011)				(0.011)
Temperature (winter)					-0.001		-0.001	-0.000
					(0.001)		(0.001)	(0.001)
Temperature (spring)					-0.001		-0.000	-0.001
					(0.002)		(0.002)	(0.002)
Temperature (summer)					-0.000		-0.000	-0.000
					(0.002)		(0.002)	(0.002)
Temperature (autumn)					0.001		0.001	0.001
					(0.002)		(0.002)	(0.002)
Precipitation (winter)						0.001	0.001	0.001
						(0.002)	(0.002)	(0.002)
Precipitation (spring)						0.004**	0.004**	0.004**
						(0.002)	(0.002)	(0.002)
Precipitation (summer)						-0.003*	-0.003**	-0.003**
						(0.001)	(0.001)	(0.001)
Precipitation (autumn)						-0.000	-0.000	0.000
						(0.001)	(0.002)	(0.002)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	No	No	No	No	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	14,162	14,162	14,162	14,162	14,162	14,162	14,162	14,162

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A 60 Average partial effects (APE) of the robustness check for economic and environmental variables for adaptation of arable farms from Southern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.030***	-0.030***	-0.032***	-0.032***	-0.031***	-0.030***	-0.030***	-0.032***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
ATO	0.017***	0.018***	0.018***	0.018***	0.019***	0.017***	0.018***	0.019***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Log(land)	0.002	0.002	0.002	0.002	-0.000	0.002**	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.000	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	-0.002	-0.002	-0.001	-0.001	-0.000	-0.001	0.000	0.001
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)
Rural development payments	0.011	0.011	0.010	0.010	0.013*	0.010	0.013*	0.013*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Price volatility		-0.017**		-0.007				-0.006
		(0.007)		(0.007)				(0.007)
Price shock			-0.047***	-0.046***				-0.054***
			(0.006)	(0.006)				(0.006)
Temperature (winter)					-0.007***		-0.007***	-0.007***
					(0.001)		(0.001)	(0.001)
Temperature (spring)					0.003***		0.002***	0.003***
					(0.001)		(0.001)	(0.001)
Temperature (summer)					0.005***		0.004***	0.003***
					(0.001)		(0.001)	(0.001)
Temperature (autumn)					-0.002***		-0.001	-0.000
					(0.001)		(0.001)	(0.001)
Precipitation (winter)						0.002***	0.004***	0.004***
						(0.000)	(0.001)	(0.001)
Precipitation (spring)						0.004***	0.004***	0.004***
						(0.001)	(0.001)	(0.001)
Precipitation (summer)						0.000	-0.001	-0.002*
						(0.001)	(0.001)	(0.001)
Precipitation (autumn)						0.007***	0.006***	0.006***
						(0.001)	(0.001)	(0.001)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	54,105	54,105	54,105	54,105	54,105	54,105	54,105	54,105

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A 61 Average partial effects (APE) of the robustness check for economic and environmental variables for adaptation of livestock farms from Southern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	0.002	0.002	0.001	0.002	0.003	0.002	0.002	0.003
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
ATO	0.011	0.011	0.012	0.012*	0.012*	0.012	0.012*	0.013*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Log(land)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age	-0.000	-0.000	-0.000	-0.000	-0.000*	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	0.012	0.013	0.013*	0.012	0.019**	0.016**	0.016*	0.016*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Rural development payments	0.001	0.001	0.001	0.001	0.000	-0.001	0.002	0.002
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Price volatility		-0.028**		-0.033***				-0.044***
		(0.012)		(0.012)				(0.012)
Price shock			0.016	0.023**				0.027**
			(0.011)	(0.011)				(0.011)
Temperature (winter)					-0.006***		-0.005***	-0.005***
					(0.001)		(0.001)	(0.001)
Temperature (spring)					0.002**		0.001	0.002
					(0.001)		(0.001)	(0.001)
Temperature (summer)					-0.001		0.000	0.000
					(0.001)		(0.001)	(0.001)
Temperature (autumn)					0.004***		0.004***	0.004***
					(0.001)		(0.001)	(0.001)
Precipitation (winter)						-0.001	-0.001	-0.001
						(0.001)	(0.001)	(0.001)
Precipitation (spring)						-0.002***	-0.000	-0.000
						(0.001)	(0.001)	(0.001)
Precipitation (summer)						0.003***	0.003**	0.003**
						(0.001)	(0.001)	(0.001)
Precipitation (autumn)						0.002***	0.002**	0.002***
						(0.001)	(0.001)	(0.001)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	23,369	23,369	23,369	23,369	23,369	23,369	23,369	23,369

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 62 Average partial effects (APE) of the robustness check for economic and environmental variables for adaptation of mixed farms from Southern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.049*	-0.051*	-0.048*	-0.049*	-0.044*	-0.045*	-0.046*	-0.046*
	(0.028)	(0.028)	(0.028)	(0.028)	(0.026)	(0.027)	(0.027)	(0.027)
ATO	0.014	0.014	0.013	0.013	0.012	0.008	0.011	0.010
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)	(0.015)
Log(land)	0.002	0.002	0.002	0.002	0.002	0.004	0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age	-0.000	-0.000	-0.000	-0.000	-0.001*	-0.000	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	-0.018	-0.022	-0.019	-0.023	-0.016	-0.016	-0.015	-0.019
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Rural development payments	0.027	0.030	0.028	0.031	0.029	0.028	0.028	0.031
	(0.036)	(0.036)	(0.036)	(0.036)	(0.037)	(0.037)	(0.038)	(0.038)
Price volatility		0.067***		0.065***				0.064***
		(0.022)		(0.022)				(0.022)
Price shock			0.017	0.001				-0.015
			(0.021)	(0.021)				(0.021)
Temperature (winter)					-0.007***		-0.005**	-0.005**
					(0.002)		(0.002)	(0.002)
Temperature (spring)					0.012***		0.011***	0.011***
					(0.003)		(0.003)	(0.003)
Temperature (summer)					-0.003		-0.004	-0.004
					(0.003)		(0.003)	(0.003)
Temperature (autumn)					-0.003		-0.002	-0.003
					(0.002)		(0.002)	(0.002)
Precipitation (winter)						0.000	-0.001	-0.000
						(0.002)	(0.002)	(0.002)
Precipitation (spring)						0.003	0.005*	0.004
						(0.003)	(0.003)	(0.003)
Precipitation (summer)						0.006**	0.003	0.003
						(0.003)	(0.004)	(0.004)
Precipitation (autumn)						0.006***	0.004**	0.004*
						(0.002)	(0.002)	(0.002)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	No	No	No	No	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,920	3,920	3,920	3,920	3,920	3,920	3,920	3,920

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A 63 Average partial effects (APE) of the robustness check for economic and environmental variables for adaptation of arable farms from Northern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.036	-0.038	-0.033	-0.036	-0.011	-0.035	-0.012	-0.011
	(0.067)	(0.068)	(0.067)	(0.069)	(0.067)	(0.067)	(0.067)	(0.069)
ATO	-0.038	-0.038	-0.040	-0.038	-0.037	-0.020	-0.024	-0.022
	(0.040)	(0.039)	(0.040)	(0.039)	(0.041)	(0.039)	(0.040)	(0.040)
Log(land)	-0.039***	-0.041***	-0.040***	-0.042***	-0.041***	-0.044***	-0.048***	-0.049***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)
Age	-0.005***	-0.004***	-0.005***	-0.004***	-0.005***	-0.005***	-0.005***	-0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Decoupled payments	0.066	0.065	0.053	0.058	0.086	0.094	0.084	0.089
	(0.066)	(0.066)	(0.066)	(0.066)	(0.065)	(0.064)	(0.068)	(0.067)
Rural development payments	-0.053	-0.044	-0.048	-0.042	-0.068	-0.055	-0.047	-0.038
	(0.092)	(0.092)	(0.091)	(0.091)	(0.095)	(0.092)	(0.098)	(0.095)
Price volatility		0.068		0.055				0.043
		(0.060)		(0.068)				(0.072)
Price shock			0.046	0.030				0.031
			(0.044)	(0.050)				(0.051)
Temperature (winter)					0.000		0.004	0.005
					(0.006)		(0.007)	(0.007)
Temperature (spring)					-0.006		-0.005	-0.009
					(0.013)		(0.016)	(0.016)
Temperature (summer)					-0.021		-0.021	-0.019
					(0.014)		(0.018)	(0.018)
Temperature (autumn)					0.011		0.010	0.013
					(0.011)		(0.011)	(0.011)
Precipitation (winter)						-0.002	0.002	0.003
						(0.011)	(0.012)	(0.012)
Precipitation (spring)						-0.000	-0.004	0.000
						(0.019)	(0.019)	(0.019)
Precipitation (summer)						-0.004	-0.007	-0.007
						(0.006)	(0.008)	(0.008)
Precipitation (autumn)						-0.019*	-0.022*	-0.022*
						(0.010)	(0.013)	(0.013)
Country[1]	No	No	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,132	1,132	1,132	1,132	1,132	1,132	1,132	1,132

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 64 Average partial effects (APE) of the robustness check for economic and environmental variables for adaptation of livestock farms from Northern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.088*	-0.088*	-0.094*	-0.093*	-0.087*	-0.080*	-0.080*	-0.083*
	(0.053)	(0.053)	(0.053)	(0.054)	(0.052)	(0.050)	(0.049)	(0.051)
ATO	0.028	0.025	0.026	0.024	0.031	0.026	0.028	0.025
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.032)
Log(land)	-0.005	-0.004	-0.004	-0.004	-0.005	-0.005	-0.005	-0.004
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Age	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001*	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Decoupled payments	0.249***	0.254***	0.254***	0.264***	0.252***	0.266***	0.266***	0.286***
	(0.086)	(0.084)	(0.086)	(0.085)	(0.086)	(0.086)	(0.086)	(0.085)
Rural development payments	-0.076	-0.085	-0.081	-0.086	-0.077	-0.083	-0.084	-0.094
	(0.069)	(0.068)	(0.068)	(0.067)	(0.069)	(0.069)	(0.069)	(0.068)
Price volatility		0.025		0.022				0.021
		(0.062)		(0.063)				(0.063)
Price shock			-0.050	-0.040				-0.030
			(0.049)	(0.049)				(0.049)
Temperature (winter)					-0.000		-0.001	-0.001
					(0.003)		(0.003)	(0.003)
Temperature (spring)					0.006		0.007	0.006
					(0.006)		(0.006)	(0.006)
Temperature (summer)					0.010		0.009	0.007
					(0.008)		(0.008)	(0.008)
Temperature (autumn)					-0.008		-0.010*	-0.009
					(0.005)		(0.005)	(0.005)
Precipitation (winter)						0.002	-0.001	-0.001
						(0.006)	(0.006)	(0.006)
Precipitation (spring)						0.005	0.006	0.006
						(0.010)	(0.010)	(0.010)
Precipitation (summer)						-0.001	-0.000	0.000
						(0.004)	(0.005)	(0.005)
Precipitation (autumn)						0.008	0.008	0.008
						(0.005)	(0.006)	(0.006)
Country[1]	No	No	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,601	3,601	3,601	3,601	3,601	3,601	3,601	3,601

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 65 Average partial effects (APE) of the robustness check for economic and environmental variables for adaptation of mixed farms from Northern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.230**	-0.243**	-0.252**	-0.260**	-0.238**	-0.254**	-0.300***	-0.367***
	(0.111)	(0.116)	(0.115)	(0.118)	(0.119)	(0.105)	(0.116)	(0.119)
ATO	0.013	0.042	0.039	0.056	0.050	0.045	0.084	0.098
	(0.123)	(0.120)	(0.119)	(0.116)	(0.113)	(0.113)	(0.107)	(0.103)
Log(land)	0.017	0.015	0.015	0.016	0.011	0.022	0.005	0.001
	(0.021)	(0.021)	(0.021)	(0.021)	(0.023)	(0.022)	(0.024)	(0.024)
Age	-0.003*	-0.003*	-0.003*	-0.003*	-0.003	-0.003*	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Decoupled payments	0.259	0.224	0.251	0.227	0.288	0.173	0.122	0.060
	(0.203)	(0.202)	(0.207)	(0.203)	(0.201)	(0.198)	(0.189)	(0.187)
Rural development payments	0.124	0.161	0.136	0.126	0.080	0.081	0.117	0.205
	(0.308)	(0.303)	(0.308)	(0.313)	(0.310)	(0.315)	(0.300)	(0.285)
Price volatility		0.093		0.100				0.078
		(0.066)		(0.067)				(0.067)
Price shock			-0.028	-0.032				-0.081
			(0.070)	(0.070)				(0.076)
Temperature (winter)					0.004		0.005	0.009
					(0.011)		(0.012)	(0.013)
Temperature (spring)					-0.002		-0.010	-0.015
					(0.027)		(0.031)	(0.032)
Temperature (summer)					-0.014		0.008	0.009
					(0.024)		(0.025)	(0.026)
Temperature (autumn)					-0.027		-0.038*	-0.034*
					(0.020)		(0.021)	(0.020)
Precipitation (winter)						-0.007	-0.005	-0.005
						(0.017)	(0.018)	(0.018)
Precipitation (spring)						0.003	-0.004	-0.007
						(0.033)	(0.032)	(0.032)
Precipitation (summer)						0.004	0.001	0.001
						(0.009)	(0.011)	(0.010)
Precipitation (autumn)						0.011	0.006	0.002
						(0.019)	(0.021)	(0.021)
Country[1]	No	No	No	No	No	No	No	No
Farm type[2]	No	No	No	No	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	437	437	437	437	437	437	437	437

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A 66 Average partial effects (APE) of the robustness check for economic and environmental variables for adaptation of arable farms from Eastern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.080***	-0.082***	-0.079***	-0.084***	-0.086***	-0.084***	-0.086***	-0.089***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
ATO	0.059***	0.062***	0.059***	0.063***	0.066***	0.064***	0.066***	0.069***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)
Log(land)	0.004	0.004	0.004	0.004	0.003	0.004	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	0.007	0.007	0.007	0.007	-0.005	-0.001	-0.005	-0.004
	(0.023)	(0.022)	(0.023)	(0.022)	(0.022)	(0.021)	(0.021)	(0.021)
Rural development payments	0.025	0.026	0.024	0.026	0.032**	0.030*	0.032*	0.032*
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Price volatility		0.035***		0.038***				0.035***
		(0.011)		(0.012)				(0.012)
Price shock			0.000	-0.009				-0.003
			(0.010)	(0.010)				(0.010)
Temperature (winter)					0.006***		0.005**	0.004**
					(0.002)		(0.002)	(0.002)
Temperature (spring)					0.003		0.002	0.002
					(0.003)		(0.003)	(0.003)
Temperature (summer)					-0.000		-0.000	0.000
					(0.003)		(0.004)	(0.004)
Temperature (autumn)					-0.002		-0.001	-0.001
					(0.003)		(0.004)	(0.004)
Precipitation (winter)						0.004	0.003	0.003
						(0.004)	(0.004)	(0.004)
Precipitation (spring)						-0.004	-0.004	-0.004
						(0.003)	(0.003)	(0.003)
Precipitation (summer)						0.004**	0.002	0.002
						(0.002)	(0.002)	(0.002)
Precipitation (autumn)						-0.002	-0.000	-0.001
						(0.003)	(0.003)	(0.003)
Country[1]	No	No	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15,898	15,898	15,898	15,898	15,898	15,898	15,898	15,898

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 67 Average partial effects (APE) of the robustness check for economic and environmental variables for adaptation of livestock farms from Eastern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	0.005	0.008	0.005	0.008	0.004	0.004	0.003	0.006
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
ATO	0.012	0.009	0.013	0.010	0.015	0.012	0.016	0.016
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Log(land)	0.009	0.009	0.009	0.009	0.010	0.009	0.009	0.009
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Age	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	0.087***	0.103***	0.087***	0.103***	0.095***	0.086***	0.097***	0.107***
	(0.032)	(0.032)	(0.032)	(0.032)	(0.033)	(0.033)	(0.033)	(0.033)
Rural development payments	-0.033*	-0.035**	-0.033*	-0.035**	-0.032*	-0.033*	-0.032*	-0.032*
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Price volatility		-0.010		-0.010				-0.015
		(0.021)		(0.021)				(0.021)
Price shock			0.005	0.004				0.007
			(0.020)	(0.020)				(0.020)
Temperature (winter)					-0.001		-0.001	-0.001
					(0.002)		(0.002)	(0.002)
Temperature (spring)					0.007**		0.008**	0.008**
					(0.003)		(0.004)	(0.004)
Temperature (summer)					-0.012***		-0.011***	-0.012***
					(0.004)		(0.004)	(0.004)
Temperature (autumn)					-0.000		-0.000	-0.000
					(0.004)		(0.004)	(0.004)
Precipitation (winter)						0.002	0.000	-0.000
						(0.004)	(0.005)	(0.005)
Precipitation (spring)						0.003	0.003	0.003
						(0.003)	(0.003)	(0.003)
Precipitation (summer)						0.001	-0.000	-0.000
						(0.002)	(0.002)	(0.002)
Precipitation (autumn)						0.003	0.004	0.004
						(0.003)	(0.003)	(0.003)
Country[1]	No	No	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19,543	19,543	19,543	19,543	19,543	19,543	19,543	19,543

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A 68 Average partial effects (APE) of the robustness check for economic and environmental variables for adaptation of mixed farms from Eastern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	0.005	-0.002	0.003	-0.004	0.008	0.011	0.010	0.004
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
ATO	-0.000	0.007	0.002	0.009	-0.004	-0.009	-0.007	-0.002
	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)
Log(land)	0.006*	0.006*	0.006*	0.006*	0.007**	0.007**	0.007**	0.007**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	0.117***	0.109***	0.118***	0.111***	0.124***	0.126***	0.126***	0.124***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)
Rural development payments	0.012	0.014	0.013	0.016	0.009	0.009	0.009	0.011
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Price volatility		0.041***		0.042***				0.041***
		(0.009)		(0.009)				(0.009)
Price shock			-0.010	-0.016*				-0.016*
			(0.009)	(0.009)				(0.009)
Temperature (winter)					0.001		0.001	0.002
					(0.002)		(0.002)	(0.002)
Temperature (spring)					0.004*		0.004*	0.003
					(0.002)		(0.003)	(0.003)
Temperature (summer)					0.000		0.001	0.000
					(0.002)		(0.003)	(0.003)
Temperature (autumn)					-0.007**		-0.008**	-0.006**
					(0.003)		(0.003)	(0.003)
Precipitation (winter)						0.001	0.000	0.001
						(0.003)	(0.003)	(0.003)
Precipitation (spring)						0.002	0.003	0.003
						(0.002)	(0.002)	(0.002)
Precipitation (summer)						0.000	-0.001	-0.001
						(0.001)	(0.002)	(0.002)
Precipitation (autumn)						0.000	0.000	0.000
						(0.002)	(0.002)	(0.002)
Country[1]	No	No	No	No	No	No	No	No
Farm type[2]	No	No	No	No	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	21,459	21,459	21,459	21,459	21,459	21,459	21,459	21,459

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * p < 0.10, ** p < 0.05, *** p < 0.01.

4.3.3. Robustness checks based on adding economic and environmental variables for farm transformation

Section 4.3.3 presents the robustness checks that add economic and environmental variables to the model for farm transformation. Including these economic and environmental variables resulted in seven alternative model specifications. The following variables were added to the original model: (i) price volatility, (ii) price shocks, (iii) price volatility and price shocks, (iv) temperature, (v) precipitation, (vi) temperature and precipitation, (vii) price volatility, price shocks, temperature, and precipitation. These findings are presented in Table A.69-80.

Table A 69 Average partial effects (APE) of the robustness check for economic and environmental variables for transformation of arable farms from Western Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	0.013	0.009	0.014	0.009	0.013	0.014	0.014	0.009
	(0.017)	(0.016)	(0.016)	(0.016)	(0.017)	(0.016)	(0.016)	(0.016)
ATO	-0.013	-0.011	-0.014*	-0.012	-0.014*	-0.013*	-0.014*	-0.014*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Log(land)	-0.007*	-0.008**	-0.006	-0.008**	-0.006	-0.006	-0.005	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	0.273***	0.223***	0.256***	0.228***	0.272***	0.270***	0.272***	0.226***
	(0.045)	(0.043)	(0.044)	(0.043)	(0.044)	(0.044)	(0.044)	(0.042)
Rural development payments	-0.064	-0.060	-0.062	-0.059	-0.062	-0.067	-0.062	-0.047
	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.055)
Price volatility		0.102***		0.103***				0.107***
		(0.019)		(0.019)				(0.019)
Price shock			-0.021	-0.026*				-0.024
			(0.015)	(0.015)				(0.016)
Temperature (winter)					-0.001		-0.002	-0.002
					(0.002)		(0.002)	(0.002)
Temperature (spring)					0.005*		0.006*	0.007**
					(0.003)		(0.003)	(0.003)
Temperature (summer)					0.004		0.003	0.002
					(0.003)		(0.003)	(0.003)
Temperature (autumn)					0.003		0.004	0.005*
					(0.003)		(0.003)	(0.003)
Precipitation (winter)						0.007***	0.008***	0.007***
						(0.002)	(0.003)	(0.002)
Precipitation (spring)						0.002	0.003	0.005
						(0.003)	(0.003)	(0.003)
Precipitation (summer)						-0.003	-0.001	-0.003
						(0.003)	(0.003)	(0.003)
Precipitation (autumn)						0.003	0.002	0.003
						(0.002)	(0.003)	(0.002)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	38,888	38,888	38,888	38,888	38,888	38,888	38,888	38,888

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 70 Average partial effects (APE) of the robustness check for economic and environmental variables for transformation of livestock farms from Western Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.051	-0.056*	-0.051	-0.056*	-0.053	-0.053*	-0.053	-0.054
	(0.032)	(0.032)	(0.033)	(0.033)	(0.033)	(0.032)	(0.033)	(0.033)
ATO	-0.010	-0.011	-0.011	-0.012	-0.010	-0.008	-0.007	-0.009
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Log(land)	-0.000	-0.000	-0.001	-0.001	0.001	-0.001	0.000	-0.001
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age	-0.000	0.000	-0.000	0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	0.026	0.027	0.018	0.023	0.035	0.033	0.045	0.046
	(0.036)	(0.036)	(0.036)	(0.036)	(0.037)	(0.036)	(0.036)	(0.036)
Rural development payments	0.049***	0.044***	0.047***	0.044***	0.043**	0.036**	0.030*	0.023
	(0.017)	(0.016)	(0.017)	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)
Price volatility		0.057**		0.056**				0.044
		(0.028)		(0.028)				(0.029)
Price shock			0.023	0.012				0.005
			(0.023)	(0.023)				(0.024)
Temperature (winter)					-0.002		-0.003*	-0.004*
					(0.002)		(0.002)	(0.002)
Temperature (spring)					0.008**		0.008**	0.006*
					(0.003)		(0.003)	(0.003)
Temperature (summer)					-0.002		-0.001	-0.001
					(0.003)		(0.003)	(0.003)
Temperature (autumn)					-0.003		-0.004	-0.005*
					(0.002)		(0.003)	(0.003)
Precipitation (winter)						0.002	0.003	0.003
						(0.003)	(0.003)	(0.003)
Precipitation (spring)						-0.005*	-0.003	-0.004
						(0.003)	(0.003)	(0.003)
Precipitation (summer)						0.004*	0.004*	0.003
						(0.002)	(0.002)	(0.002)
Precipitation (autumn)						0.001	0.000	0.000
						(0.002)	(0.002)	(0.002)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	42,969	42,969	42,969	42,969	42,969	42,969	42,969	42,969

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A 71 Average partial effects (APE) of the robustness check for economic and environmental variables for transformation of mixed farms from Western Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.127	-0.125	-0.129	-0.128	-0.113	-0.123	-0.110	-0.110
	(0.079)	(0.079)	(0.079)	(0.080)	(0.079)	(0.079)	(0.079)	(0.079)
ATO	-0.015	-0.016	-0.015	-0.016	-0.017	-0.012	-0.013	-0.014
	(0.037)	(0.037)	(0.037)	(0.036)	(0.037)	(0.037)	(0.037)	(0.037)
Log(land)	0.004	0.002	0.004	0.002	0.002	0.005	0.003	0.002
	(0.017)	(0.017)	(0.017)	(0.017)	(0.016)	(0.017)	(0.017)	(0.016)
Age	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Decoupled payments	-0.032	-0.020	-0.024	-0.012	-0.013	-0.009	0.008	0.020
	(0.140)	(0.139)	(0.141)	(0.140)	(0.141)	(0.141)	(0.140)	(0.140)
Rural development payments	-0.103	-0.102	-0.103	-0.107	-0.133	-0.097	-0.134	-0.134
	(0.183)	(0.183)	(0.183)	(0.182)	(0.184)	(0.184)	(0.183)	(0.183)
Price volatility		-0.035		-0.031				-0.040
		(0.049)		(0.050)				(0.050)
Price shock			-0.034	-0.026				-0.003
			(0.055)	(0.056)				(0.057)
Temperature (winter)					-0.006		-0.006	-0.006
					(0.005)		(0.005)	(0.005)
Temperature (spring)					-0.000		-0.000	0.001
					(0.009)		(0.009)	(0.009)
Temperature (summer)					0.013		0.021**	0.020**
					(0.009)		(0.009)	(0.009)
Temperature (autumn)					-0.009		-0.013*	-0.012
					(0.008)		(0.008)	(0.008)
Precipitation (winter)						0.013	0.015*	0.016*
						(0.009)	(0.009)	(0.009)
Precipitation (spring)						-0.006	-0.006	-0.005
						(0.008)	(0.009)	(0.009)
Precipitation (summer)						0.018**	0.019**	0.019***
						(0.007)	(0.007)	(0.007)
Precipitation (autumn)						-0.009	-0.012	-0.012*
						(0.007)	(0.007)	(0.007)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	No	No	No	No	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	14,162	14,162	14,162	14,162	14,162	14,162	14,162	14,162

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A 72 Average partial effects (APE) of the robustness check for economic and environmental variables for transformation of arable farms from Southern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.020	-0.020	-0.018	-0.020	-0.019	-0.021	-0.022	-0.021
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
ATO	-0.008	-0.008	-0.009	-0.009	-0.007	-0.008	-0.007	-0.008
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Log(land)	0.018***	0.017***	0.017***	0.017***	0.017***	0.018***	0.017***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	-0.005	-0.005	-0.006	-0.006	-0.005	-0.005	-0.006	-0.006
	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)
Rural development payments	0.065***	0.063**	0.065***	0.064***	0.068***	0.065***	0.069***	0.068***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.024)
Price volatility		0.082***		0.069***				0.073***
		(0.025)		(0.025)				(0.025)
Price shock			0.044**	0.037**				0.033*
			(0.017)	(0.017)				(0.017)
Temperature (winter)					-0.005***		-0.006***	-0.006***
					(0.002)		(0.002)	(0.002)
Temperature (spring)					-0.001		0.000	-0.001
					(0.002)		(0.002)	(0.003)
Temperature (summer)					0.006**		0.008***	0.009***
					(0.003)		(0.003)	(0.003)
Temperature (autumn)					0.002		0.002	0.002
					(0.002)		(0.002)	(0.002)
Precipitation (winter)						0.002	0.003*	0.003*
						(0.002)	(0.002)	(0.002)
Precipitation (spring)						0.005**	0.006***	0.005**
						(0.002)	(0.002)	(0.002)
Precipitation (summer)						0.003	0.006**	0.007**
						(0.003)	(0.003)	(0.003)
Precipitation (autumn)						-0.005***	-0.006***	-0.006***
						(0.002)	(0.002)	(0.002)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	54,105	54,105	54,105	54,105	54,105	54,105	54,105	54,105

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 73 Average partial effects (APE) of the robustness check for economic and environmental variables for transformation of livestock farms from Southern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	0.025	0.021	0.021	0.020	0.029	0.025	0.022	0.018
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.038)	(0.038)
ATO	-0.019	-0.015	-0.017	-0.015	-0.017	-0.019	-0.012	-0.007
	(0.027)	(0.027)	(0.027)	(0.026)	(0.026)	(0.027)	(0.026)	(0.025)
Log(land)	0.002	0.001	0.001	0.000	0.002	0.002	0.002	0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	-0.004	0.001	-0.001	0.001	0.005	-0.001	0.008	0.012
	(0.024)	(0.025)	(0.025)	(0.025)	(0.028)	(0.026)	(0.028)	(0.029)
Rural development payments	0.067**	0.067**	0.068**	0.068**	0.064*	0.068**	0.068**	0.069**
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Price volatility		-0.015		-0.007				-0.023
		(0.042)		(0.043)				(0.043)
Price shock			-0.046	-0.042				-0.041
			(0.040)	(0.040)				(0.040)
Temperature (winter)					-0.008***		-0.006**	-0.006**
					(0.002)		(0.002)	(0.002)
Temperature (spring)					-0.001		-0.007*	-0.007*
					(0.003)		(0.004)	(0.004)
Temperature (summer)					0.002		0.006*	0.007**
					(0.003)		(0.004)	(0.004)
Temperature (autumn)					0.002		0.001	0.000
					(0.003)		(0.003)	(0.003)
Precipitation (winter)						-0.001	0.002	0.002
						(0.002)	(0.002)	(0.002)
Precipitation (spring)						-0.008***	-0.013***	-0.012***
						(0.003)	(0.003)	(0.003)
Precipitation (summer)						0.003	0.002	0.002
						(0.003)	(0.004)	(0.004)
Precipitation (autumn)						0.005*	0.005**	0.005
						(0.002)	(0.002)	(0.002)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	23,369	23,369	23,369	23,369	23,369	23,369	23,369	23,369

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A 74 Average partial effects (APE) of the robustness check for economic and environmental variables for transformation of mixed farms from Southern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.090	-0.110	-0.091	-0.108	-0.099	-0.110	-0.128	-0.149
	(0.171)	(0.171)	(0.171)	(0.171)	(0.171)	(0.169)	(0.169)	(0.17)
ATO	-0.156	-0.151	-0.152	-0.147	-0.135	-0.131	-0.099	-0.088
	(0.111)	(0.111)	(0.111)	(0.111)	(0.112)	(0.110)	(0.109)	(0.109)
Log(land)	-0.007	-0.005	-0.006	-0.005	-0.011	-0.015	-0.017	-0.015
	(0.021)	(0.021)	(0.021)	(0.021)	(0.020)	(0.021)	(0.020)	(0.02)
Age	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Decoupled payments	0.134	0.102	0.136	0.109	0.110	0.141	0.120	0.089
	(0.107)	(0.106)	(0.106)	(0.105)	(0.107)	(0.106)	(0.105)	(0.103)
Rural development payments	0.002	0.009	0.010	0.020	0.016	0.011	0.034	0.053
	(0.208)	(0.206)	(0.206)	(0.204)	(0.207)	(0.209)	(0.207)	(0.202)
Price volatility		0.234*		0.302**				0.336**
		(0.128)		(0.133)				(0.133)
Price shock			-0.197	-0.268**				-0.257*
			(0.131)	(0.136)				(0.134)
Temperature (winter)					-0.004		-0.009	-0.010
					(0.012)		(0.012)	(0.012)
Temperature (spring)					-0.025		-0.012	-0.011
					(0.017)		(0.018)	(0.018)
Temperature (summer)					0.041**		0.041**	0.045**
					(0.016)		(0.018)	(0.018)
Temperature (autumn)					-0.000		-0.001	-0.003
					(0.013)		(0.014)	(0.014)
Precipitation (winter)						-0.018*	-0.018*	-0.016
						(0.011)	(0.011)	(0.011)
Precipitation (spring)						0.003	-0.000	-0.001
						(0.016)	(0.017)	(0.016)
Precipitation (summer)						-0.009	0.012	0.015
						(0.018)	(0.021)	(0.021)
Precipitation (autumn)						-0.034***	-0.037***	-0.038***
						(0.011)	(0.012)	(0.012)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	No	No	No	No	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,920	3,920	3,920	3,920	3,920	3,920	3,920	3,920

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 75 Average partial effects (APE) of the robustness check for economic and environmental variables for transformation of arable farms from Northern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	0.031	0.014	0.029	0.023	0.083	0.029	0.066	0.075
	(0.194)	(0.186)	(0.199)	(0.197)	(0.193)	(0.202)	(0.189)	(0.188)
ATO	-0.060	-0.069	-0.056	-0.054	-0.089	-0.069	-0.082	-0.076
	(0.105)	(0.095)	(0.111)	(0.110)	(0.103)	(0.102)	(0.097)	(0.099)
Log(land)	-0.052*	-0.031	-0.013	-0.015	-0.022	-0.024	-0.021	-0.019
	(0.027)	(0.021)	(0.022)	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)
Age	-0.003	-0.001	0.000	-0.000	-0.002	-0.002	-0.003	-0.003
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Decoupled payments	0.060	-0.039	-0.060	-0.058	0.114	0.083	0.057	0.028
	(0.207)	(0.181)	(0.204)	(0.205)	(0.208)	(0.209)	(0.201)	(0.209)
Rural development payments	-0.090	-0.019	-0.020	-0.021	-0.092	-0.125	-0.108	-0.093
	(0.226)	(0.204)	(0.213)	(0.214)	(0.229)	(0.238)	(0.233)	(0.237)
Price volatility		0.360**		0.045				-0.022
		(0.156)		(0.154)				(0.165)
Price shock			0.319***	0.305**				0.177
			(0.108)	(0.126)				(0.127)
Temperature (winter)					-0.002		-0.007	-0.008
					(0.014)		(0.015)	(0.015)
Temperature (spring)					-0.053*		-0.069**	-0.069**
					(0.031)		(0.034)	(0.034)
Temperature (summer)					0.012		0.035	0.041
					(0.027)		(0.033)	(0.034)
Temperature (autumn)					0.027		0.029	0.027
					(0.022)		(0.023)	(0.024)
Precipitation (winter)						0.012	0.027	0.028
						(0.026)	(0.026)	(0.026)
Precipitation (spring)						-0.024	-0.025	-0.016
						(0.044)	(0.043)	(0.043)
Precipitation (summer)						-0.009	0.010	0.008
						(0.016)	(0.018)	(0.018)
Precipitation (autumn)						0.032	0.042*	0.041*
						(0.021)	(0.021)	(0.022)
Country[1]	No	No	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,132	1,132	1,132	1,132	1,132	1,132	1,132	1,132

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A 76 Average partial effects (APE) of the robustness check for economic and environmental variables for transformation of livestock farms from Northern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.049	-0.004	-0.009	-0.024	0.016	-0.002	0.005	-0.025
	(0.143)	(0.147)	(0.147)	(0.146)	(0.145)	(0.146)	(0.144)	(0.145)
ATO	-0.244**	-0.313***	-0.307***	-0.309***	-0.314***	-0.307***	-0.311***	-0.312***
	(0.107)	(0.113)	(0.110)	(0.110)	(0.113)	(0.111)	(0.113)	(0.113)
Log(land)	-0.030	-0.030	-0.029	-0.031	-0.028	-0.033	-0.031	-0.032
	(0.028)	(0.028)	(0.027)	(0.028)	(0.028)	(0.028)	(0.029)	(0.029)
Age	-0.004	-0.004*	-0.004*	-0.004*	-0.004	-0.004	-0.004	-0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Decoupled payments	0.393*	0.597***	0.566***	0.528**	0.600***	0.573***	0.588***	0.577***
	(0.211)	(0.216)	(0.211)	(0.209)	(0.210)	(0.213)	(0.210)	(0.208)
Rural development payments	-0.138	-0.091	-0.084	-0.055	-0.096	-0.076	-0.088	-0.084
	(0.194)	(0.193)	(0.195)	(0.191)	(0.194)	(0.194)	(0.194)	(0.193)
Price volatility		0.106		0.279**				0.193
		(0.160)		(0.137)				(0.131)
Price shock			-0.100	-0.100				-0.200
			(0.151)	(0.146)				(0.148)
Temperature (winter)					0.001		0.002	0.002
					(0.007)		(0.007)	(0.007)
Temperature (spring)					-0.013		-0.011	-0.011
					(0.012)		(0.013)	(0.013)
Temperature (summer)					-0.004		-0.009	-0.010
					(0.016)		(0.017)	(0.017)
Temperature (autumn)					-0.003		-0.002	-0.001
					(0.012)		(0.013)	(0.013)
Precipitation (winter)						-0.026**	-0.017	-0.016
						(0.013)	(0.014)	(0.014)
Precipitation (spring)						0.006	-0.012	-0.012
						(0.026)	(0.026)	(0.026)
Precipitation (summer)						0.001	0.006	0.007
						(0.010)	(0.011)	(0.011)
Precipitation (autumn)						-0.018	-0.008	-0.009
						(0.011)	(0.011)	(0.011)
Country[1]	No	No	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,601	3,601	3,601	3,601	3,601	3,601	3,601	3,601

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 77 Average partial effects (APE) of the robustness check for economic and environmental variables for transformation of mixed farms from Northern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.388	-0.446	-0.329	-0.424	-0.390	-0.366	-0.289	-0.388
	(0.608)	(0.610)	(0.623)	(0.618)	(0.609)	(0.623)	(0.616)	(0.627)
ATO	-0.002	0.029	0.053	0.017	0.038	0.136	0.100	0.168
	(0.361)	(0.362)	(0.340)	(0.362)	(0.357)	(0.353)	(0.352)	(0.348)
Log(land)	0.026	0.026	0.035	0.026	0.026	0.012	0.017	0.011
	(0.105)	(0.104)	(0.104)	(0.103)	(0.106)	(0.105)	(0.105)	(0.104)
Age	0.003	0.003	0.004	0.003	0.004	0.004	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Decoupled payments	1.248*	1.170	1.129	1.122	1.219*	1.237*	1.124	1.068
	(0.734)	(0.739)	(0.744)	(0.741)	(0.731)	(0.712)	(0.713)	(0.717)
Rural development payments	0.113	0.201	0.053	0.213	0.131	0.101	0.084	0.198
	(0.975)	(0.973)	(0.995)	(0.969)	(0.980)	(0.932)	(0.938)	(0.924)
Price volatility		0.295		0.268				0.314
		(0.278)		(0.288)				(0.300)
Price shock			0.264	0.182				0.089
			(0.333)	(0.341)				(0.341)
Temperature (winter)					0.015		-0.012	-0.004
					(0.038)		(0.038)	(0.037)
Temperature (spring)					-0.010		-0.058	-0.023
					(0.046)		(0.077)	(0.047)
Temperature (summer)					-0.022		0.020	0.007
					(0.079)		(0.092)	(0.085)
Temperature (autumn)					-0.010		0.039	0.010
					(0.044)		(0.067)	(0.048)
Precipitation (winter)						-0.013	-0.003	0.004
						(0.061)	(0.062)	(0.060)
Precipitation (spring)						-0.277**	-0.278**	-0.295**
						(0.121)	(0.121)	(0.115)
Precipitation (summer)						0.067*	0.089**	0.077*
						(0.037)	(0.045)	(0.041)
Precipitation (autumn)						0.043	0.047	0.035
						(0.044)	(0.045)	(0.047)
Country[1]	No	No	No	No	No	No	No	No
Farm type[2]	No	No	No	No	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	437	437	437	437	437	437	437	437

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). For this robustness, the original CRE-specification was included and all other model specification due to sample size limitations. The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A 78 Average partial effects (APE) of the robustness check for economic and environmental variables for transformation of arable farms from Eastern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	0.090	0.079	0.085	0.089	0.101	0.080	0.092	0.089
	(0.072)	(0.072)	(0.073)	(0.073)	(0.074)	(0.072)	(0.073)	(0.073)
ATO	-0.134**	-0.124**	-0.131**	-0.134**	-0.153***	-0.124**	-0.140**	-0.138**
	(0.057)	(0.057)	(0.057)	(0.057)	(0.059)	(0.057)	(0.058)	(0.059)
Log(land)	-0.008	-0.008	-0.007	-0.008	-0.006	-0.007	-0.006	-0.005
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Age	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Decoupled payments	0.006	0.002	0.003	0.008	0.017	0.012	0.017	0.017
	(0.071)	(0.069)	(0.069)	(0.070)	(0.071)	(0.072)	(0.071)	(0.070)
Rural development payments	-0.097	-0.093	-0.091	-0.094	-0.106*	-0.103*	-0.107*	-0.102*
	(0.060)	(0.059)	(0.059)	(0.059)	(0.060)	(0.060)	(0.060)	(0.060)
Price volatility		0.018		0.032				0.031
		(0.044)		(0.046)				(0.046)
Price shock			-0.008	-0.019				-0.028
			(0.035)	(0.037)				(0.037)
Temperature (winter)					-0.010		-0.005	-0.007
					(0.007)		(0.007)	(0.007)
Temperature (spring)					-0.032***		-0.021*	-0.020*
					(0.010)		(0.011)	(0.011)
Temperature (summer)					0.003		0.009	0.009
					(0.012)		(0.013)	(0.013)
Temperature (autumn)					-0.011		-0.009	-0.011
					(0.012)		(0.013)	(0.013)
Precipitation (winter)						-0.054***	-0.042***	-0.040***
						(0.014)	(0.016)	(0.015)
Precipitation (spring)						0.015	0.013	0.014
						(0.010)	(0.010)	(0.010)
Precipitation (summer)						0.008	0.009	0.009
						(0.007)	(0.007)	(0.007)
Precipitation (autumn)						0.022**	0.015	0.014
						(0.009)	(0.010)	(0.009)
Country[1]	No	No	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15,898	15,898	15,898	15,898	15,898	15,898	15,898	15,898

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 79 Average partial effects (APE) of the robustness check for economic and environmental variables for transformation of livestock farms from Eastern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	0.044	0.069	0.053	0.079	0.035	0.046	0.039	0.068
	(0.069)	(0.069)	(0.069)	(0.068)	(0.068)	(0.069)	(0.068)	(0.067)
ATO	-0.136***	-0.159***	-0.129**	-0.152***	-0.116**	-0.133***	-0.120**	-0.121**
	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)
Log(land)	-0.015	-0.016	-0.016	-0.017	-0.014	-0.015	-0.013	-0.015
	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)	(0.013)
Age	-0.000	0.000	-0.000	0.000	-0.000	-0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Decoupled payments	0.110	0.125	0.099	0.125	0.095	0.076	0.083	0.111
	(0.086)	(0.088)	(0.084)	(0.085)	(0.085)	(0.085)	(0.084)	(0.084)
Rural development payments	-0.059	-0.075	-0.054	-0.071	-0.042	-0.045	-0.035	-0.034
	(0.050)	(0.050)	(0.050)	(0.050)	(0.049)	(0.049)	(0.049)	(0.049)
Price volatility		-0.080		-0.084				-0.103*
		(0.054)		(0.055)				(0.054)
Price shock			0.457***	0.446***				0.457***
			(0.061)	(0.060)				(0.06)
Temperature (winter)					-0.007		-0.006	-0.008
					(0.007)		(0.007)	(0.007)
Temperature (spring)					0.024**		0.023**	0.026**
					(0.010)		(0.011)	(0.011)
Temperature (summer)					-0.010		-0.012	-0.011
					(0.011)		(0.012)	(0.012)
Temperature (autumn)					-0.011		-0.014	-0.016
					(0.011)		(0.012)	(0.012)
Precipitation (winter)						0.011	0.005	0.007
						(0.013)	(0.013)	(0.013)
Precipitation (spring)						0.001	0.003	0.002
						(0.009)	(0.009)	(0.009)
Precipitation (summer)						-0.009	-0.012*	-0.013**
						(0.006)	(0.006)	(0.006)
Precipitation (autumn)						-0.013	-0.010	-0.011
						(0.009)	(0.009)	(0.009)
Country[1]	No	No	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19,543	19,543	19,543	19,543	19,543	19,543	19,543	19,543

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A 80 Average partial effects (APE) of the robustness check for economic and environmental variables for transformation of mixed farms from Eastern Europe

	Original	Price volatility	Price shock	Price volatility, price shock	Temperature	Precipitation	Temperature, precipitation	Price volatility, price shock, temperature, precipitation
ROA	-0.068	-0.095	-0.097	-0.128	-0.032	-0.037	-0.027	-0.078
	(0.084)	(0.083)	(0.083)	(0.082)	(0.085)	(0.084)	(0.085)	(0.083)
ATO	0.054	0.072	0.067	0.096	0.002	0.017	-0.000	0.036
	(0.065)	(0.064)	(0.065)	(0.063)	(0.068)	(0.067)	(0.069)	(0.067)
Log(land)	0.025**	0.022*	0.027**	0.022*	0.028**	0.027**	0.028**	0.025**
	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)	(0.011)
Age	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Decoupled payments	-0.033	-0.048	0.067	0.050	0.009	0.017	0.001	0.115
	(0.114)	(0.107)	(0.113)	(0.105)	(0.118)	(0.115)	(0.119)	(0.109)
Rural development payments	0.010	0.023	0.016	0.033	-0.013	-0.006	-0.010	0.003
	(0.054)	(0.053)	(0.054)	(0.053)	(0.055)	(0.054)	(0.055)	(0.054)
Price volatility		0.063		0.076*				0.080**
		(0.039)		(0.039)				(0.039)
Price shock			-0.370***	-0.368***				-0.381***
			(0.039)	(0.040)				(0.040)
Temperature (winter)					0.012**		0.010	0.007
					(0.006)		(0.007)	(0.007)
Temperature (spring)					0.003		0.001	-0.005
					(0.009)		(0.010)	(0.010)
Temperature (summer)					0.016		0.012	0.008
					(0.011)		(0.013)	(0.013)
Temperature (autumn)					-0.006		-0.005	-0.004
					(0.012)		(0.012)	(0.012)
Precipitation (winter)						0.010	0.007	0.002
						(0.013)	(0.014)	(0.014)
Precipitation (spring)						-0.012	-0.010	-0.004
						(0.009)	(0.010)	(0.010)
Precipitation (summer)						-0.005	-0.005	-0.003
						(0.006)	(0.007)	(0.006)
Precipitation (autumn)						-0.011	-0.013	-0.007
						(0.010)	(0.010)	(0.010)
Country[1]	No	No	No	No	No	No	No	No
Farm type[2]	No	No	No	No	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	21,459	21,459	21,459	21,459	21,459	21,459	21,459	21,459

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.4 Robustness checks that investigate if decoupled payment and rural development payments are exogenous or endogenous explanatory variables

The potential endogeneity of decoupled payments (DP) and rural development payments (RDP) could be introduced by the non-random assignment of these payments, which potentially causes a correlation with the error-term. The non-random assignment of DP could be caused by the cross-compliance that is needed in order to receive payments. Hence, some farmers may decide not to comply and not receive any payments. For RDP, non-random assignment could occur when farmers receive one-time subsidies for investments.

To further investigate if DP and RDP were endogenous or exogenous explanatory variables, we investigated if the assignment of DP and RDP was mostly time-invariant or time-variant. If the assignment is time-invariant (i.e. farms (do not) receive DP or RDP each year that they are present in our sample), it is accounted for by the time-invariant farm heterogeneity (see equation (5)) within our econometric model. If the assignment of DP and RDP is time-varying (e.g. farms receive payments in year t but not in year $t+1$), then the non-random assignment implies that these variables could be considered as endogenous.

As a first step, we computed some summary statistics to describe if the assignment of DP and RDP is varying over time. We distinguish three groups of farmers: (i) farms that have never received payments (time-invariant), (ii) farm that have received payments in some years, but not in other years (time-variant), and (iii) farms that have received payments in each year that they were included in our sample (time-invariant). We present these summary statistics for each region and each farm type in Table A.81-82.

These tables reveal that DP are almost always time-invariantly assigned (94.48% = 10.77% + 83.71%). Hence, we believe that this large percentage of time-invariant non-random assignment can be sufficiently captured by accounting for the time-invariant unobserved heterogeneity. No further actions are required to address this source of potential endogeneity. The assignment of RDP tends to be more time-varying, as Table A.82 shows that 31.15% of the farms received DP in some years but not in all years. This might imply that this source of endogeneity is not captured by the time-invariant unobserved heterogeneity.

To further investigate if RDP should be considered as a exogenous or endogenous explanatory variable, we applied the control function approach that is described in section 3.2.3. We inspected the instrument validity (i.e. inspecting the Kleibergen-Paap F-statistics, Kleibergen-Paap LM-statistics and signficance of the instruments in the reduced form equations) and checked if the Hausman revealed if we should consider RDP as endogenous or exogenous explanatory variables (Table A.83-87). These tables reveal that rural development payments should be considered as being endogenous explanatory variables in 8 out of 36 models.

The output of the fractional correlated random effects models that considers RDP as endogenous explanatory variables are presented in Table A.88-90. In 6 out of the 8 models, our findings of the original model were robust to the model that treats RDP as endogenous. The 3 cases where the interpretation of our results slightly differ when treating RDP as endogenous are discussed in the main text of the paper. However, the overall findings of the paper remain the same. Hence, we are confident that our results are robust to the potential presence of endogeneity based on the non-random assignment of DP and RDP.

Table A 81 Overview of the time-variant and time-invariant assignment of decoupled payments (DP) in different regions and farm types

	Western Europe				Southern Europe			
	ACP	Livestock	Mixed	Total	ACP	Livestock	Mixed	Total
Never received DP[1] (time-invariant)	12,476 (32.08%)	264 (0.61%)	19 (0.13%)	12,759 (13.29%)	12,161 (22.48%)	441 (1.89%)	116 (2.96%)	12,718 (15.63%)
Sometimes received DP (time-variant)	1,867 (4.80%)	303 (0.71%)	19 (0.13%)	2,189 (2.28%)	7,961 (14.71%)	2,577 (11.03%)	366 (9.34%)	10,904 (13.40%)
Always received DP (time-invariant)	24,545 (63.12%)	42,402 (98.68%)	14,124 (99.73%)	81,071 (84.43%)	33,983 (62.81%)	20,351 (87.09%)	3,438 (87.70%)	57,772 (70.98%)
Total	38,888 (100.00%)	42,969 (100.00%)	14,162 (100.00%)	96,019 (100.00%)	54,105 (100.00%)	23,369 (100.00%)	3,920 (100.00%)	81,394 (100.00%)

	Northern Europe				Eastern Europe				All regions
	ACP	Livestock	Mixed	Total	ACP	Livestock	Mixed	Total	Total
Never received DP (time-invariant)	57 (5.04%)	24 (0.67%)	0 (0.00%)	81 (1.57%)	222 (1.40%)	5 (0.03%)	8 (0.04%)	235 (0.41%)	25,793 (10.77%)
Sometimes received DP (time-variant)	2 (0.18%)	14 (0.39%)	5 (1.14%)	21 (0.41%)	95 (0.60%)	1 (0.01%)	0 (0.00%)	96 (0.17%)	13,210 (5.52%)
Always received DP (time-invariant)	1,073 (94.79%)	3,563 (98.94%)	432 (98.86%)	5,068 (98.03%)	15,581 (98.01%)	19,537 (99.97%)	21,451 (99.96%)	56,569 (99.42%)	200,480 (83.71%)
Total	1,132 (100.00%)	3,601 (100.00%)	437 (100.00%)	5,170 (100.00%)	15,898 (100.00%)	19,543 (100.00%)	21,459 (100.00%)	56,900 (100.00%)	239,483 (100.00%)

[1]DP = decoupled payments

Table A 82 Overview of the time-variant and time-invariant assignment of rural development payments (RDP) in different regions and farm types

	Western Europe				Southern Europe			
	ACP	Livestock	Mixed	Total	ACP	Livestock	Mixed	Total
Never received RDP[1] (time-invariant)	24,357 (62.63%)	10,902 (25.37%)	4,218 (29.78%)	39,477 (41.11%)	26,557 (49.08%)	4,163 (17.81%)	1,060 (27.04%)	31,780 (39.04%)
Sometimes received RDP (time-variant)	7,709 (19.82%)	7,850 (18.27%)	3,442 (24.30%)	19,001 (19.79%)	21,019 (38.85%)	12,329 (52.76%)	2,032 (51.84%)	35,380 (43.47%)
Always received RDP (time-invariant)	6,822 (17.54%)	24,217 (56.36%)	6,502 (45.91%)	37,541 (39.10%)	6,529 (12.07%)	6,877 (29.43%)	828 (21.12%)	14,234 (17.49%)
Total	38,888 (100.00%)	42,969 (100.00%)	14,162 (100.00%)	96,019 (100.00%)	54,105 (100.00%)	23,369 (100.00%)	3,920 (100.00%)	81,394 (100.00%)

	Northern Europe				Eastern Europe				All regions
	ACP	Livestock	Mixed	Total	ACP	Livestock	Mixed	Total	Total
Never received RDP (time-invariant)	174 (15.37%)	75 (2.08%)	13 (2.97%)	262 (5.07%)	6,127 (38.54%)	3,218 (16.47%)	4,774 (22.25%)	14,119 (24.81%)	85,638 (35.76%)
Sometimes received RDP (time-variant)	239 (21.11%)	137 (3.80%)	26 (5.95%)	402 (7.78%)	4,690 (29.50%)	7,257 (37.13%)	7,859 (36.62%)	19,806 (34.81%)	74,589 (31.15%)
Always received RDP (time-invariant)	719 (63.52%)	3,389 (94.11%)	398 (91.08%)	4,506 (87.16%)	5,081 (31.96%)	9,068 (46.40%)	8,826 (41.13%)	22,975 (40.38%)	79,256 (33.09%)
Total	1,132 (100.00%)	3,601 (100.00%)	437 (100.00%)	5,170 (100.00%)	15,898 (100.00%)	19,543 (100.00%)	21,459 (100.00%)	56,900 (100.00%)	239,483 (100.00%)

[1]RDP = Rural development payments

Table A 83 Parameter estimates of the first-stage pooled OLS regression for the robustness check that investigates if rural development payments are endogenous or exogenous explanatory variables for farm adaptation. ACP = Arable, crops, and perennials farms.

	Adaptation	Adaptation	Adaptation	Adaptation
	Western Europe	Northern Europe	Eastern Europe	Eastern Europe
Farm type	ACP	ACP	Livestock	Mixed
Dependent variable reduced form	RDP	RDP	RDP	RDP
Rural development payments at *t-2*	0.791***	0.753***	0.364***	0.437***
	(0.014)	(0.077)	(0.018)	(0.013)
ROA	0.004***	0.047	0.348***	0.484***
	(0.001)	(0.037)	(0.018)	(0.023)
ATO	-0.001**	0.004	-0.139***	-0.283***
	(0.000)	(0.016)	(0.012)	(0.016)
Log(land)	-0.002***	-0.001	-0.016***	-0.005
	(0.000)	(0.006)	(0.003)	(0.003)
Age	-0.000**	-0.001	-0.001***	-0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
Decoupled payments	0.099***	0.337***	0.619***	0.421***
	(0.010)	(0.096)	(0.044)	(0.038)
Constant	0.002	-0.016	0.086***	0.094***
	(0.002)	(0.031)	(0.013)	(0.013)
Country[1]	Yes	No	No	No
Farm type[2]	Yes	Yes	Yes	No
Year[3]	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes
Endogenous variables[5]	RDP	RDP	RDP	RDP
N	38,888	1,132	19,543	21,459

ROA at *t-2* is included as regressor if ROA is considered to be endogenous. If this is not the case, then ROA is included as regressor. [1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region. [2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model of a specific farm type (i.e. for mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are clustered at farm level. $p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$.

Table A 84 Parameter estimates of the first-stage pooled OLS regression for the robustness check that investigates if rural development payments are endogenous or exogenous explanatory variables for farm transformation. ACP = Arable, crops, and perennials farms.

	Transformation	Transformation	Transformation	Transformation
	Western Europe	Southern Europe	Southern Europe	Northern Europe
Farm type	ACP	ACP	Livestock	Mixed
Dependent variable reduced form	RDP	RDP	RDP	RDP
Rural development payments at *t-2*	0.791***	0.538***	0.646***	0.437***
	(0.014)	(0.018)	(0.067)	(0.013)
ROA	0.004***	0.008**	0.063***	0.484***
	(0.001)	(0.003)	(0.009)	(0.023)
ATO	-0.001**	-0.012***	-0.058***	-0.283***
	(0.000)	(0.002)	(0.007)	(0.016)
Log(land)	-0.002***	0.001	0.003***	-0.005
	(0.000)	(0.001)	(0.001)	(0.003)
Age	-0.000**	-0.000***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Decoupled payments	0.099***	0.075***	0.065***	0.421***
	(0.010)	(0.010)	(0.025)	(0.038)
Constant	0.002	0.010***	0.016***	0.094***
	(0.002)	(0.002)	(0.006)	(0.013)
Country[1]	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes
Endogenous variables[5]	RDP	RDP	RDP	RDP
N	38,888	54,105	23,369	437

[1]Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country is included in the model because there is only one country in a region. [2]Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model of a specific farm type (i.e. for mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are clustered at farm level. $p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$.

Table A 85 Validity tests for instruments for the models with adaptation as dependent variable for the robustness check that investigates if rural development payments (RDP) are endogenous or exogenous explanatory variables. For Western and Northern Europe. ACP = Arable, crops, and perennials farms.

	Western Europe	Northern Europe
	ACP	ACP
Instrumental validity		
F-statistic	2980.334	94.555
Kleibergen-Paap LM-statistic	152.346***	24.940***
Endogenous variables	RDP	RDP
Hausman test for endogeneity		
Residuals RDP	-0.509***	-1.150**
	(0.144)	(0.448)

The Hausman test tests for endogeneity by including the residuals of the first-stage regressions in the second stage model. If the residuals are significant, we treat the corresponding variable as endogenous. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 86 Validity tests for instruments for the models with adaptation as dependent variable for the robustness check that investigates if rural development payments (RDP) are endogenous or exogenous explanatory variables. ACP = Arable, crops, and perennials farms.

	Eastern Europe	
	Livestock	Mixed
Instrumental validity		
F-statistic	361.993	1074.922
Kleibergen-Paap LM-statistic	240.016***	671.134***
Hausman test for endogeneity		
Endogenous variables	RDP	RDP
Residuals RDP	0.489**	0.227**
	(0.217)	(0.115)

The Hausman test tests for endogeneity by including the residuals of the first-stage regressions in the second stage model. If the residuals are significant, we treat the corresponding variable as endogenous. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 87 Validity tests for instruments for the models with transformation as dependent variable for the robustness check that investigates if rural development payments (RDP) are endogenous or exogenous explanatory variables. ACP = Arable, crops, and perennials farms. Some regions and farm types are omitted because a Hausman test indicated that both RDP is not endogenous.

	Western Europe	Southern Europe		Northern Europe
	ACP	ACP	Livestock	Mixed
Instrumental validity				
F-statistic	2980.334	891.859	94.274	295.556
Kleibergen-Paap LM-statistic	152.346***	249.104***	385.486***	19.255***
Endogenous variables	RDP	RDP	RDP	RDP
Hausman test for endogeneity				
Residuals RDP	-2.630***	-1.989***	-1.263***	5.665**
	(0.762)	(0.418)	(0.479)	(2.576)

The Hausman test tests for endogeneity by including the residuals of the first-stage regressions in the second stage model. If the residuals are significant, we treat the corresponding variable as endogenous. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 88 Average partial effects (APE) of models with farm adaptation for Western and Northern Europe to compare the original model to a model with rural development payments as endogenous explanatory variables

	Western Europe		Northern Europe	
	ACP		ACP	
	Original	RDP endogenous	Original	RDP endogenous
ROA	-0.023***	-0.024***	-0.036	-0.186
	(0.005)	(0.005)	(0.067)	(0.296)
ATO	0.003	0.003	-0.038	-0.168
	(0.002)	(0.002)	(0.040)	(0.185)
Log(land)	-0.001	-0.000	-0.039***	-0.167**
	(0.001)	(0.002)	(0.015)	(0.070)
Age	-0.000***	-0.000***	-0.005***	-0.019**
	(0.000)	(0.000)	(0.002)	(0.007)
Decoupled payments	0.005	-0.015	0.066	-0.318
	(0.016)	(0.016)	(0.066)	(0.385)
Rural development payments	-0.015	0.106***	-0.053	-0.388
	(0.026)	(0.019)	(0.092)	(0.610)
Country[1]	Yes	Yes	No	No
Farm type[2]	Yes	Yes	Yes	Yes
Year[3]	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes
Endogenous variables[5]	None	RDP	None	RDP
N	38,888	38,888	1,132	1,132

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5] Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 89 Average partial effects (APE) of models with farm adaptation of Eastern Europe to compare the original model to a model with rural development payments as endogenous explanatory variables

	Eastern Europe			
	Livestock		Mixed	
	Original	RDP endogenous	Original	RDP endogenous
ROA	0.005	0.181	0.005	0.092
	(0.024)	(0.131)	(0.021)	(0.106)
ATO	0.012	0.000	-0.000	-0.047
	(0.016)	(0.078)	(0.016)	(0.081)
Log(land)	0.009	0.033	0.006*	0.026*
	(0.006)	(0.027)	(0.003)	(0.014)
Age	-0.001***	-0.005***	-0.001***	-0.003***
	(0.000)	(0.001)	(0.000)	(0.001)
Decoupled payments	0.087***	0.761***	0.117***	0.580***
	(0.032)	(0.203)	(0.027)	(0.135)
Rural development payments	-0.033*	-0.580***	0.012	-0.090
	(0.017)	(0.210)	(0.013)	(0.115)
Country[1]	Yes	Yes	No	No
Farm type[2]	Yes	Yes	No	No
Year[3]	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes
Endogenous variables[5]	None	RDP	None	RDP
N	19,543	19,543	21,459	21,459

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5] Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 90 Average partial effects (APE) of models with farm transformation to compare the original model to a model with rural development payments as endogenous explanatory variables

	Western Europe		Southern Europe				Northern Europe	
	ACP		ACP		Livestock		Mixed	
	Original	RDP endogenous	Original	RDP endogenous	Original	RDP endogenous	Original	RDP endogenous
ROA	0.013	0.006	-0.020	-0.024	0.025	0.022	-0.388	-0.138
	(0.017)	(0.016)	(0.018)	(0.019)	(0.039)	(0.039)	(0.608)	(0.093)
ATO	-0.013	-0.010	-0.008	-0.004	-0.019	-0.016	-0.002	0.084
	(0.008)	(0.008)	(0.011)	(0.011)	(0.027)	(0.027)	(0.361)	(0.070)
Log(land)	-0.007*	-0.006	0.018***	0.017***	0.002	0.001	0.026	0.028**
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.105)	(0.012)
Age	-0.000	-0.000	-0.001**	-0.001**	0.000	0.000	0.003	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.001)
Decoupled	0.273***	0.194***	-0.005	-0.018	-0.004	-0.008	1.248*	-0.138
payments	(0.045)	(0.044)	(0.013)	(0.012)	(0.024)	(0.025)	(0.734)	(0.124)
Rural development	-0.064	0.337***	0.065***	0.226***	0.067**	0.128***	0.113	0.124
payments	(0.056)	(0.049)	(0.025)	(0.035)	(0.033)	(0.037)	(0.975)	(0.097)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	None	RDP	None	RDP	None	RDP	None	RDP
N	38,888	38,888	54,105	54,105	23,369	23,369	437	437

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5] Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.5 Robustness checks based on squared relationships of land and age

Section 4.5.1 presents the robustness checks for farm robustness, section 4.5.2 describes the robustness checks for farm adaptation, and section 4.5.3 presents the findings for farm transformation.

We conducted a series of robustness checks for alternative model specifications that include age squared and land squared as explanatory variables (Table A.91-102). The following variables were added to the original model: (i) age squared, (ii) land squared, (iii) age and land squared.

As the reduced form equations slightly change under alternative model specifications (see section 3.2.3), it is important to first verify if the instrumental variables remain valid. We did this by inspecting the Kleibergen-Paap F-statistics and Kleibergen-Paap LM-statistic, the signficance of the instruments in the reduced form equations, and checking the outcomes of the Hausman test for each alternative model specification. The instruments remained valid in all cases. To limit the length of this appendix, we decided not to present this output but describe our approach and findings in words.

4.5.1 Robustness checks based on squared relationships of land and age for farm robustness

Section 4.5.1 presents the robustness checks that add squared terms of age and land to the model for farm robustness. Including age and land squared resulted in three alternative model specifications. The following variables were added to the original model: (i) age squared, (ii) land squared, (iii) land and age squared. These findings are presented in Table A91-94.

Table A 91 Average partial effects (APE) of the robustness check for age squared and land squared for robustness of farms from Western Europe.

	ACP				Livestock				Mixed			
	Original	Age^2	Land^2	Age^2 Land^2	Original	Age^2	Land^2	Age^2 Land^2	Original	Age^2	Land^2	Age^2 Land^2
ROA	-0.059**	-0.059**	-0.073***	-0.073***	0.076*	0.076*	0.062	0.062	-0.027	-0.031	-0.079	-0.083
	(0.024)	(0.024)	(0.024)	(0.024)	(0.041)	(0.041)	(0.041)	(0.041)	(0.076)	(0.077)	(0.080)	(0.081)
ATO	0.181***	0.181***	0.179***	0.179***	-0.086***	-0.086***	-0.081***	-0.081***	0.384***	0.385***	0.400***	0.401***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.009)	(0.009)	(0.010)	(0.010)	(0.034)	(0.034)	(0.035)	(0.035)
Log(land)	0.054***	0.054***			0.025***	0.025***			0.006	0.006		
	(0.004)	(0.004)			(0.006)	(0.006)			(0.011)	(0.011)		
Age	0.001**	0.001	0.001**	0.001	0.000	0.004**	0.000	0.004*	0.002***	0.002	0.002***	0.002
	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)	(0.002)	(0.001)	(0.004)	(0.001)	(0.004)
Decoupled	-0.926***	-0.926***	-0.689***	-0.688***	-0.662***	-0.664***	-0.630***	-0.632***	-0.872***	-0.873***	-0.864***	-0.865***
payments	(0.054)	(0.054)	(0.052)	(0.052)	(0.051)	(0.051)	(0.052)	(0.052)	(0.084)	(0.084)	(0.083)	(0.083)
Rural	0.481***	0.480***	0.444***	0.442***	0.028	0.029	0.027	0.027	0.425***	0.427***	0.417***	0.419***
development payments	(0.091)	(0.091)	(0.089)	(0.088)	(0.074)	(0.074)	(0.078)	(0.078)	(0.110)	(0.110)	(0.110)	(0.110)
Age^2		-0.000		-0.000		-0.000*		-0.000*		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Land			0.000	0.000			-0.000***	-0.000***			-0.000***	-0.000***
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Land^2			0.000	0.000			0.000	0.000			0.000	0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	ROA	ROA	ROA	ROA	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	ROA	ROA	ROA	ROA
N	38,888	38,888	38,888	38,888	42,969	42,969	42,969	42,969	14,162	14,162	14,162	14,162

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5]Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A 92 Average partial effects (APE) of the robustness check for age squared and land squared for robustness of farms from Southern Europe.

	ACP				Livestock				Mixed			
	Original	Age^2	$Land^2$	Age^2Land^2	Original	Age^2	$Land^2$	Age^2 $Land^2$	Original	Age^2	$Land^2$	Age^2Land^2
ROA	-0.377***	-0.377***	-0.374***	-0.375***	-0.620***	-0.621***	-0.619***	-0.620***	-0.786***	-0.802***	-0.813***	-0.836***
	(0.047)	(0.047)	(0.047)	(0.047)	(0.064)	(0.064)	(0.064)	(0.064)	(0.241)	(0.246)	(0.242)	(0.248)
ATO	0.007	0.007	0.005	0.004	0.000	0.001	-0.002	-0.002	1.014***	1.023***	1.015***	1.026***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.028)	(0.028)	(0.027)	(0.028)	(0.166)	(0.169)	(0.166)	(0.168)
Log(land)	0.021***	0.021***			0.010**	0.010**			-0.026**	-0.027**		
	(0.004)	(0.004)			(0.005)	(0.005)			(0.012)	(0.012)		
Age	0.001***	-0.002	0.001***	-0.002	0.001	0.002	0.001	0.002	0.000	0.005	0.001	0.006
	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)	(0.003)	(0.000)	(0.003)	(0.001)	(0.007)	(0.001)	(0.007)
Decoupled payments	-0.163***	-0.163***	-0.148**	-0.148**	-0.193*	-0.193*	-0.195*	-0.194*	-0.170**	-0.170**	-0.182***	-0.181***
	(0.062)	(0.062)	(0.058)	(0.058)	(0.109)	(0.109)	(0.109)	(0.109)	(0.067)	(0.067)	(0.068)	(0.069)
Rural development payments	-0.029	-0.028	-0.024	-0.024	0.171***	0.170***	0.178***	0.177***	0.446***	0.448***	0.434***	0.435***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.061)	(0.060)	(0.060)	(0.060)	(0.125)	(0.126)	(0.126)	(0.127)
Age^2		0.000**		0.000*		-0.000		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Land			0.000	0.000			0.000	0.000			0.000	0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
$Land^2$			-0.000	-0.000			-0.000	-0.000			-0.000	-0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	ROA,ATO	ROA,ATO	ROA,ATO	ROA,ATO	ROA,ATO	ROA,ATO	ROA,ATO	ROA,ATO	ROA	ROA	ROA	ROA
N	54,105	54,105	54,105	54,105	23,369	23,369	23,369	23,369	3,920	3,920	3,920	3,920

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5] Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 93 Average partial effects (APE) of the robustness check for age squared and land squared for robustness of farms from Northern Europe.

	ACP				Livestock				Mixed			
	Original	Age^2	Land^2	Age^2 Land^2	Original	Age^2	Land^2	Age^2 Land^2	Original	Age^2	Land^2	Age^2 Land^2
ROA	1.979***	1.976***	1.971***	1.967***	0.281**	0.284**	0.281**	0.282**	2.936***	2.913***	2.834***	2.852***
	(0.159)	(0.155)	(0.162)	(0.164)	(0.131)	(0.133)	(0.133)	(0.135)	(0.350)	(0.338)	(0.328)	(0.344)
ATO	-0.358***	-0.352***	-0.366***	-0.348***	-0.339***	-0.340***	-0.329***	-0.330***	0.488***	0.544***	0.390**	0.420***
	(0.118)	(0.117)	(0.112)	(0.124)	(0.045)	(0.045)	(0.045)	(0.045)	(0.132)	(0.129)	(0.154)	(0.149)
Log(land)	0.056**	0.054**			0.030	0.027			-0.083	-0.086*		
	(0.025)	(0.026)			(0.020)	(0.020)			(0.052)	(0.051)		
Age	0.005*	-0.004	0.002**	-0.005	0.002	0.013	0.001	0.014	-0.005	0.024	-0.003	0.008
	(0.003)	(0.020)	(0.001)	(0.008)	(0.002)	(0.010)	(0.002)	(0.010)	(0.004)	(0.024)	(0.002)	(0.011)
Decoupled payments	-0.473*** (0.135)	-0.448*** (0.136)	-0.458*** (0.135)	-0.454*** (0.135)	-1.191*** (0.184)	-1.188*** (0.182)	-1.181*** (0.184)	-1.179*** (0.183)	0.454 (0.382)	0.467 (0.390)	0.455 (0.378)	0.483 (0.394)
Rural development payments	0.510*** (0.162)	0.485*** (0.162)	0.546*** (0.157)	0.544*** (0.156)	0.087 (0.140)	0.093 (0.138)	0.089 (0.139)	0.094 (0.137)	-0.404 (0.483)	-0.353 (0.511)	-0.620 (0.478)	-0.636 (0.486)
Age^2		0.000		0.000		-0.000		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Land			0.000	0.000			0.000	0.000			-0.000	-0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Land^2			-0.000	-0.000			0.000	0.000			0.000	0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Country[1]	No	No	No	No	No	No	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	None	None	None	None	ROA, ATO	ROA, ATO	ROA, ATO	ROA, ATO	None	None	None	None
N	1,132	1,132	1,132	1,132	3,601	3,601	3,601	3,601	437	437	437	437

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5]Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 94 Average partial effects (APE) of the robustness check for age squared and land squared for robustness of farms from Eastern Europe.

	ACP				Livestock				Mixed			
	Original	Age^2	Land^2	Age^2 Land^2	Original	Age^2	Land^2	Age^2 Land^2	Original	Age^2	Land^2	Age^{2}Land^2
ROA	-1.354***	-1.357***	-1.361***	-1.362***	0.045	0.041	0.059	0.056	-1.177***	-1.188***	-1.406***	-1.413***
	(0.174)	(0.174)	(0.182)	(0.183)	(0.117)	(0.118)	(0.116)	(0.117)	(0.162)	(0.162)	(0.169)	(0.170)
ATO	1.585***	1.587***	1.616***	1.617***	-0.141***	-0.139***	-0.151***	-0.149***	1.657***	1.664***	1.794***	1.798***
	(0.111)	(0.111)	(0.116)	(0.116)	(0.040)	(0.040)	(0.040)	(0.040)	(0.096)	(0.096)	(0.100)	(0.101)
Log(land)	0.019	0.018			0.064***	0.064***			-0.039**	-0.039**		
	(0.016)	(0.016)			(0.014)	(0.014)			(0.016)	(0.016)		
Age	0.001	0.000	0.001	-0.000	0.004***	0.001	0.004***	0.002	0.003***	0.005	0.003***	0.004
	(0.001)	(0.006)	(0.001)	(0.006)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)
Decoupled payments	-0.682***	-0.684***	-0.663***	-0.665***	-2.215***	-2.219***	-2.171***	-2.173***	-1.222***	-1.223***	-1.278***	-1.279***
	(0.177)	(0.178)	(0.165)	(0.166)	(0.120)	(0.120)	(0.116)	(0.117)	(0.087)	(0.088)	(0.090)	(0.090)
Rural development payments	0.563***	0.564***	0.566***	0.566***	0.811***	0.812***	0.799***	0.800***	1.036***	1.040***	1.088***	1.091***
	(0.091)	(0.091)	(0.088)	(0.089)	(0.062)	(0.062)	(0.061)	(0.061)	(0.052)	(0.052)	(0.053)	(0.053)
Age^2		0.000		0.000		0.000		0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Land			0.000	0.000			0.001***	0.001***			-0.000***	-0.000***
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Land^2			-0.000***	-0.000***			0.000	0.000			-0.000	-0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Country[1]	No	No	No	No	No	No	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous variables[5]	ROA	ROA	ROA	ROA	ROA,ATO	ROA,ATO	ROA,ATO	ROA,ATO	ROA	ROA	ROA	ROA
N	15,898	15,898	15,898	15,898	19,543	19,543	19,543	19,543	21,459	21,459	21,459	21,459

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). [5] Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. The presented standard errors are obtained by 1,000 bootstrap replications and are fully robust. * p < 0.10, ** p < 0.05, *** p < 0.01.

4.5.2 Robustness checks based on squared relationships of land and age for farm adaptation

Section 4.5.2 presents the robustness checks that add squared terms of age and land to the model for farm adaptation. Including age and land squared resulted in three alternative model specifications. The following variables were added to the original model: (i) age squared, (ii) land squared, (iii) land and age squared. These findings are presented in Table A 95-98.

Table A 95 Average partial effects (APE) of the robustness check for age squared and land squared for adaptation of farms from Western Europe.

	ACP				Livestock				Mixed			
	Original	Age^2	Land^2	Age^2 Land^2	Original	Age^2	Land^2	Age^2 Land^2	Original	Age^2	Land^2	Age^{2}Land^2
ROA	-0.023***	-0.023***	-0.024***	-0.025***	-0.046***	-0.046***	-0.044***	-0.044***	-0.021	-0.021	-0.025	-0.025
	(0.005)	(0.005)	(0.005)	(0.005)	(0.014)	(0.014)	(0.014)	(0.014)	(0.018)	(0.018)	(0.018)	(0.018)
ATO	0.003	0.003	0.005**	0.004*	0.008	0.008	0.013**	0.008	-0.007	-0.008	0.006	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.007)	(0.007)	(0.006)	(0.007)	(0.009)	(0.009)	(0.008)	(0.009)
Log(land)	-0.001	-0.001			0.010***	0.010***			0.001	0.001		
	(0.001)	(0.001)			(0.003)	(0.003)			(0.004)	(0.004)		
Age	-0.000***	-0.002**	-0.000**	-0.001***	-0.001***	-0.003***	-0.000***	-0.002***	-0.001***	-0.002	-0.000**	0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Decoupled payments	0.005	0.005	-0.001	-0.009	0.019	0.020	0.037**	0.026*	0.028	0.027	0.075**	0.043
	(0.016)	(0.016)	(0.014)	(0.015)	(0.016)	(0.016)	(0.015)	(0.016)	(0.033)	(0.033)	(0.029)	(0.031)
Rural development payments	-0.015	-0.015	-0.011	-0.011	-0.000	-0.000	-0.001	-0.001	0.017	0.016	0.007	0.010
	(0.026)	(0.026)	(0.025)	(0.026)	(0.001)	(0.001)	(0.001)	(0.001)	(0.038)	(0.038)	(0.037)	(0.037)
Age^2		0.000*		0.000**		0.000*		0.000***		0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Land			0.000	0.000			0.000***	0.000***			-0.000***	-0.000***
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Land^2			-0.000	-0.000			-0.000***	-0.000***			0.000	0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	38,888	38,888	38,888	38,888	42,969	42,969	42,969	42,969	14,162	14,162	14,162	14,162

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 96 Average partial effects (APE) of the robustness check for age squared and land squared for adaptation of farms from Southern Europe.

	ACP				Livestock				Mixed			
	Original	Age^2	Land^2	Age^2 Land^2	Original	Age^2	Land^2	Age^2 Land^2	Original	Age^2	Land^2	Age^{2}Land^2
ROA	-0.030***	-0.030***	-0.030***	-0.031***	0.002	0.001	0.002	0.002	-0.049*	-0.050*	-0.052*	-0.053*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.011)	(0.011)	(0.011)	(0.011)	(0.028)	(0.028)	(0.028)	(0.028)
ATO	0.017***	0.017***	0.017***	0.017***	0.011	0.011	0.012*	0.012	0.014	0.014	0.025*	0.018
	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)	(0.007)	(0.015)	(0.015)	(0.015)	(0.015)
Log(land)	0.002	0.002			0.000	0.000			0.002	0.002		
	(0.001)	(0.001)			(0.002)	(0.002)			(0.004)	(0.004)		
Age	0.000	-0.001*	-0.000***	-0.001***	-0.000	-0.001**	-0.000	-0.001*	-0.000	-0.002	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.001)
Decoupled payments	-0.002	-0.002	-0.001	-0.001	0.012	0.012	0.016**	0.014*	-0.018	-0.018	-0.011	-0.017
	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)	(0.008)	(0.019)	(0.019)	(0.020)	(0.020)
Rural development payments	0.011	0.011	0.011	0.012	0.001	0.002	0.001	0.001	0.027	0.026	0.036	0.030
	(0.008)	(0.008)	(0.008)	(0.008)	(0.012)	(0.012)	(0.012)	(0.012)	(0.036)	(0.036)	(0.037)	(0.037)
Age^2		0.000*		0.000***		0.000**		0.000		0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Land			-0.000***	-0.000***			0.000**	0.000**			-0.000***	-0.000***
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Land^2			0.000***	0.000***			-0.000	-0.000			0.000***	0.000***
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	54,105	54,105	54,105	54,105	23,369	23,369	23,369	23,369	3,920	3,920	3,920	3,920

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 97 Average partial effects (APE) of the robustness check for age squared and land squared for adaptation of farms from Northern Europe.

	ACP				Livestock				Mixed			
	Original	Age^2	Land^2	Age^{2}Land^2	Original	Age^2	Land^2	Age^2 Land^2	Original	Age^2	Land^2	Age^{2}Land^2
ROA	-0.036	-0.033	-0.018	-0.018	-0.088*	-0.083	-0.087	-0.086	-0.230**	-0.232**	-0.240**	-0.240**
	(0.067)	(0.066)	(0.071)	(0.069)	(0.053)	(0.053)	(0.053)	(0.053)	(0.111)	(0.110)	(0.112)	(0.110)
ATO	-0.038	-0.045	-0.015	-0.039	0.028	0.027	0.031	0.034	0.013	0.008	0.081	0.040
	(0.040)	(0.040)	(0.040)	(0.040)	(0.033)	(0.033)	(0.031)	(0.033)	(0.123)	(0.125)	(0.107)	(0.119)
Log(land)	-0.039***	-0.037***			-0.005	-0.003			0.017	0.016		
	(0.015)	(0.014)			(0.010)	(0.010)			(0.021)	(0.022)		
Age	-0.005***	-0.020**	-0.001**	-0.008*	-0.001	-0.012***	-0.001**	-0.006***	-0.003*	-0.009	-0.000	-0.003
	(0.002)	(0.010)	(0.001)	(0.005)	(0.001)	(0.004)	(0.000)	(0.002)	(0.002)	(0.013)	(0.001)	(0.007)
Decoupled	0.066	0.071	0.069	0.050	0.249***	0.245***	0.252***	0.254***	0.259	0.237	0.290	0.234
payments	(0.066)	(0.065)	(0.068)	(0.068)	(0.086)	(0.086)	(0.085)	(0.085)	(0.203)	(0.206)	(0.204)	(0.206)
Rural	-0.053	-0.074	-0.081	-0.080	-0.076	-0.082	-0.069	-0.071	0.124	0.134	0.115	0.154
development	(0.092)	(0.092)	(0.098)	(0.097)	(0.069)	(0.068)	(0.069)	(0.068)	(0.308)	(0.309)	(0.293)	(0.292)
payments												
Age^2		0.000		0.000		0.000**		0.000**		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Land			-0.000	-0.000			0.000	0.000			0.000	0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Land^2			0.000**	0.000*			-0.000**	-0.000**			-0.000	-0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Country[1]	No	No	No	No	No	No	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,132	1,132	1,132	1,132	3,601	3,601	3,601	3,601	437	437	437	437

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 98 Average partial effects (APE) of the robustness check for age squared and land squared for adaptation of farms from Eastern Europe.

	ACP				Livestock				Mixed			
	Original	Age²	Land²	Age² Land²	Original	Age²	Land²	Age² Land²	Original	Age²	Land²	Age²Land²
ROA	-0.080***	-0.079***	-0.085***	-0.082***	0.005	0.004	0.009	0.009	0.005	0.006	-0.005	-0.001
	(0.020)	(0.020)	(0.020)	(0.020)	(0.024)	(0.024)	(0.024)	(0.024)	(0.021)	(0.021)	(0.021)	(0.021)
ATO	0.059***	0.058***	0.071***	0.061***	0.012	0.010	0.029	0.012	-0.000	-0.003	0.033**	0.012
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.019)	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)
Log(land)	0.004	0.004			0.009	0.010*			0.006*	0.007*		
	(0.003)	(0.003)			(0.006)	(0.006)			(0.003)	(0.003)		
Age	-0.001***	0.001	-0.000	-0.002**	-0.001***	-0.007***	-0.000**	-0.005***	-0.001***	-0.004***	-0.000	-0.004***
	(0.000)	(0.002)	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Decoupled payments	0.007	0.008	0.015	0.008	0.087***	0.082**	0.125***	0.098***	0.117***	0.114***	0.155***	0.125***
	(0.023)	(0.023)	(0.023)	(0.022)	(0.032)	(0.032)	(0.032)	(0.032)	(0.027)	(0.027)	(0.026)	(0.027)
Rural development payments	0.025	0.024	0.027*	0.024	-0.033*	-0.032*	-0.032*	-0.035**	0.012	0.011	0.018	0.010
	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)	(0.013)	(0.013)	(0.013)	(0.013)
Age²		-0.000		0.000		0.000***		0.000***		0.000**		0.000***
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Land			0.000	-0.000			0.000***	0.000***			-0.000	-0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Land²			-0.000**	-0.000**							-0.000	-0.000
			(0.000)	(0.000)							(0.000)	(0.000)
Country[1]	No	No	No	No	No	No	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15,898	15,898	15,898	15,898	19,543	19,543	19,543	19,543	21,459	21,459	21,459	21,459

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.5.3 Robustness checks based on squared relationships of land and age for farm transformation

Section 4.5.3 presents the robustness checks that add squared terms of age and land to the model for farm transformation. Including age and land squared resulted in three alternative model specifications. The following variables were added to the original model: (i) age squared, (ii) land squared, (iii) land and age squared. These findings are presented in Table A.99-102.

Table A 99Average partial effects (APE) of the robustness check for age squared and land squared for transformation of farms from Western Europe.

	ACP				Livestock				Mixed			
	Original	Age^2	Land^2	Age^2 Land^2	Original	Age^2	Land^2	Age^2 Land^2	Original	Age^2	Land^2	Age^{2}Land^2
ROA	0.013	0.013	0.009	0.009	-0.051	-0.051	-0.053	-0.053*	-0.127	-0.127	-0.128	-0.126
	(0.017)	(0.017)	(0.016)	(0.016)	(0.032)	(0.032)	(0.032)	(0.032)	(0.079)	(0.079)	(0.079)	(0.079)
ATO	-0.013	-0.013	-0.013*	-0.011	-0.010	-0.010	-0.002	-0.007	-0.015	-0.015	-0.007	-0.008
	(0.008)	(0.008)	(0.008)	(0.008)	(0.017)	(0.017)	(0.016)	(0.017)	(0.037)	(0.037)	(0.035)	(0.037)
Log(land)	-0.007*	-0.007*			-0.000	-0.000			0.004	0.004		
	(0.004)	(0.004)			(0.007)	(0.007)			(0.017)	(0.017)		
Age	-0.000	-0.001	-0.001***	-0.002**	-0.000	-0.002	0.000	0.000	-0.000	0.002	-0.000	0.006*
	(0.000)	(0.002)	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)	(0.001)	(0.001)	(0.006)	(0.001)	(0.004)
Decoupled payments	0.273***	0.272***	0.230***	0.241***	0.026	0.027	0.036	0.027	-0.032	-0.031	0.004	-0.003
	(0.045)	(0.045)	(0.039)	(0.041)	(0.036)	(0.036)	(0.035)	(0.036)	(0.140)	(0.140)	(0.131)	(0.138)
Rural development payments	-0.064	-0.065	-0.054	-0.054	0.049***	0.048***	0.048***	0.048***	-0.103	-0.100	-0.119	-0.112
	(0.056)	(0.056)	(0.056)	(0.056)	(0.017)	(0.017)	(0.017)	(0.017)	(0.183)	(0.183)	(0.182)	(0.183)
Age^2		0.000		0.000		0.000		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Land			-0.000**	-0.000**			0.000***	0.000***			-0.000***	-0.000***
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Land^2			0.000	0.000			-0.000*	-0.000			0.000**	0.000**
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	38,888	38,888	38,888	38,888	42,969	42,969	42,969	42,969	14,162	14,162	14,162	14,162

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 100 Average partial effects (APE) of the robustness check for age squared and land squared for transformation of farms from Southern Europe.

	ACP				Livestock				Mixed			
	Original	Age^2	Land^2	Age^2 Land^2	Original	Age^2	Land^2	Age^2 Land^2	Original	Age^2	Land^2	Age^{2}Land^2
ROA	-0.020	-0.020	-0.020	-0.020	0.025	0.025	0.029	0.026	-0.090	-0.080	-0.071	-0.071
	(0.018)	(0.018)	(0.018)	(0.018)	(0.039)	(0.039)	(0.039)	(0.040)	(0.171)	(0.172)	(0.174)	(0.172)
ATO	-0.008	-0.008	-0.008	-0.008	-0.019	-0.019	-0.036	-0.022	-0.156	-0.160	-0.170	-0.166
	(0.011)	(0.011)	(0.011)	(0.011)	(0.027)	(0.027)	(0.027)	(0.027)	(0.111)	(0.112)	(0.113)	(0.112)
Log(land)	0.018***	0.018***			0.002	0.002			-0.007	-0.008		
	(0.003)	(0.003)			(0.004)	(0.004)			(0.021)	(0.021)		
Age	-0.001**	0.001	-0.001***	-0.001	0.000	-0.001	-0.001***	-0.002	0.000	0.016*	0.000	0.008
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)	(0.001)	(0.002)	(0.009)	(0.001)	(0.005)
Decoupled	-0.005	-0.005	-0.005	-0.004	-0.004	-0.004	-0.014	-0.006	0.134	0.132	0.122	0.118
payments	(0.013)	(0.013)	(0.013)	(0.013)	(0.024)	(0.024)	(0.020)	(0.023)	(0.107)	(0.107)	(0.106)	(0.107)
Rural	0.065***	0.065***	0.067***	0.068***	0.067**	0.067**	0.049	0.062*	0.002	0.006	0.008	0.004
development payments	(0.025)	(0.025)	(0.025)	(0.025)	(0.033)	(0.033)	(0.033)	(0.033)	(0.208)	(0.208)	(0.206)	(0.207)
Age^2		-0.000		0.000		0.000		0.000		-0.000*		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Land			0.000***	0.000***			0.000***	0.000***			-0.000	-0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Land^2			-0.000***	-0.000***			-0.000	-0.000			0.000	0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Country[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	54,105	54,105	54,105	54,105	23,369	23,369	23,369	23,369	3,920	3,920	3,920	3,920

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 101 Average partial effects (APE) of the robustness check for age squared and land squared for transformation of farms from Northern Europe.

	ACP				Livestock				Mixed			
	Original	Age^2	Land^2	Age^{2}Land^2	Original	Age^2	Land^2	Age^2 Land^2	Original	Age^2	Land^2	Age^{2}Land^2
ROA	0.031	0.030	0.028	0.036	-0.049	-0.058	-0.054	-0.036	-0.388	-0.396	-0.550	-0.575
	(0.194)	(0.193)	(0.198)	(0.188)	(0.143)	(0.143)	(0.143)	(0.143)	(0.608)	(0.598)	(0.592)	(0.585)
ATO	-0.060	-0.061	0.002	-0.019	-0.244**	-0.238**	-0.227**	-0.280***	-0.002	-0.011	-0.124	-0.095
	(0.105)	(0.106)	(0.094)	(0.100)	(0.107)	(0.107)	(0.102)	(0.108)	(0.361)	(0.380)	(0.335)	(0.340)
Log(land)	-0.052*	-0.054**			-0.030	-0.034			0.026	0.035		
	(0.027)	(0.027)			(0.028)	(0.029)			(0.105)	(0.106)		
Age	-0.003	0.004	-0.002	0.004	-0.004	0.016	-0.001	0.007	0.003	-0.056**	-0.003	-0.050**
	(0.004)	(0.010)	(0.002)	(0.010)	(0.002)	(0.014)	(0.001)	(0.006)	(0.004)	(0.022)	(0.003)	(0.020)
Decoupled	0.060	0.061	0.042	0.038	0.393*	0.406*	0.387*	0.365*	1.248*	1.084	1.323*	1.184*
payments	(0.207)	(0.205)	(0.204)	(0.199)	(0.211)	(0.209)	(0.210)	(0.211)	(0.734)	(0.734)	(0.699)	(0.709)
Rural	-0.090	-0.080	-0.083	-0.049	-0.138	-0.131	-0.126	-0.150	0.113	0.214	-0.061	0.074
development payments	(0.226)	(0.226)	(0.229)	(0.222)	(0.194)	(0.192)	(0.194)	(0.194)	(0.975)	(1.000)	(0.945)	(0.966)
Age^2		-0.000		-0.000		-0.000		-0.000		0.001***		0.000**
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Land			0.000	0.000			0.000***	0.000***			0.001**	0.001
			(0.000)	(0.000)			(0.000)	(0.000)			(0.001)	(0.001)
Land^2			-0.000	-0.000			-0.000*	-0.000**			-0.000	-0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Country[1]	No	No	No	No	No	No	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,132	1,132	1,132	1,132	3,601	3,601	3,601	3,601	437	437	437	437

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 102 Average partial effects (APE) of the robustness check for age squared and land squared for transformation of farms from Eastern Europe.

	ACP				Livestock				Mixed			
	Original	Age^2	$Land^2$	Age^2 $Land^2$	Original	Age^2	$Land^2$	Age^2 $Land^2$	Original	Age^2	$Land^2$	$Age^2 Land^2$
ROA	0.090	0.089	0.095	0.092	0.044	0.047	0.044	0.046	-0.068	-0.065	-0.086	-0.085
	(0.072)	(0.072)	(0.072)	(0.072)	(0.069)	(0.069)	(0.070)	(0.070)	(0.084)	(0.084)	(0.085)	(0.085)
ATO	-0.134**	-0.134**	-0.132**	-0.120**	-0.136***	-0.138***	-0.139***	-0.144***	0.054	0.052	0.123**	0.092
	(0.057)	(0.057)	(0.056)	(0.057)	(0.051)	(0.051)	(0.049)	(0.051)	(0.065)	(0.065)	(0.062)	(0.064)
Log(land)	-0.008	-0.009			-0.015	-0.015			0.025**	0.025**		
	(0.010)	(0.010)			(0.014)	(0.014)			(0.012)	(0.012)		
Age	0.000	-0.003	-0.001	-0.004	-0.000	0.001	-0.000	-0.003	-0.001	-0.006	0.000	-0.001
	(0.001)	(0.006)	(0.001)	(0.003)	(0.001)	(0.005)	(0.000)	(0.003)	(0.001)	(0.005)	(0.001)	(0.003)
Decoupled payments	0.006	0.005	0.009	0.015	0.110	0.113	0.114	0.106	-0.033	0.000		0.000
	(0.071)	(0.071)	(0.069)	(0.070)	(0.086)	(0.086)	(0.084)	(0.086)	(0.114)	(0.000)		(0.000)
Rural development payments	-0.097	-0.097	-0.109*	-0.103*	-0.059	-0.060	-0.058	-0.058	0.010	-0.032	0.031	-0.012
	(0.060)	(0.060)	(0.059)	(0.060)	(0.050)	(0.050)	(0.051)	(0.050)	(0.054)	(0.114)	(0.108)	(0.112)
Age^2		0.000		0.000		-0.000		0.000		0.007	0.023	0.012
		(0.000)		(0.000)		(0.000)		(0.000)		(0.054)	(0.054)	(0.054)
Land			-0.001***	-0.001***			-0.000**	-0.000**			0.000***	0.000***
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
$Land^2$			0.000***	0.000***			-0.000	-0.000			-0.000	-0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
Country[1]	No	No	No	No	No	No	No	No	No	No	No	No
Farm type[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CRE parameters[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15,898	15,898	15,898	15,898	19,543	19,543	19,543	19,543	21,459	21,459	21,459	21,459

Notes: ACP = arable, crop, and perennial farms; ROA = rate of return on assets; ATO = asset turnover. [1] Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)). [2] Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8-farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms). [3] Year indicates if year dummies are included in the model (Yes) or not (No). [4] CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No). The presented standard errors are robust to general second-moment misspecification (i.e. conditional variance and serial correlation).
[*] $p < 0.10$, [**] $p < 0.05$, [***] $p < 0.01$.

5. Seemingly unrelated estimation

To test if the estimated parameters are statistically different or equal across regions (i.e. Northern, Western, Southern, and Eastern European countries), we estimated the models using seemingly unrelated estimation. A robust Hausman test is used to determine if the parameter estimates are different or equal across regions. In Table A103-111, "All variables" refers to a test if all variables are jointly significantly different from other regions. The findings imply that most of the estimated parameters are significantly different across different regions, indicating that addressing spatial heterogeneity is important.

Table A 103 Chi-square statistics of the Hausman test based on seemingly unrelated estimation for robustness of ACP farms

	All regions jointly	West vs South	West vs North	West vs East	South vs North	South vs East	North vs East
All variables	4024.864***	1485.178***	215.753***	1751.524***	296.228***	2798.826***	510.673***
ROA	138.906***	37.090***	1.719	113.297***	0.745	56.808***	0.179
ATO	499.391***	52.977***	1.346	406.126***	4.268**	497.543***	21.695***
Log(land)	74.133***	68.211***	2.850*	24.807***	0.002	0.154	0.007
Age	3.619	0.000	3.532*	0.031	3.558*	0.039	3.577*
Decoupled payments	279.756***	263.896***	0.448	16.409***	19.104***	30.381***	1.992
Rural development payments	153.701***	41.625***	1.087	0.006	17.908***	115.152***	1.330
All variables df[1]	129	43	43	43	43	43	43
Single variable df[2]	3	1	1	1	1	1	1

[1] Refers to the degrees of freedom for the Chi-square statistic for the test if the parameter estimates of all variables are jointly equal to each across models. [2] Refers to the degrees of freedom for the Chi-square for the test if the parameter estimates of a specific variable is equal across models. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 104 Chi-square statistics of the Hausman test based on seemingly unrelated estimation for robustness of livestock farms

	All regions jointly	West vs South	West vs North	West vs East	South vs North	South vs East	North vs East
All variables	4294.556***	1253.698***	441.95***	1876.898***	371.932***	2894.009***	1253.502***
ROA	99.184***	86.911***	2.856*	0.863	40.714***	25.605***	4.102**
ATO	67.185***	16.327***	43.753***	0.967	65.687***	10.63***	20.714***
Log(land)	21.178***	7.862***	0.063	5.678**	1.209	16.016***	1.066
Age	28.961***	0.619	1.27	27.035***	0.783	20.218***	0.748
Decoupled payments	648.475***	177.209***	14.838***	270.293***	58.014***	564.582***	19.567***
Rural development payments	264.122***	8.095***	0.305	255.89***	0.224	86.206***	25.346***
All variables df[1]	123	44	44	44	44	44	44
Single variable df[2]	3	1	1	1	1	1	1

[1] Refers to the degrees of freedom for the Chi-square statistic for the test if the parameter estimates of all variables are jointly equal to each across models. [2] Refers to the degrees of freedom for the Chi-square for the test if the parameter estimates of a specific variable is equal across models. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 105 Chi-square statistics of the Hausman test based on seemingly unrelated estimation for robustness of mixed farms

	All regions jointly	West vs South	West vs North	West vs East	South vs North	South vs East	North vs East
All variables	2293.563***	315.670***	207.019***	1646.895***	183.668***	1081.333***	427.399***
ROA	72.959***	10.584***	3.011*	63.276***	8.658***	1.973	14.224***
ATO	302.583***	33.952***	7.990***	282.232***	0.330	21.804***	13.372***
Log(land)	13.146***	5.837**	1.888	11.508***	0.466	0.559	0.225
Age	8.604**	3.233*	3.046*	0.545	1.398	5.525**	3.613*
Decoupled payments	181.791***	67.094***	7.721***	4.929**	0.610	160.281***	11.486***
Rural development payments	43.056***	0.002	1.925	21.583***	1.880	21.216***	6.143**
All variables df[1]	144	48	48	48	48	48	48
Single variable df[2]	3	1	1	1	1	1	1

[1] Refers to the degrees of freedom for the Chi-square statistic for the test if the parameter estimates of all variables are jointly equal to each across models. [2] Refers to the degrees of freedom for the Chi-square for the test if the parameter estimates of a specific variable is equal across models. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 106 Chi-square statistics of the Hausman test based on seemingly unrelated estimation for adaptation of ACP farms

	All regions jointly	West vs South	West vs North	West vs East	South vs North	South vs East	North vs East
All variables	1133.941***	1064.325***	183.160***	239.169***	258.721***	750.216***	209.163***
ROA	6.680*	1.196	0.138	6.052**	0.315	3.516*	1.405
ATO	28.177***	15.379***	1.523	12.847***	3.453*	4.423**	6.852***
Log(land)	9.551**	1.269	6.325**	1.906	7.481***	0.453	8.132***
Age	23.607***	11.895***	6.071**	0.132	8.636***	6.838***	5.533**
Decoupled payments	1.481	0.336	0.480	0.000	0.912	0.321	0.465
Rural development payments	2.381	1.515	0.125	1.463	0.818	0.012	0.845
All variables df[1]	165	55	55	55	55	55	55
Single variable df[2]	3	1	1	1	1	1	1

[1] Refers to the degrees of freedom for the Chi-square statistic for the test if the parameter estimates of all variables are jointly equal to each across models. [2] Refers to the degrees of freedom for the Chi-square for the test if the parameter estimates of a specific variable is equal across models. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 107 Chi-square statistics of the Hausman test based on seemingly unrelated estimation for adaptation of livestock farms

	All regions jointly	West vs South	West vs North	West vs East	South vs North	South vs East	North vs East
All variables	756.600***	315.928***	146.756***	209.896***	201.067***	357.757***	203.994***
ROA	6.922*	3.939**	0.473	3.660*	2.278	0.031	2.415
ATO	1.216	0.985	0.353	0.054	0.037	0.276	0.205
Log(land)	7.391*	6.112**	2.039	0.168	0.169	1.839	1.198
Age	9.895**	6.259**	0.026	0.240	1.125	7.320***	0.002
Decoupled payments	10.509**	0.009	6.428**	3.222*	6.704***	4.065**	3.137*
Rural development payments	4.907	0.109	1.156	3.638*	1.265	2.236	0.391
All variables df[1]	168	56	56	56	56	56	56
Single variable df[2]	3	1	1	1	1	1	1

[1] Refers to the degrees of freedom for the Chi-square statistic for the test if the parameter estimates of all variables are jointly equal to each across models. [2] Refers to the degrees of freedom for the Chi-square for the test if the parameter estimates of a specific variable is equal across models. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 108 Chi-square statistics of the Hausman test based on seemingly unrelated estimation for adaptation of mixed farms

	All regions jointly	West vs South	West vs North	West vs East	South vs North	South vs East	North vs East
All variables	1417.146***	248.706***	668.022***	204.218***	442.491***	232.907***	742.918***
ROA	3.954	0.983	2.978*	0.000	1.470	0.968	2.968*
ATO	2.130	0.705	0.093	1.760	0.010	0.021	0.003
Log(land)	0.355	0.097	0.091	0.310	0.034	0.014	0.023
Age	4.221	0.502	2.453	1.226	2.990*	0.004	3.093*
Decoupled payments	11.310**	1.562	0.575	2.193	1.159	10.733***	0.155
Rural development payments	0.226	0.074	0.162	0.016	0.111	0.057	0.149
All variables df[1]	162	54	54	54	54	54	54
Single variable df[2]	3	1	1	1	1	1	1

[1] Refers to the degrees of freedom for the Chi-square statistic for the test if the parameter estimates of all variables are jointly equal to each across models. [2] Refers to the degrees of freedom for the Chi-square for the test if the parameter estimates of a specific variable is equal across models. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 109 Chi-square statistics of the Hausman test based on seemingly unrelated estimation for transformation of arable farms

	All regions jointly	West vs South	West vs North	West vs East	South vs North	South vs East	North vs East
All variables	856.465***	245.378***	196.922***	342.207***	188.938***	476.715***	186.598***
ROA	8.099**	2.490	0.028	3.187*	0.145	6.917***	0.095
ATO	10.191**	0.183	0.302	9.069***	0.364	9.874***	0.285
Log(land)	33.698***	24.178***	2.943*	0.415	7.378***	8.979***	3.522*
Age	2.335	0.288	0.750	0.399	0.640	1.512	0.962
Decoupled payments	44.616***	43.802***	1.338	16.912***	0.429	1.347	0.112
Rural development payments	17.121***	7.532***	0.002	0.198	0.761	11.953***	0.037
All variables df[1]	165	55	55	55	55	55	55
Single variable df[2]	3	1	1	1	1	1	1

[1] Refers to the degrees of freedom for the Chi-square statistic for the test if the parameter estimates of all variables are jointly equal to each across models. [2] Refers to the degrees of freedom for the Chi-square for the test if the parameter estimates of a specific variable is equal across models. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 110 Chi-square statistics of the Hausman test based on seemingly unrelated estimation for transformation of livestock farms

	All regions jointly	West vs South	West vs North	West vs East	South vs North	South vs East	North vs East
All variables	888.762***	270.866***	142.896***	516.045***	159.232***	323.506***	247.904***
ROA	4.163	3.646*	0.030	1.833	0.380	0.093	0.207
ATO	7.896**	0.326	5.279**	3.278*	4.206**	1.430	2.109
Log(land)	3.232	0.522	0.818	0.518	1.378	1.895	0.286
Age	2.692	0.110	2.343	0.005	2.649	0.128	2.205
Decoupled payments	5.116	0.469	3.308*	0.267	4.043**	1.063	2.442
Rural development payments	6.249	0.794	0.693	3.974**	1.033	5.254**	0.114
All variables df[1]	168	56	56	56	56	56	56
Single variable df[2]	3	1	1	1	1	1	1

[1] Refers to the degrees of freedom for the Chi-square statistic for the test if the parameter estimates of all variables are jointly equal to each across models. [2] Refers to the degrees of freedom for the Chi-square for the test if the parameter estimates of a specific variable is equal across models. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A 111 Chi-square statistics of the Hausman test based on seemingly unrelated estimation for transformation of mixed farms

	All regions jointly	West vs South	West vs North	West vs East	South vs North	South vs East	North vs East
All variables	7866.460***	133.916***	6565.062***	395.895***	6215.676***	117.917***	7036.578***
ROA	0.941	0.103	0.189	0.660	0.273	0.136	0.417
ATO	1.406	1.191	0.000	0.433	0.107	0.130	0.039
Log(land)	4.369	0.415	0.043	1.600	0.135	4.196**	0.010
Age	2.185	0.119	1.246	0.314	0.938	0.746	1.740
Decoupled payments	5.547	0.189	3.002*	0.738	2.729*	2.462	4.060**
Rural development payments	0.310	0.281	0.019	0.264	0.001	0.022	0.000
All variables df[1]	162	54	54	54	54	54	54
Single variable df[2]	3	1	1	1	1	1	1

[1] Refers to the degrees of freedom for the Chi-square statistic for the test if the parameter estimates of all variables are jointly equal to each across models. [2] Refers to the degrees of freedom for the Chi-square for the test if the parameter estimates of a specific variable is equal across models. * $p < 0.10$, ** $p < 0.05$, *** $p <0.01$.

Appendix 4 Description of data sources and selected variables

Table A 1 Overview of the data sources used in this study

Data	Description	Source	Notes
Farm-level data	Dataset from the Farm Accountancy Data Network (FADN) consisting of accounting and farm-specific variables.	FADN (2018)	
Minimum wage	Minimum wage (EUR) per hour	Eurostat (2020a,b); SCB (2020)	Sweden and Italy do not have minimum wages. We used 10th percentile wage (Sweden) and income (Italy). Germany introduced minimum wages from 2015 onwards.
10-year government bond	Long-term interest rate (10 year government bond) %	ECB (2020)	
Farmgate prices	Yearly producer price indices (for period 2007-2013)	FAO (2020)	

Table A 2 Descriptive statistics. Standard deviations are presented in parentheses.

	Belgium	Bulgaria	France	Germany	Italy	The Netherlands	Poland	Romania	Spain	Sweden	United Kingdom	Total
N	6,209	3,062	35,411	33,582	40,684	5,692	58,923	3,781	40,142	4,928	10,820	243,234
STV	0.818	0.708	0.854	0.788	0.614	0.768	0.780	0.746	0.714	0.467	0.756	0.745
LTV	0.467	0.641	0.542	0.339	0.414	0.214	0.361	0.637	0.568	0.126	0.261	0.425
DDP (ST)	0.091	0.118	0.121	0.120	0.101	0.056	0.105	0.102	0.131	0.143	0.185	0.116
	(0.070)	(0.110)	(0.089)	(0.093)	(0.117)	(0.061)	(0.072)	(0.070)	(0.132)	(0.086)	(0.118)	(0.102)
DDP (LT)	0.090	0.105	0.117	0.121	0.099	0.051	0.093	0.090	0.121	0.140	0.193	0.110
	(0.066)	(0.090)	(0.083)	(0.091)	(0.109)	(0.056)	(0.060)	(0.061)	(0.115)	(0.080)	(0.119)	(0.094)
RDP (ST)	0.021	0.035	0.029	0.028	0.026	0.008	0.046	0.011	0.024	0.090	0.068	0.034
	(0.050)	(0.101)	(0.067)	(0.067)	(0.066)	(0.029)	(0.078)	(0.043)	(0.061)	(0.098)	(0.101)	(0.072)
RDP (LT)	0.020	0.028	0.030	0.029	0.026	0.008	0.048	0.010	0.023	0.090	0.071	0.034
	(0.044)	(0.079)	(0.065)	(0.066)	(0.058)	(0.026)	(0.070)	(0.034)	(0.050)	(0.094)	(0.100)	(0.066)
Land tenure	0.349	0.344	0.185	0.442	0.650	0.679	0.780	0.623	0.697	0.552	0.671	0.581
	(0.294)	(0.411)	(0.293)	(0.306)	(0.407)	(0.323)	(0.242)	(0.430)	(0.381)	(0.334)	(0.378)	(0.388)
Unpaid labour	0.901	0.381	0.811	0.812	0.850	0.791	0.915	0.692	0.834	0.888	0.777	0.841
	(0.215)	(0.380)	(0.262)	(0.264)	(0.247)	(0.272)	(0.183)	(0.398)	(0.234)	(0.214)	(0.268)	(0.252)
Size (100 ESU)	2.651	1.285	1.909	2.422	0.993	4.298	0.490	0.769	0.879	1.683	1.933	1.359
	(2.323)	(2.174)	(1.951)	(3.322)	(4.507)	(4.399)	(0.719)	(1.597)	(1.706)	(2.089)	(2.435)	(2.799)
Age	47.737	51.596	48.933	50.820	56.231	50.644	44.938	50.084	53.882	54.448	56.106	50.755
	(8.620)	(12.616)	(8.577)	(9.226)	(13.641)	(9.289)	(9.008)	(11.258)	(11.524)	(9.462)	(10.669)	(11.271)
Price volatility	0.106	0.136	0.103	0.138	0.102	0.129	0.143	0.097	0.098	0.102	0.124	0.118
	(0.073)	(0.065)	(0.086)	(0.081)	(0.073)	(0.076)	(0.094)	(0.072)	(0.063)	(0.083)	(0.080)	(0.083)
Price shock	0.043	0.048	0.037	0.051	0.036	0.054	0.038	0.043	0.040	0.037	0.019	0.040
	(0.076)	(0.079)	(0.073)	(0.100)	(0.075)	(0.093)	(0.075)	(0.053)	(0.074)	(0.073)	(0.050)	(0.078)
Diversification	0.395	0.372	0.363	0.420	0.349	0.226	0.531	0.489	0.283	0.459	0.457	0.402
	(0.263)	(0.245)	(0.247)	(0.229)	(0.254)	(0.223)	(0.204)	(0.248)	(0.229)	(0.179)	(0.202)	(0.247)
LFA	0.186	0.185	0.402	0.366	0.542	0.055	0.560	0.290	0.680	0.581	0.460	0.493
<u>Farm type</u>												
Fieldcrops	0.105	0.457	0.256	0.216	0.314	0.166	0.226	0.448	0.303	0.213	0.185	0.256
Horticulture	0.133	0.127	0.053	0.072	0.091	0.231	0.033	0.024	0.103	0.017	0.042	0.071
Wine	0.000	0.047	0.147	0.055	0.115	0.000	0.000	0.019	0.070	0.000	0.000	0.061
OPC	0.053	0.089	0.039	0.024	0.190	0.032	0.035	0.039	0.150	0.000	0.012	0.079
Dairy	0.204	0.128	0.149	0.227	0.104	0.342	0.210	0.074	0.117	0.360	0.187	0.172

OGL	0.218	0.082	0.183	0.072	0.116	0.063	0.023	0.140	0.170	0.222	0.443	0.124
Granivores	0.098	0.014	0.042	0.145	0.023	0.118	0.098	0.011	0.040	0.106	0.043	0.070
Mixed	0.188	0.056	0.131	0.188	0.049	0.048	0.373	0.245	0.048	0.083	0.089	0.168

Notes: STV = short-term viability; LTV = long-term viability; DDP (ST) = short-term decoupled direct payments; DDP (LT) = long-term decoupled direct payments; RDP (ST) = short-term rural development payments; RDP (LT) = long-term rural development payments; LFA = less favoured area; OPC = other permanent crops, OGL = other grazing livestock. STV, LTV, and LFA are dummy variables; therefore, only means are presented.

Validity instrumental variables

This appendix presents the outcomes of the Kleibergen-Paap rk LM test and Hausman test in Table A3. Table A4-A7 present the first-stage regression estimates, including the change in R^2.

Table A 3 Endogeneity and validity tests for potential endogenous variables

	Belgium	Bulgaria	France	Germany	Italy	The Netherlands	Poland	Romania	Spain	Sweden	United Kingdom
Short-term viability											
Instrument validity											
Kleibergen-Paap rk LM-statistic	174.3***	47.05***	895.5***	723.7***	971.2***		1094.1***	155.3***	1359.4***	91.17***	496.2***
Hausman test for endogeneity											
Residuals DDP	-5.939***	-5.151***	-6.201***	-4.869***	-2.153***	-0.919	-9.969***	-8.107***	-2.219***	-1.864**	-7.097***
	(1.127)	(0.797)	(0.385)	(0.361)	(0.148)	(0.968)	(0.359)	(1.072)	(0.148)	(0.814)	(0.602)
Residuals RDP	1.689	5.695***	0.804*	1.344***	-0.003	1.338	5.069***	-0.267	0.110	1.009	1.322**
	(1.279)	(0.942)	(0.457)	(0.434)	(0.219)	(1.442)	(0.272)	(1.731)	(0.322)	(0.688)	(0.577)
Endogenous variables	DDP	DDP, RDP	DDP	DDP, RDP	DDP		DDP, RDP	DDP	DDP	DDP	DDP, RDP
Long-term viability											
Instrument validity											
Kleibergen-Paap rk LM-statistic	203.1***	62.33***	1230.4***	802.5***	975.0***		1527.4***	153.3***	1465.0***	86.19***	513.7***
Hausman test for endogeneity											
Residuals DDP	-18.604***	-5.491***	-8.577***	-15.938***	-6.879***	-2.109	-33.734***	-23.658***	-3.306***	-13.443***	-15.163***
	(2.454)	(1.146)	(0.728)	(0.848)	(0.365)	(2.497)	(0.922)	(3.088)	(0.251)	(2.812)	(1.425)
Residuals RDP	2.495	3.593***	-0.393	4.129***	0.736	-5.944	5.997***	2.108	-0.353	5.389**	6.713***
	(2.902)	(0.864)	(1.101)	(1.258)	(0.480)	(3.651)	(0.448)	(2.498)	(0.458)	(2.302)	(1.451)
Endogenous variables	DDP	DDP, RDP	DDP	DDP, RDP	DDP		DDP, RDP	DDP	DDP	DDP, RDP	DDP, RDP

Notes: DDP = decoupled direct payments; RDP = rural development payments. Standard errors are presented in parentheses. The Hausman test tests for endogeneity by including the residuals of the first-stage regressions in the second stage model. If the residuals are significant, we treat the corresponding variable as endogenous. For the Netherlands, no Kleibergen-Paap rk LM-statistics are presented for both short and long-term viability as there are no endogenous variables. For short-term viability in France, the p-value of the Hausman test for RDP is between 0.05 and 0.10. We treated RDP as exogenous as the p-value is below 0.10. Treating RDP as endogenous does not change the results of the dynamic correlated random effects probit model. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table A 4 Parameter estimates of the first-stage pooled OLS regression for short-term viability with decoupled direct payments as dependent variable

	Belgium	Bulgaria	France	Germany	Italy	Poland	Romania	Spain	Sweden	United Kingdom
DDP at *t-1*	0.852***	0.571***	0.817***	0.808***	0.787***	0.826***	0.817***	0.683***	0.654***	0.797***
	(0.019)	(0.033)	(0.008)	(0.007)	(0.007)	(0.009)	(0.024)	(0.007)	(0.024)	(0.009)
RDP	0.148***		0.564***		0.150***		0.101***	0.355***	0.512***	
	(0.037)		(0.050)		(0.018)		(0.036)	(0.023)	(0.045)	
RDP at *t-1*		0.072**		0.088***		0.039***				0.026***
		(0.029)		(0.007)		(0.004)				(0.008)
Land tenure	-0.001	-0.057***	-0.002	-0.002	0.006	-0.025***	-0.025***	0.012***	0.004	0.010
	(0.003)	(0.014)	(0.004)	(0.002)	(0.004)	(0.003)	(0.009)	(0.005)	(0.008)	(0.007)
Unpaid labour	0.005	0.006	0.003	0.000	0.020***	0.029***	0.019*	0.038***	-0.007	0.009
	(0.006)	(0.014)	(0.002)	(0.004)	(0.004)	(0.004)	(0.010)	(0.004)	(0.010)	(0.006)
Size	0.000	0.006***	0.000	-0.000*	-0.000	-0.003**	0.005**	-0.001**	0.001***	-0.001**
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)
Age	0.000	-0.001	0.000	0.000	0.000	0.000**	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Price volatility	-0.029***	0.023	-0.033***	-0.001	-0.025***	-0.028***	0.048***	-0.082***	-0.044***	-0.010
	(0.007)	(0.056)	(0.004)	(0.004)	(0.008)	(0.003)	(0.014)	(0.010)	(0.016)	(0.009)
Price shock	0.055***	0.088***	0.139***	0.055***	0.032***	0.091***	0.007	0.097***	0.194***	0.161***
	(0.005)	(0.025)	(0.003)	(0.003)	(0.006)	(0.003)	(0.015)	(0.007)	(0.015)	(0.014)
Diversification	0.026**	-0.048**	0.004	0.024***	0.009*	-0.035***	0.005	-0.021***	0.006	-0.013
	(0.012)	(0.021)	(0.005)	(0.006)	(0.005)	(0.003)	(0.016)	(0.006)	(0.011)	(0.009)
LFA	-0.003***	0.016***	0.001***	0.002***	-0.000	0.005***	0.001	-0.002*	-0.008***	0.005***
	(0.001)	(0.004)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)
Constant	0.009**	0.026**	-0.003	0.001	0.001	-0.005***	0.012**	0.024***	0.021***	0.014***
	(0.004)	(0.011)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.004)	(0.007)	(0.004)
Farm type					Included, for all countries					
Year					Included, for all countries					
c_i					Included, for all countries					
Endogenous variables	DDP	DDP, RDP	DDP	DDP, RDP	DDP	DDP, RDP	DDP	DDP	DDP	DDP, RDP
R^2 without IVs	0.681	0.365	0.645	0.679	0.338	0.527	0.421	0.343	0.622	0.699
R^2 including IVs	0.908	0.552	0.889	0.884	0.753	0.766	0.784	0.642	0.802	0.885

Notes: DDP = decoupled direct payments; RDP = rural development payments; LFA = less favoured area. c_i refers to unobserved heterogeneity. Standard errors are presented in parentheses. DDP at *t-1* is used as instrument for DDP. R^2 without IVs refers to the first-stage regression excluding IVs, R^2 including IVs refers to first-stage regression including IVs. The Netherlands is missing because DDP is considered to be exogenous. For countries with both DDP and RDP as endogenous variables, RDP at *t-1* is included in the first-stage regression. For countries with only DDP as endogenous variable, we include RDP in the first-stage regression. **p* < 0.10, ***p* < 0.05, ****p* < 0.01.

Table A 5 Parameter estimates of the first-stage pooled OLS regression for short-term viability with rural development payments as dependent variable

	Bulgaria	Germany	Poland	United Kingdom
DDP at *t-1*	0.120***	0.015***	0.253***	-0.000
	(0.031)	(0.005)	(0.012)	(0.009)
RDP at *t-1*	0.438***	0.890***	0.504***	0.845***
	(0.054)	(0.008)	(0.011)	(0.010)
Land tenure	-0.023	-0.000	0.013***	0.000
	(0.018)	(0.001)	(0.004)	(0.007)
Unpaid labour	-0.014	-0.005*	0.012***	-0.004
	(0.013)	(0.003)	(0.004)	(0.006)
Size	-0.003	0.000	0.001	-0.000*
	(0.002)	(0.000)	(0.001)	(0.000)
Age	-0.000	-0.000**	-0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Price volatility	0.013	0.007**	-0.002	0.018*
	(0.045)	(0.003)	(0.004)	(0.009)
Price shock	-0.002	0.018***	0.026***	0.088***
	(0.033)	(0.002)	(0.004)	(0.013)
Diversification	-0.007	-0.000	-0.010**	-0.033***
	(0.019)	(0.004)	(0.004)	(0.008)
LFA	0.047***	0.004***	0.019***	0.004***
	(0.006)	(0.000)	(0.001)	(0.001)
Constant	0.030**	0.001	-0.017***	0.024***
	(0.014)	(0.001)	(0.003)	(0.004)
Farm type	Included, for all countries			
Year	Included, for all countries			
c_i	Included, for all countries			
Endogenous variables	DDP, RDP	DDP, RDP	DDP, RDP	DDP, RDP
R^2 without IVs	0.195	0.451	0.348	0.501
R^2 including IVs	0.305	0.873	0.505	0.838

Notes: DDP = decoupled direct payments; RDP = rural development payments; LFA = less favoured area. c_i refers to unobserved heterogeneity. Standard errors are presented in parentheses. RDP at *t-1* is used as instrument for RDP. R^2 without IVs refers to the first-stage regression excluding IVs, R^2 including IVs refers to first-stage regression including IVs. Only these countries included where DDP and RDP both considered endogenous. **p* < 0.10, ***p* < 0.05, ****p* < 0.01.

Table A 6 Parameter estimates of the first-stage pooled OLS regression for long-term viability with decoupled direct payments as dependent variable

	Belgium	Bulgaria	France	Germany	Italy	Poland	Romania	Spain	Sweden	United Kingdom
DDP at *t-1*	0.975***	0.919***	0.964***	0.941***	0.976***	1.034***	1.005***	0.956***	0.928***	0.937***
	(0.008)	(0.020)	(0.004)	(0.003)	(0.003)	(0.003)	(0.010)	(0.004)	(0.013)	(0.005)
RDP	0.022		0.226***		0.063***		-0.007	0.240***		
	(0.031)		(0.028)		(0.012)		(0.014)	(0.021)		
RDP at *t-1*		0.047***		0.053***		0.018***			0.006	0.030***
		(0.015)		(0.004)		(0.002)			(0.006)	(0.005)
Land tenure	-0.003	-0.020***	0.000	-0.003***	0.002	-0.015***	-0.012***	0.010***	-0.010***	0.005
	(0.003)	(0.005)	(0.003)	(0.001)	(0.002)	(0.001)	(0.004)	(0.003)	(0.004)	(0.005)
Unpaid labour	0.001	0.006	0.005***	-0.000	0.006***	0.008***	0.002	0.015***	0.009	0.003
	(0.005)	(0.004)	(0.001)	(0.002)	(0.002)	(0.001)	(0.005)	(0.002)	(0.005)	(0.003)
Size	0.000	-0.001	-0.001***	-0.000*	-0.000	-0.001**	0.000	-0.000	0.000	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Age	-0.000	-0.000	-0.000*	0.000	0.000**	0.000	-0.000	-0.000	0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Price volatility	0.009**	0.020	0.057***	0.041***	0.036***	-0.004***	-0.011**	0.026***	0.055***	-0.050***
	(0.003)	(0.022)	(0.002)	(0.002)	(0.003)	(0.001)	(0.005)	(0.005)	(0.007)	(0.004)
Price shock	-0.013***	0.024***	0.021***	0.004***	-0.009***	0.010***	-0.000	-0.012***	0.012**	0.056***
	(0.002)	(0.009)	(0.001)	(0.001)	(0.002)	(0.001)	(0.005)	(0.003)	(0.005)	(0.006)
Diversification	0.004	-0.007	-0.002	0.000	0.005**	-0.008***	0.008	-0.008***	0.008*	-0.032***
	(0.004)	(0.008)	(0.002)	(0.002)	(0.002)	(0.001)	(0.005)	(0.003)	(0.005)	(0.005)
LFA	-0.000	0.007***	0.000	-0.000	-0.001***	0.001***	0.001	-0.001	0.001	0.000
	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.026***	0.012***	0.026***	0.032***	0.025***	-0.001	0.003	0.034***	0.031***	0.058***
	(0.002)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)	(0.002)
Farm type					Included, for all countries					
Year					Included, for all countries					
c_i					Included, for all countries					
Endogenous variables	DDP	DDP, RDP	DDP	DDP, RDP	DDP	DDP, RDP	DDP	DDP	DDP, RDP	DDP, RDP
R^2 without IVs	0.701	0.460	0.677	0.718	0.375	0.647	0.470	0.411	0.653	0.746
R^2 including IVs	0.969	0.890	0.966	0.972	0.939	0.958	0.945	0.895	0.945	0.967

Notes: DDP = decoupled direct payments; RDP = rural development payments; LFA = less favoured area. c_i refers to unobserved heterogeneity. Standard errors are presented in parentheses. DDP at *t-1* is used as instrument for DDP. R^2 without IVs refers to the first-stage regression excluding IVs, R^2 including IVs refers to first-stage regression including IVs. The Netherlands is missing because DDP is considered to be exogenous. For countries with both DDP and RDP as endogenous variables, RDP at *t-1* is included in the first-stage regression. For countries with only DDP as endogenous variable, we include RDP in the first-stage regression. **p* < 0.10, ***p* < 0.05, ****p* < 0.01.

Table A 7 Parameter estimates of the first-stage pooled OLS regression for long-term viability with rural development payments as dependent variable

	Bulgaria	Germany	Poland	Sweden	United Kingdom
DDP at *t-1*	0.093***	0.006*	0.038***	-0.006	0.001
	(0.019)	(0.003)	(0.005)	(0.012)	(0.005)
RDP at *t-1*	0.822***	0.966***	0.933***	0.953***	0.954***
	(0.040)	(0.004)	(0.004)	(0.007)	(0.005)
Land tenure	-0.002	-0.000	0.003	-0.006	0.001
	(0.007)	(0.001)	(0.002)	(0.004)	(0.003)
Unpaid labour	-0.003	-0.000	0.005***	0.009*	-0.003
	(0.005)	(0.001)	(0.002)	(0.005)	(0.004)
Size	-0.001	0.000	0.001*	0.000	-0.001
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Age	-0.000	-0.000*	-0.000***	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Price volatility	0.019	0.005***	0.002	-0.025***	-0.030***
	(0.022)	(0.001)	(0.002)	(0.005)	(0.004)
Price shock	-0.000	0.002***	0.004**	-0.002	0.012**
	(0.019)	(0.001)	(0.001)	(0.004)	(0.005)
Diversification	-0.003	-0.003*	-0.003**	0.004	-0.005
	(0.011)	(0.002)	(0.002)	(0.004)	(0.004)
LFA	0.024***	0.000	0.004***	0.004***	-0.002***
	(0.003)	(0.000)	(0.000)	(0.001)	(0.001)
Constant	0.006	-0.000	0.009***	-0.001	0.019***
	(0.006)	(0.001)	(0.001)	(0.003)	(0.002)
Farm type			Included, for all countries		
Year			Included, for all countries		
c_i			Included, for all countries		
Endogenous variables	DDP, RDP	DDP, RDP	DDP, RDP	DDP, RDP	DDP, RDP
R^2 without IVs	0.185	0.484	0.470	0.567	0.553
R^2 including IVs	0.686	0.975	0.887	0.961	0.964

Notes: DDP = decoupled direct payments; RDP = rural development payments; LFA = less favoured area. c_i refers to unobserved heterogeneity. Standard errors are presented in parentheses. RDP at *t-1* is used as instrument for RDP. R^2 without IVs refers to the first-stage regression excluding IVs, R^2 including IVs refers to first-stage regression including IVs. Only these countries included where DDP and RDP both considered endogenous. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table A 8 Annual short-term viability inflow and outflow rates (%) for Belgium

Short-term viability status, year t – 1	Short-term viability status, year t	
	Non-viable	Viable
Non-viable	47.78	52.22
Viable	11.52	88.48
Total	18.29	81.71

Table A 9 Annual long-term viability inflow and outflow rates (%) for Belgium

Long-term viability status, year t – 1	Long-term viability status, year t	
	Non-viable	Viable
Non-viable	90.69	9.31
Viable	13.14	86.86
Total	54.69	45.31

Table A 10 Annual short-term viability inflow and outflow rates (%) for Bulgaria

Short-term viability status, year t – 1	Short-term viability status, year t	
	Non-viable	Viable
Non-viable	45.65	54.35
Viable	22.76	77.24
Total	28.92	71.08

Table A 11 Annual long-term viability inflow and outflow rates (%) for Bulgaria

Long-term viability status, year t – 1	Long-term viability status, year t	
	Non-viable	Viable
Non-viable	76.81	23.19
Viable	11.92	88.08
Total	36.01	63.99

Table A 12 Annual short-term viability inflow and outflow rates (%) for France

Short-term viability status, year t – 1	Short-term viability status, year t	
	Non-viable	Viable
Non-viable	40.40	59.60
Viable	10.72	89.28
Total	14.79	85.21

Table A 13 Annual long-term viability inflow and outflow rates (%) for France

Long-term viability status, year t – 1	Long-term viability status, year t	
	Non-viable	Viable
Non-viable	84.81	15.19
Viable	10.83	89.17
Total	45.45	54.55

Table A 14 Annual short-term viability inflow and outflow rates (%) for Germany

Short-term viability status, year t – 1	Short-term viability status, year t	
	Non-viable	Viable
Non-viable	48.33	51.67
Viable	14.80	85.20
Total	21.85	78.15

Table A 15 Annual long-term viability inflow and outflow rates (%) for Germany

Long-term viability status, year t – 1	Long-term viability status, year t	
	Non-viable	Viable
Non-viable	90.40	9.60
Viable	12.19	87.81
Total	66.02	33.98

Table A 16 Annual short-term viability inflow and outflow rates (%) for Italy

Short-term viability status, year t – 1	Short-term viability status, year t	
	Non-viable	Viable
Non-viable	55.74	44.26
Viable	37.06	62.94
Total	44.11	55.89

Table A 17 Annual long-term viability inflow and outflow rates (%) for Italy

Long-term viability status, year t – 1	Long-term viability status, year t	
	Non-viable	Viable
Non-viable	91.58	8.42
Viable	14.68	85.32
Total	58.67	41.33

Table A 18 Annual short-term viability inflow and outflow rates (%) for the Netherlands

Short-term viability status, year *t – 1*	Short-term viability status, year *t*	
	Non-viable	Viable
Non-viable	47.14	52.86
Viable	15.18	84.82
Total	22.78	77.22

Table A 19 Annual long-term viability inflow and outflow rates (%) for the Netherlands

Long-term viability status, year t – 1	Long-term viability status, year t	
	Non-viable	Viable
Non-viable	91.56	8.44
Viable	18.42	81.58
Total	78.12	21.88

Table A 20 Annual short-term viability inflow and outflow rates (%) for Poland

Short-term viability status, year t – 1	Short-term viability status, year t	
	Non-viable	Viable
Non-viable	33.05	66.95
Viable	18.89	81.11
Total	22.10	77.90

Table A 21 Annual long-term viability inflow and outflow rates (%) for Poland

Long-term viability status, year t – 1	Long-term viability status, year t	
	Non-viable	Viable
Non-viable	92.29	7.71
Viable	19.35	80.65
Total	66.09	33.91

Table A 22 Annual short-term viability inflow and outflow rates (%) for Romania

Short-term viability status, year t – 1	Short-term viability status, year t	
	Non-viable	Viable
Non-viable	60.11	39.89
Viable	14.64	85.36
Total	26.85	73.15

Table A 23 Annual long-term viability inflow and outflow rates (%) for Romania

Long-term viability status, year t – 1	Long-term viability status, year t	
	Non-viable	Viable
Non-viable	85.26	14.74
Viable	5.35	94.65
Total	41.33	58.67

Table A 24 Annual short-term viability inflow and outflow rates (%) for Spain

Short-term viability status, year t – 1	Short-term viability status, year t	
	Non-viable	Viable
Non-viable	47.76	52.24
Viable	12.40	87.60
Total	23.23	76.77

Table A 25 Annual long-term viability inflow and outflow rates (%) for Spain

Long-term viability status, year t – 1	Long-term viability status, year t	
	Non-viable	Viable
Non-viable	86.08	13.92
Viable	14.30	85.70
Total	44.28	55.72

Table A 26 Annual short-term viability inflow and outflow rates (%) for Sweden

Short-term viability status, year t – 1	Short-term viability status, year t	
	Non-viable	Viable
Non-viable	71.83	28.17
Viable	43.49	56.51
Total	58.97	41.03

Table A 27 Annual long-term viability inflow and outflow rates (%) for Sweden

Long-term viability status, year t – 1	Long-term viability status, year t	
	Non-viable	Viable
Non-viable	96.65	3.35
Viable	21.24	78.76
Total	87.42	12.58

Table A 28 Annual short-term viability inflow and outflow rates (%) for the United Kingdom

Short-term viability status, year t – 1	Short-term viability status, year t	
	Non-viable	Viable
Non-viable	38.79	61.21
Viable	18.96	81.04
Total	24.15	75.85

Table A 29 Annual long-term viability inflow and outflow rates (%) for the United Kingdom

Long-term viability status, year t – 1	Long-term viability status, year t	
	Non-viable	Viable
Non-viable	93.23	6.77
Viable	9.86	90.14
Total	72.63	27.37

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