Viticultural innovation: a social capital and absorptive capacity integrated approach

MSc Thesis report

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Abstract

Water scarcity is a major threat in many parts of the world. Irrigation is highly responsible for the global water consumption: 70-80% of freshwater use is consumed through irrigation. Italy is one of the countries that are facing an increase in droughts, higher temperatures, and more irregular precipitation patterns. The application of efficient irrigation systems (such as drip irrigation systems and sub-surface irrigation systems) might reduce water consumption through the reduction of water waste. However, information about the determinants of adoption of these technologies are still scarce. This research explores the determinants that influence farmers to innovate in water-saving technologies in the viticultural sector from the Verona wine province. That is done by analysing the role that organizational resources, such as social capital and absorptive capacity, have on innovation. In this analysis, we also consider farm and farmer level characteristics to better isolate organizational resource effects. The analysis is composed of two parts: structural equation modelling, and logistic regressions. Using a survey that includes 77 usable observations, it was found that farmers' social networks, geographical location, and other farmers' characteristics (such as type of education and age) have a significant effect on the likelihood of implementation of such technologies. Trust and absorptive capacity do not seem to have an effect on the implementation of such technologies. We argue that it is due to the strong presence of such technologies in the Verona wine province.

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1. Introduction

Grapevine is an important crop worldwide, grapes being the fruit crop with the highest value of production (Roselli et al., 2020). In 2019, the global production of grape was 77.1 million tonnes (FAO, 2020). Italy is the second highest producing country in the world, with 7.9 million tonnes, after China (14.4 million tonnes) (FAO, 2020). Grapes are related to wine and table grapes production. In 2014, 85% of the Italian grape production was used for wine making (FAO, 2020; ISMEA, 2020). Italy is the largest wine producer in terms of production quantities (5.4 million tonnes) and the second largest in terms of wine export, with 1.9 million tonnes, after Spain (2.1 million tonnes)(OIV, 2019). In Italy, the largest wine-producing region is Veneto, contributing approximately with the 20% of the total production (1.1 million tonnes) (ISTAT, 2020). In 2020, Verona was one of the largest wine-producing provinces in Veneto, with an annual production of 0.30 million tonnes of wine, of which 0.18 of PDO wine[1] (ISTAT, 2020).

Grapes have high requirements in terms of water and can be very susceptible to droughts. Changes in water availability can have negative effects on quality and quantity (Boatto et al., 2017; Seccia & Santeramo, 2018). It is often necessary to supply water through irrigation techniques. In 2014, in Italy, 22.7% of the total vineyard surface was irrigated (FAO, 2020). 37.3% of the water supplied to vineyards was groundwater; this share represents the 18.6% of the total groundwater used in Italy (Bellini, 2014).

Water is a scarce resource in many parts of the world, and water saving is becoming a priority due to the expected increase in population and global climate change (FAO, 2012). Irrigation is responsible to a great extent of the global water consumption: 70-80% of freshwater use is consumed through irrigation (Francaviglia & Di Bene, 2019). In the last century, rainwater has decreased by 50mm per year in Northern Italy. At the same time, rainy days have higher rainfall intensity on average. The consequence is an increase in drought periods (Seccia & Santeramo, 2018). Therefore, improving the efficiency of irrigation is strongly needed. Technology can help contributing to managing water consumption in the agricultural sector (Pino et al., 2017).

Different irrigation systems have different efficiency levels. The most common irrigation techniques in vineyards are basin irrigation, sprinkler irrigation, drip irrigation and subsurface drip irrigation. Irrigation techniques are characterized by different levels of efficiency (Kanda et al., 2020). Among the four, basin irrigation is the least efficient: more than 50% of the supplied water is lost by evaporation and percolation (Dasberg & Or, 1999). Sprinkler irrigation is more efficient than basin irrigation as the water use efficiency is up to 75% (Locascio, 2005). Kahlown et al. (2007) observed that sprinkler irrigation requires 67% water less than basin irrigation. Drip irrigation is even more efficient because 90-95% of the water is absorbed by the plants (Locascio, 2005). Subsurface drip irrigation minimizes runoff and evaporation, so water loss is close to zero (Kanda et al., 2020).

[1] Protected designation of origin (PDO) is a European scheme of geographical indication. Products that are registered under the scheme can be marked with a specific label, that guarantees that some production standards are fulfilled.

Farmers are often skeptical towards innovations (Kerr et al., 2001). Despite the high levels of efficiency of drip irrigation methods, low efficient irrigation techniques are still a relevant proportion of the systems adopted in Italy: 15% of the irrigated surface uses basin irrigation, and 27% is irrigated with sprinklers (Bellini, 2014; Pino et al., 2017). Therefore, how to increase farmers' sensitiveness to innovations is a relevant concern. The investigation of the factors that most likely influence farmers' implementation of technologies could benefit policy making through ad hoc policies (Pino et al., 2017).

Research has focused on understanding which are the reasons behind the low uptake of technologies by farmers. The standard approach for explaining innovation within farms is through the use of utility models (Hunecke et al., 2017). Such models consider profitability, farmer characteristics, and farm structure as factors affecting technology adoptions. Farmer characteristics, also described as human capital, are individual's knowledge, skills, and abilities (Kaasa, 2009). To represent human capital scholars normally use indicators such as farmer's age, gender, level of education, years of experience, household size, and income (Hunecke et al., 2017; Petridis et al., 2018; Ugochukwu & Phillips, 2018). The farm structure, the physical capital, is measured using indicators such as farm size, land ownership, soil quality, machinery, type of crops, or livestock (Handschuch et al., 2013; Ramirez, 2013).

Considering only human and physical capital for explaining innovation ignores the fact that individuals' decisions are affected by communities' share interests, activities, and concerns (Oreszczyn et al., 2010). Innovation is a process that involves interactions and exchange of knowledge from multiple actors to achieve social and economic goals (King et al., 2019). Peer-groups can have a role in facilitating innovation through spill-over effect; farmers that have more contacts with peers may be more likely to adopt a new technology (Lambrecht et al., 2015). Moreover, if farmers trust their sources of information, it is more likely that they will assimilate and interpret the information and that they will implement innovations if their trusted sources will advise to do so (Fisher, 2013; Gellynck et al., 2015). Both networks and trust are components of social capital. Ostrom (2005) identifies social capital as an essential complement to the concepts of physical, human, and natural capital. Adler & Kwon (2002) defined social capital as goodwill that is developed through social interactions and is available by groups or individuals; goodwill is referred as sympathy, trust, and forgiveness offered us by others. The core intuition behind it is that "the goodwill that others have toward us is a valuable resource" (Adler & Kwon, 2002, p. 18). Benefits of having social capital is that it improves the access to information and the quality and relevance of information (Adler & Kwon, 2002).

The ability of a farm to assimilate and use new knowledge has also been considered as a driver of innovation (Micheels & Nolan, 2016). Research has shown that farms that have greater absorptive capacity (ACAP), that is farms' ability to recognize information value, assimilate information, and use it to commercial ends, may have greater exploitability of a given technology compared to farms with less ACAP, possibly leading to greater adoption of new processes or products (Micheels & Nolan, 2016). Several authors have highlighted the positive correlation between ACAP and innovation. While most of these studies focus on manufacturing or high technology sectors (García-Morales et al., 2007; Murovec & Prodan, 2009), other studies show that absorptive capacity is a key component of innovation also in the agricultural sector (Gellynck et al., 2015; Micheels & Nolan, 2016). Moreover, research suggests that social capital and ACAP may be interconnected; Cohen and Levinthal (1990) argued that if an organization develops broad and active networks, individuals' awareness of others' knowledge will be enhanced. Therefore, individual ACAP increases, and the organization's ACAP is enhanced (Cohen & Levinthal, 1990). Fisher (2013) found out that the main factor that makes information into knowledge, so that increases assimilation of information and therefore ACAP, is trust.

To our knowledge, however, no studies have focused on the effects that social capital and ACAP have on the implementation of water-saving technologies in the Italian viticultural sector. The Italian viticultural sector is one of the largest in the world and have high requirements in terms of water, that needs to be supplied from sources that are often decreasing due to the climate change. Reducing the use of water is therefore a crucial issue. Understanding factors that influence the implementation of water-saving technologies can help policy makers to create ad hoc policies that goes beyond technical capabilities by considering other aspects, such as social abilities.

The objective of this research is to help understanding the determinants that influence farmers to innovate in water-saving technologies in the Verona wine province by investigating social capital, ACAP, and innovation. The investigation will be conducted under the following research questions:

RQ1) What is the correlation between social networks and absorptive capacity (ACAP)?

RQ2) What is the correlation between trust and ACAP?

RQ1) What is the correlation between social networks and the implementation of water-saving technologies?

RQ4) What is the correlation between trust and the implementation of water-saving technologies?

RQ5) What is the correlation between ACAP and the implementation of water-saving technologies?

To answer the research questions, and to make it possible to generalize the results to the entire population of the Verona grape farms, this report takes a quantitative approach. Given the importance of the viticultural sector in the Verona province (Italy), the population of the study is from that area. The target population is composed of farms producing grapes that are suitable for producing at least one of the PDO wines from Verona. The population includes approximately 5400 farmers. From the population, 400 farmers were randomly selected. From 400 farmers, 116 farmers answered the survey (29% response rate). The survey was administered by phone interviews. Since the variables for trust, social network, and ACAP are latent variables, so unobservable, two different statistical analyses were conducted: structural equation modelling (SEM), to answer research questions 1 and 2, and logistic regression, to answer research questions 3, 4, and 5. To limit spurious relationships, a set of control variables was used together with the regressors.

The report continues as follows. The following chapter describes the theoretical framework, firstly defining innovation, then describing social capital theory and absorptive capacity theory, and finally linking them together. Following, the report presents the case study and the methods. Then, the descriptive statistics are shown. The following two chapters present the results of the SEM and the logistic regressions, respectively. Finally, the discussion and the conclusions are presented.

2. Theoretical framework

The following chapter describes the theoretical framework of the study. The first section introduces innovation; the second describes the concepts of social capital, social network and trust, and the expected effect they have on innovation; then, absorptive capacity (ACAP) is described within the framework of resource-based view and its expected effect on innovation is described; the fourth section shows the relationships between social capital and ACAP; then, the hypotheses are listed; finally, a list and description of the control variables is included.

2.1 Innovation

Innovation can be defined as both the creation and/or adoption of something new to the farm, to the market, or to the world (Kaasa, 2009; OECD, 2013). Innovation can be divided in two types: internal innovation, which pertains to changes in the processes, and external innovation, which includes the creation or improvement of new products (Akcigit & Kerr, 2018). The implementation of more efficient irrigation systems are definable as internal innovations, as they relate to production techniques (OECD, 2013). At the farm level, innovation can help farmers improving the allocation of resources, improving productivity, and therefore income. Some innovations, such as irrigation technologies, can also enhance the environmental performance of the farm (OECD, 2013).

How to increase farmers' sensitiveness to innovations is a relevant question. In this research, innovation is operationalized as the implementation of a water-saving technology within the farm: drip and/or subsurface irrigation systems. This study will investigate the factors that influence farmers to innovate in water-saving technologies focusing on social capital and ACAP.

2.2 Social Capital

The concept of social capital has been used since the start of the 20th century by several authors. The first known user of the term was Hanifan (1916). The author wrote about the importance of community involvement for schools' success, basing his reasoning on social capital. When Hanifan refers to social capital, he does "not refer to real estate, or to personal property or to cold cash, but rather … goodwill, fellowship, mutual sympathy, and social intercourse among a group of individuals and families who make up a social unit, the rural community" (Hanifan, 1916, p. 130). For Hanifan, when the individual is exposed to his neighbours and they have contacts with other individuals, there will be an accumulation of social capital. Over the years, many definitions of social capital have been given. Some definitions are vague while some others are based on intuitions and theory. Ostrom (2005) identifies social capital as an essential complement to the concepts of physical, human, and natural capital. He argues that all forms of capital are essential for development but none of them is sufficient by itself.

Putnam (2000) describes social capital as the characteristics of social organization such as networks, social trust, and norms that facilitate coordination and cooperation for mutual benefit. He further proposes to distinguish structural and cognitive social capital. Structural social capital refers to tangible observable social structures - the networks – such as associations, institutions, and the rules and procedures they embody (Hjerppe, 2003). Networks can be defined as the links among individual members through which individuals exchange information, money, services, and goods flow (Maertens & Barrett, 2013). Cognitive social capital refers to more intangible elements that are embedded in society, such as accepted norms, shared values, and trust (Hjerppe, 2003). Structural social capital can be distinguished further into bridging and bonding social capital (Putnam, 2000). Bonding social capital - exclusive social capital - refers to ties among individuals sharing similar characteristics (e.g., farmers within the same cooperative). Bridging social capital, also called inclusive social capital, are outward-looking networks and gather people across different groups (such as relationships between farmers and scientists).

Several authors have highlighted the positive correlation between social capital and innovations. Farmers with higher social capital are more inclined to adopt new technologies (Micheels & Nolan, 2016). The leading benefit of social capital is that it encourages access to information, it improves the quality and the relevance of information and it enlarges information sources (Adler & Kwon, 2002). The means by which farmers of developed countries build social capital is through membership in organizations, i.e. producer organizations, consortia, peer networking and local and regional civic and community organizations (Dowd et al., 2014).

Scholars have studied the effect of networks on farms' innovation (Bernard et al., 2007). Bonding social capital, i.e. the network within the same group, has been linked to the innovation of production processes (Lambrecht et al., 2015). If farmers are uncertain about the value of new technologies then they are more hesitant to implement it (Sauer & Zilberman, 2009). In addition, farmers have a very practical approach to problem-solving and thus this may lead to scepticism towards the adoption of certain technologies (Kerr et al., 2001). Therefore, a driving force of innovation comes from peer-groups through spillover effects. Farmers that have higher contact with other farmers are more likely to implement new technologies. Bridging social capital has also been linked to the innovation of production processes (Lambrecht et al., 2015). However, the mechanism is different. Farmers trust more their peers than intermediate actors, but intermediate actors are better for information diffusion (Ramirez, 2013). Intermediate actors such as an innovation intermediary can have a role in initiating innovation in the agricultural sector, bridging the gap between innovation and the adopters (Klerkx & Leeuwis, 2008).

Trust has been defined as both a type of behaviour and a psychological state. In both cases, it's based on another party's expectation to act in a specific way (Fisher, 2013). One definition of trust is "the intention to accept vulnerability based upon positive expectations of the intentions or behaviour of another" (Rousseau et al., 1998, p.395). Trust reduces the complexity people are faced with. Instead of making rational judgments based on knowledge, individuals select experts who are trustworthy and whose opinion can be believed (Siegrist & Cvetkovich, 2000). It can be useful to make a distinction between information and knowledge. Knowledge is information that has been internalized by an individual (Lejeune, 2011). Providing information to the farmers won't necessarily make the farmer more knowledgeable (Fisher, 2013). Fisher (2013) found out that the main factor that makes information into knowledge is trust. If farmers trust their information source, it is more likely that they will assimilate and interpret the information and it will become knowledge. Farmers' main sources of information are extension agents and peers (Hunecke et al., 2017; Ramirez, 2013). Gellynck et al. (2015) wrote that farmers are more likely to adopt the solutions suggested by trustworthy agents. According to Ramirez (2013), farmers might be more likely to trust their peers than extension agents. Therefore, the information provided by peer farmers is more likely to become useful knowledge. Trust in scientists and technology companies are positively correlated to attitudes towards technologies (Siegrist, 2000). Distrust in the government was shown to cause a delay in sustainable practices implementation (Hall & Pretty, 2008).

2.3 Resource-Based View and Absorptive Capacity

2.3.1 Resource-Based View

The resource-based view (RBV) has been one of the most influential frameworks for studying strategic management. The theory was developed by Penrose (1959). He described firms as bundles of resources shaping their competitive positions. Barney (1991) argued that to bear a competitive advantage, resources must be valuable, rare, inimitable, and non-substitutable (VRIN). Scholars have classified these resources in different ways: Barney (1991) described it as physical, human, and organizational capital; Grant (1991) wrote about technological, financial, and reputational resources; and other divided it as tangible and intangible assets. This perspective can be synthesized as a resource picking or Ricardian perspective. Resource selection is the main mechanism for generating economic value.

Over the years, the RBV has been criticized for a perceived inability to explain a firm's strategic adaptation to changing environments (Winter, 2003). Other critiques regard the inability to consider the industrial context analysing the firm and the inability to considering that resources might devaluate over time.

The critiques led to the idea that VRIN resources do not ensure competitive advantages but rather bring benefits when used efficiently (Katkalo et al., 2010). Porter (1985) noticed that similar firms might have very different results according to their ability to combine resources. Over the years, scholars started to highlight processes and resource allocation and moved towards a Schumpeterian perspective or capabilities building. A Schumpeterian perspective highlights the role that a well-suited design of a firm's systems has on value creation and refers to it as the firm's capabilities.

According to the literature, there is not a single definition of capabilities. Penrose (1959) firstly described capabilities as resources that should not be considered as mere inputs, but rather should be regarded considering the utility and the services that these resources have. Winter (2000) defines capabilities as "a high-level routine that, together with its implementing input flows, confers upon an organization's management a set of decision options for producing significant outputs of a particular type" (Winter, 2000, p. 983).

Some scholars further expanded the model to examine the influence of dynamic markets. Teece et al. (1997) proposed the dynamic capability view. Fast-changing environments are better explained by the dynamic capability view than RBV (Teece et al., 1997). Dynamic capability view studies the contribution of dynamic capabilities to competitive advantages (Lin & Wu, 2014). There is not a unique definition of dynamic capabilities. Teece et al. (1997, p. 516) firstly defined it as the "firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environment". After the birth of the concept, many scholars changed this definition. Wójcik (2015, p.100) defined dynamic capabilities as "the company's ability to transform resources, processes, and capabilities at its disposal to address a rapidly or moderately rapidly changing environment". What changes from Teece's definition is that dynamic capabilities are about changes in resource base alteration – such as a change in resources and capabilities via routines, processes, and capabilities - and they do not emerge only in the face of rapid changes.

Among the dynamic capabilities of a firm, we find absorptive capacity (Zahra & George, 2002).

2.3.2 Absorptive capacity

In 1990, Cohen and Levinthal described the ability of a firm to recognize information value, assimilate information, and use it to commercial ends as absorptive capacity (ACAP). They argued that if the firm invests in developing its ACAP, the firm's cost of acquiring knowledge will reduce (Cohen & Levinthal, 1990). Learning in a specific area increases the firm's knowledge in that area, which additionally enhances its ACAP and eases learning in that domain (Autio et al., 2000). Zahra and George (2002) further analysed ACAP introducing four dimensions and giving a dynamic perspective to the topic: acquisition, assimilation, transformation, and exploitation of information. Acquisition concerns a firm's ability to acquire information; assimilation refers to the firm's processes that help to internalize information creating knowledge; transformation is the process of changing firm's routines combining existing knowledge with the newly acquired knowledge; exploitation refers to a firm's capability to incorporate knowledge into its operations (Zahra & George, 2002). Two dimensions compose ACAP: the potential and the realized ACAP. Potential absorptive capacity (PACAP) includes the acquisition and assimilation of information. It reflects the firm's ability to value and acquire knowledge, but it does not guarantee the exploitation of such knowledge. Realized absorptive capacity (RACAP) makes the firm receptive to transformation and exploitation of knowledge. RACAP captures the firm's ability to leverage the knowledge that has acquired (Zahra & George, 2002).

A firm with great ACAP may exhibit more applicability and exploitability of a given technology than firms with little absorptive capacity, leading to greater adoption of innovations. Several authors have highlighted the positive correlation between ACAP and innovation. While most of these studies focus on manufacturing or high technology sectors (García-Morales et al., 2007; Murovec & Prodan, 2009), other studies show that absorptive capacity is a key component of innovation also in the agricultural sector (Gellynck et al., 2015; Micheels & Nolan, 2016). Specifically, acquisition capacity, the ability to identify knowledge sources, discuss with business partners and participate in sector meetings, positively contributes to the ability to recognize changes in the market, regulations and technical possibilities, increasing the likelihood that a farmer will invest in innovations (Tepic et al., 2012). Farmers with higher assimilation capacity have larger networks, assisting them to recognize changes in the market, regulations, and technical possibilities and increasing the likelihood that a farmer will invest in innovations (Tepic et al., 2012). Farmers with high transformation capacity specifically look at how innovations can increase returns through negotiations about prices (Tepic et al., 2012).

2.4 Expected relationships between social capital and ACAP

In sections 2.1 and 2.2, the effects of social capital and absorptive capacity (ACAP) are described. The following section describes the relationships between social capital's components (social networks and trust) and ACAP.

2.4.1 Social Network and ACAP

Cohen and Levinthal (1990) argued that if an organization develops broad and active networks, individuals' awareness of others' knowledge will be enhanced. Therefore, individual ACAP increases, and the organization's ACAP is enhanced (Cohen & Levinthal, 1990). Cohen and Levinthal also suggest that the creation of close relationships with external knowledge sources that creates or amplifies information channels may improve a firm's ACAP (Cohen & Levinthal, 1994). Zahra and George (2002) argue more specifically about the effects of networks on ACAP. They said that a firm exposing to sources of knowledge is not necessarily linked to higher levels of ACAP. Instead, firms exposing to diverse and complementary sources of knowledge have a greater opportunity to develop their potential ACAP (Zahra & George, 2002). For what concerns agricultural organizations Tepic et al. (2012) studied the correlation between social networks and ACAP. They noticed that farms with higher social networks have higher ACAP, ceteris paribus (Tepic et al., 2012).

2.4.2 Trust and ACAP

The relationship between trust and ACAP has been studied and described in different models (Easterby-Smith et al., 2008; Fisher, 2013). Fisher (2013) found out that the main factor that makes information into knowledge – so that increases assimilation of information – is trust. When farmers trust their information source they will probably assimilate and interpret the information and it will become knowledge. Therefore, their ACAP will be greater than the one of farmers that have little trust. Inter-organizational learning theory specifies that in a knowledge transfer between two parties, trust motivates the knowledge receiver to accept the advice more easily. At the same time, a lack of trust might decrease the ACAP of the receiver (Easterby-Smith et al., 2008). At the basic level, trust is a substitute for the ability to verify the information. When verifying information is not possible, one way to accept the information is thanks to trust.

2.5 Hypotheses

Based on the above discussion, we can formulate the following hypotheses:

H1) The larger the level of farmer's social networks, the higher the farmer's ACAP

H2) The larger the level of farmer's trust, the higher the farmer's ACAP

H3) The larger the level of the farmer's social networks, the higher the implementation of water-saving technologies

H4) The larger the level of farmer's trust, the higher the implementation of water-saving technologies

H5) The larger the level of farmer's ACAP, the higher the implementation of water-saving technologies

The 5 hypotheses shape the theoretical model (Figure 1).

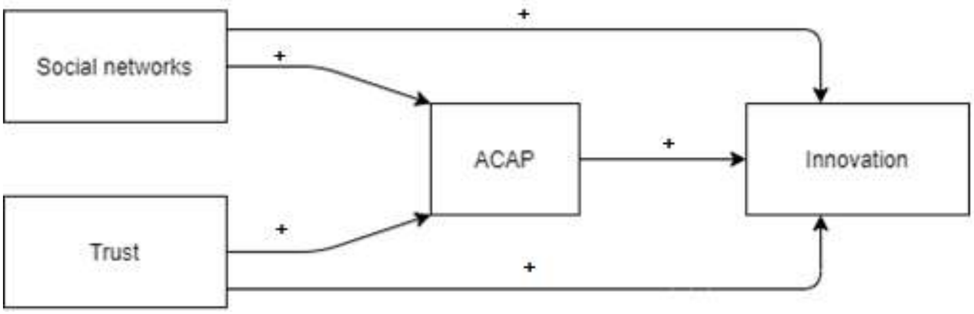

Figure 1. Theoretical model. Both trust and social networks are expected to positively influence absorptive capacity (ACAP). Social network, trust and ACAP are expected to have a positive effect on innovation.

2.6 Control variables

To limit spurious relationships, some control variables were added to the regressions. This section explains the expected relationship between such concepts and innovation. The control variables bear information about human capital, physical capital, location, and familiness (Table 1).

Human capital includes the age of the farmer, the level and type of education, and previous experience of the farmer. Research has found that older farmers may be less inclined to innovate their farms since they generally have a shorter time horizon to consider, thus investing in innovations may not pay off (Läpple et al., 2015). Kielbasa (2016) supported the argument that younger farmers are often more motivated to look at new solutions and so inclined to innovate, but they often lack the funds to implement the changes. Pierpaoli et al. (2013) reported that often the difference between the age of technology adopters and non-adopters is inconsistent. Both levels of education and previous experience have been found to affect the adoption of agricultural technologies: Paustian & Theuvsen (2017) noticed that the adoption of technologies increases for two groups of farmers: younger farmers, and experienced farmers; younger farmers who have recently graduated are "are skilled, motivated, and have a long planning horizon" making them technology adopters; more experienced farmers, on the other hand, are more able to recognize profitable technologies. Moreover, educational level is generally considered an important factor for technology adoption: farmers with higher level of education may implement more technologies (Pierpaoli et al., 2013). Farmers that have completed some forms of agricultural education may be more willing to implement new technologies, since the farmer's awareness of available technologies increases through agricultural education (Läpple et al., 2015).

Physical capital includes farm size. Proxies of farm size are the farm surface in terms of hectares (Hunecke et al., 2017), and the number of employees (Minguela-Rata et al., 2014). Studies investigating innovation of grape producers found out that the vineyard size is positively linked to the adoption of agricultural technologies (Engler et al., 2016; Hunecke et al., 2017). Research has found that variables controlling for the location are often significant descriptors of the implementation of technologies (Micheels & Nolan, 2016; Pierpaoli et al., 2013).

The term familiness is used to distinguish between family and non-family enterprises (Pearson et al., 2008). Compared to nonfamily firms, family enterprises have peculiar characteristics. Familiness refers to this difference. Habberson et al. (2003) defined familiness as the idiosyncratic bundle of resources and capabilities possessed by family firms (Habbershon et al., 2003). Since the rise of the concept by Habberson and Williams (1999), familiness has been studied from different theoretical perspectives. First, the concept has been examined from a resource-based perspective (Habbershon & Williams, 1999). From this point of view, familiness is considered as a resource that bears competitive advantages to the firm. However, the resource-based perspective has been criticized because of some limitations: limited possibility to identify the specific characteristics and the measurement associated with it; and lack of specificity and clarity (Pearson et al., 2008). Considering these aspects, Pearson et al. (2008) developed familiness from a social capital perspective. They identified the structural, relational, and cognitive dimensions of familiness and showed how social capital within the family firm has the effect to create a unique competitive advantage. Within family businesses, familial social capital is well developed. Kin develops strong ties among themselves. This increases the efficiency of information sharing within the firm. However, the strongest the ties among kin, the greatest the boundary between family members and nonfamily members. In this way, the family marginalizes its reliance on external actors limiting the magnitude of new external information that is acquired and assimilated (Daspit et al., 2019). Highly family-influenced firms recognize radical innovations later than less family-influenced counterparts (König et al., 2013). However, as far as the wine sector is concerned, the literature reveals a lack of research in the relationships between familiness and innovation (Vrontis et al., 2016). Highly family-influenced enterprises are faster to implement adoption decisions (König et al., 2013). Daspit et al. (2019) argued that familiness has different effects on different dimensions of ACAP: familiness has a negative effect on potential ACAP, due to the marginalization of external information source, and a positive effect on realized ACAP, due to the increased efficiency of information sharing within the firm.

Table 1. Summary of the possible factors influencing innovation besides social capital and absorptive capacity.

Concept	**Indicator**
Human capital	Age
	Experience
	Education
	Agricultural education
Physical capital	Farm and vineyard surface
	Number of workers
Location	Geographical area
Familiness	Family business

3. Method

The general approach taken in this study was to individuate how social capital and absorptive capacity (ACAP) influence innovation, and to elaborate the information to make it applicable at a wider scale. To answer the research questions, and to make it possible to generalize the results to the entire population of Verona grape producers, a quantitative approach was taken. The following section introduces the case study. Then, the data collection and the survey are described, followed by the description of the methods used for the data analysis.

3.1 Case study

Given the importance of the Verona wine province, farms from the province represent a key opportunity to understand factors affecting viticultural innovation. This research has a target population composed by farms producing grapes that are suitable for producing at least one of the Verona PDO wines. These grapes must be produced in specific locations: Arcole, Bardolino, Custoza, Durello, Lessini, Soave, and Valpolicella. It is important to highlight that the same farm may produce grapes from different locations.

The choice of the PDO wines within the Verona wine province has been driven by the fact that they include: both red and white wines; and high-price and low-price wines. The most expensive wines, Recioto della Valpolicella and Amarone della Valpolicella, are made with grapes that are worth approximately 1.60-1.90 €/Kg, while grapes from Custoza, the least expensive, are worth 0.40 €/Kg (Camera di commercio di Verona, 2020). The majority of the Italian PDO wine's grape is within this range of prices (UnionCamere, 2019).

The different locations are divided into three categories: area 1, that includes Bardolino and Custoza, area 2, that includes Arcole, Durello, Lessini, and Soave, and area 3, that includes Valpolicella. The choice of the three areas is because area 1 is in the western part of the province, area 2 is in the eastern part of the province, and area 3 is in the middle.

3.2 Data collection

The data collection of the study was done by administering a survey via phone interviews. A list of the research population was obtained from Siquria[2], the PDO certification body. Siquria was firstly contacted the 3rd of June 2020, asking for the list of the farms that produce grapes that are suitable for producing at least one of the Verona PDO wines. The 17th of September 2020 Siquria provided such list. The list includes 5405 farms. A sample of 400 farms was selected through a random selection procedure from the population. To randomly select the 400 farms, Excel version 2103 was used. Firstly, the list with the entire population was opened on Excel. Each subject from the list was given a random value using the command *=RAND( )* on Excel. Such command gives a random value from 0 to 1. The 400 farms with the largest random values were selected for composing the sample that will be interviewed.

Neither the phone numbers nor the e-mail address of the farms were included in the list of the population. To contact the farms, phone numbers were retrieved from the web. To retrieve phone numbers, two search engines were used: DuckDuckGo (https://duckduckgo.com/) and Google (https://www.google.com/). The key words to search for the phone number had been "the name of the farm" and "the address of the farm". If it was not enough for finding the phone number, "the name of the farmer" and "the address of the farm" were used as key words. Most of the numbers have been retrieved

[2] Siquria is the certification body responsible for certifying PDO products in the province of Verona (https://www.siquria.it/).

in the latter way and were found on the Italian phone book (https://www.paginebianche.it/). From 400 farms, 197 phone numbers were found.

Once the phone numbers were retrieved, the survey was administered by telephone interviews with a person of the selected wine farms. To ensure reliability on data collection, only people responsible for the strategic decisions concerning investments in grape production were interviewed. The surveys were administered by calling the retrieved phone number. At the phone, the researcher was introducing himself, explaining the reason of the call, asking to talk to a person responsible for the strategic decisions concerning investments in grape production and proceeding with the survey. The average survey was lasting approximately 20 minutes. Every interview was taken in Italian presenting the same questionnaire (Appendix 6).

The data collection was done in two waves: the first one from the 23rd of September until the 22nd of October and the second one from the 28th of December until the 15th of January. 87 surveys were administered during the first wave, and 29 during the second. The category of actors mostly involved were farm owners, occupying the 86% of the total (Appendix 1). Bottom line, out of 400 farms we retrieved the phone number of 197 farms and/or farmers, and we administered the survey to 116 subjects, with a response rate of 29%.

Before diving into the survey, it is important to highlight the following. Given that the study wants to investigate the implementation of water-saving technologies, only farms with an irrigation system were included in the data analysis. Not having an irrigation system might be due to other reasons, such as that the farm does not have access to water, or that the irrigation is not needed since the area is moist enough. Whichever the reason is, we have decided to exclude the farms without an irrigation system to control for these unobservable factors. Therefore, the study focuses on comparing farms that have an efficient irrigation system with farms that have a less efficient irrigation system. Moreover, only subjects without missing data have been included in the dataset. For these reasons, the usable observations are 77.

3.3 Survey

The survey consists of closed-ended questions: a part of the survey aimed at collecting information about the interviewee and the farm through 25 questions with several response formats (binary, categorical, and continuous).

The other part of the survey meant to collect information about trust, social networks, and ACAP. The variables trust, social networks, and ACAP are latent variables. Latent variables are unobservable; thus, they cannot be measured. However, latent variables can affect some observable variables that can be measured (Figure 2). Using specific statistical tools (such as factor analysis or structural equation modeling) it is possible to compute estimates of the latent variables through the observable variables. Part of the questions of the survey aimed at measuring such observable variables. Therefore, a Likert scale, i.e., a multi-item measurement scale, was used for evaluating each latent variable. The Likert scales were composed of 28 questions with a 7-point Likert-response format. For each Likert-response format question, the respondents were asked to express a judgment by declaring their level of agreement (from a minimum of 1 to a maximum of 7).

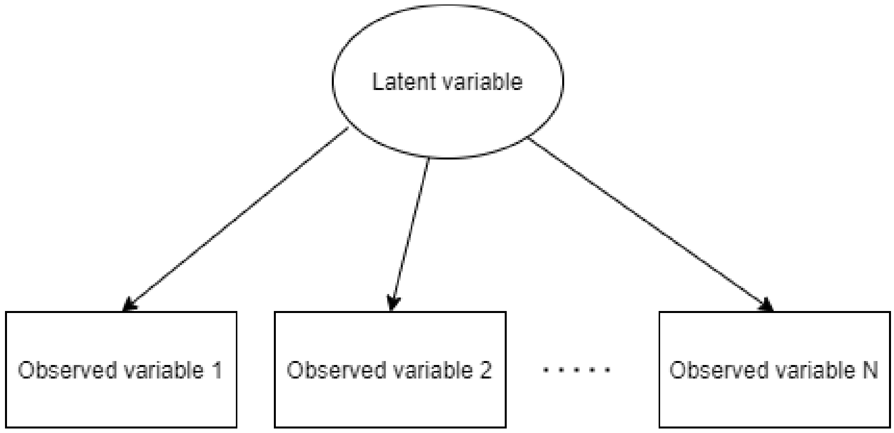

Figure 2. Circles represent latent variables; rectangles represent measured variables.

The survey measured the observable variables affected by social networks and trust with two multi-item measurement scales based on Molina-Morales & Martínez-Fernández (2010). In the survey, 8 Likert-response format questions were used to measure trust, while 6 Likert-response format questions and one continuous question was used to measure social networks. The observable variables influenced by ACAP were investigated using a measurement scale based on Jansen et al. (2005). The survey included 14 Likert-response format questions to measure ACAP. The original questionnaire in Italian can be found in Appendix 6**,** while the English translation is in Appendix 7.

The use of Likert scales, so multi-item measurement scales, was motivated by two aspects: on one hand multi-item measurement scales reduce the vulnerability of the data to measurement errors and misinterpretation, and cover a broader range of meanings of the construct compared to single items (Diamantopoulos et al., 2012). On the other hand, and more importantly, multi-item measurement scales are robust to the interval data assumption in the data analysis. Our multi-item measurement scales are mainly composed of Likert response format items. Likert response format items are ordinal data, that means that 1 is lower than 2, 2 is lower than 3, but the difference between 1 and 2 might be weighted differently compared to the difference between 2 and 3, and so on. However, when using a multi-item measurement scale based on Likert response format items with at least 7 categories, it is possible to assume that the data type is interval, in cases in which the data-analysis is based on a theoretical framework (Carifio & Perla, 2007). Therefore, given that our entire data-analysis in not exploratory but it is based on a theoretical framework, the measurement scales will be used in the data analysis assuming that they produce interval data.

3.4 Method Regarding Data Analysis

The data analysis of this study is divided in two parts. The first part aims at testing hypotheses 1 and 2 and computing the factor scores of the latent variables by using structural equation modeling (SEM); the second part uses these factor scores as regressors in the estimation of logistic regressions to test hypotheses 3, 4 and 5.

All the models that are described in this section have been estimated using Stata/IC 16.1.

3.4.1 Structural Equation Modelling

Structural equation modeling (SEM) is a statistical technique that can be used to determine unobservable variables (factors) from a set of observed variables (items), allowing to investigate the relationships between the factors. This technique is theory driven and can be used for testing a hypothesized theoretical framework, therefore is perfect for evaluating the theorized relationships between social capital and ACAP. SEM is a combination of factor analysis, either exploratory or confirmatory, and multiple regression (also called structural model) (Schreiber et al., 2006; Schumacker & Lomax, 2016). This section firstly describes the confirmatory factor analysis, and then dives into the structural model.

Confirmatory Factor Analysis

Factor analysis aims at determining which sets of observed variables have common variance-covariance characteristics that define a factor. Factor analysis expects that some factors are causing the shared variance-covariance among the observed variables. In CFA, the researcher specifies how many factors are in the model, which factors are correlated, and which observed variables measure each factor (Schumacker & Lomax, 2016).

In CFA, the specification of the model is based on prior research. Following the specification, the model can be evaluated and modified by looking at its validity and reliability. Validity evaluates the degree to which the proposed items measure the latent factor. The validity can be assessed by computing the factor loadings of the items. Factor loadings are measures that establish a relationship between the observed variables and the latent variables. A large loading factor suggests strong bonds between the observed variables and its corresponding factor. Factor loadings can be used to evaluate the validity of the observed variables. The observed variables with a factor loading lower than 0.6 are considered non-correlated enough with the factor (Hunecke et al., 2017). Reliability examines the degree to which the measurement of a set of items are error free; if the items corresponding to a factor are correlated to each other, the reliability is high (Tavakol & Dennick, 2011). To check the reliability of the factors, the Cronbach's alphas can be computed. Cronbach's alphas provide a measure of the reliability of a set of items. It is expressed as a number from 0 to 1. The greater the alpha, the greater the reliability of the set of items. The recommended minimum value for alpha is 0.7 (Nunnally & Bernstein, 1994).

Some authors have tried to address the issue of sample size, however there is not common agreement. In general, larger samples have more stable solutions, and the estimates better correspond to the population ones. Considering recommendation for the sample size per number of variables, different authors suggested this ratio to be at least in a range between 3 and 10; research with ratio values within this range has shown stable results (MacCallum et al., 1999). It has been suggested that if the observed variables have a normal distribution, 5 observations per variable would be enough for maintaining statistical power and obtaining stable parameters; other distributions need a ratio of at least 10 (Schumacker & Lomax, 2016). Another issue is the number of items per factor. It has been proven that single-item measures, i.e. one item per factor, decreases the reliability of the items by having considerable measurement error (Gliem & Gliem, 2003); moreover, a low number of items cannot discriminate among different degrees of an attribute, i.e. each item investigates a specific aspect of a factor so a multitude of items can better represent a complex concept (Gliem & Gliem, 2003). Therefore, there is general agreement that more items per factors are more reliable and bear more information than one item per factor.

Structural Model

The second component of SEM is the structural model (Schreiber et al., 2006). It aims at investigating the relationship between factors by testing the parameter estimates for statistical significance. The structural model requires to conduct different steps: *model specification*, *model identification*, *model estimation*, and *model testing* (Schumacker & Lomax, 2016).

Firstly, a model is specified based on prior research. Secondly, the model must be checked to be identified by assessing the order condition of the model. The number of free parameters that will be estimated has to be less than the number of values in the variance-covariance matrix; the number of values included in the sample variance-covariance matrix is equal to:

$$number\ of\ values\ in\ the\ variance/covariance\ matrix = p(p\ +\ 1)/2 \qquad (1)$$

where p is the number of observed variables. The difference between the number of distinct values in the matrix and the number of free parameters is equal to the degrees of freedom for the model:

$$degrees\ of\ freedom = \frac{p(p\ +\ 1)}{2} - number\ of\ free\ parameters \qquad (2)$$

If there are more than 0 degrees of freedom the model is over-identified; if there are 0 degrees of freedom the model is just identified while if negative the model is under-identified (Schumacker & Lomax, 2016):

$$\frac{p(p\ +\ 1)}{2} > number\ of\ free\ parameters \qquad (3)$$

Next, the model can be estimated. According to the underlying assumptions, there are different types of factor extraction methods in structural equation modeling. These methods include maximum likelihood (ML), quasi-maximum likelihood (QML), and asymptotic distribution free (ADF). The choice of the factor extraction method is motivated by the probability distribution of the items (Andreassen et al., 2006). ML assumes multivariate normality of the observed variables; ignoring non-normality and estimating the model with ML can lead to non-correct standard errors (Andreassen et al., 2006). ADF relaxes the assumptions of multivariate normality. However, the method requires a large sample (Hu et al., 1992). The QML method uses ML to estimate the model but it relaxes the multivariate normality assumption when estimating the standard errors (Satorra & Bentler, 1994). Therefore, to choose for the optimal extraction method, a test for multivariate normality will be run on the dataset.

The goodness of fit of a model can be tested. The chi-squared statistic is considered a global fit measure; it indicates whether the model well represents the relations among the items; a non-significant chi-squared suggests that the original variance-covariance matrix and the model variance-covariance matrix are similar, so the model well fit the relations among the items. Moreover, researchers can check the statistical significance of distinct parameter estimates.

Factor scores

Factor scores are defined as the composite (latent) scores that provide information about an individual's placement on the factor (Thompson, 2004). "[In] research, factor scores are typically only estimated when the researcher elects to use these scores in further substantive analyses" (Thompson, 2004, pp. 57-58). In this research, factor scores are computed to use them in the second part of the data analysis, the regression analysis.

Factor scores can be computed through refined methods, which use sophisticated procedures, and non-refined methods, which do not involve technical analysis. Non-refined methods are generally accepted for exploratory research situations, while refined methods aim at maximizing the validity of the scores (Distefano et al., 2009).

The approach that has been chosen for this study is a refined method called regression factor scores as it maximizes the validity of the scores. Regression factor scores uses a least squares regression approach to predict factor scores. The independent variables in the regression are the observed values of the items; these regressors are weighted by some regression coefficients; the regression coefficients are computed by multiplying the inverse of the matrix of observed variable correlation by the factor loadings matrix. The dependent variables of the regression are the factor scores. Factor scores computed in this way are standardized to a mean of zero (Distefano et al., 2009).

3.4.2 Regression analysis

This section describes the second part of the data analysis. According to hypotheses 3, 4 and 5, trust, social network, and ACAP have a positive effect on innovation in water-saving technologies. To test these hypotheses, a regression in which the "implementation of water-saving technologies" is the regressand has been developed. "Implementation of water-saving technologies" has been operationalized as a dummy variable. Farms that have drip irrigation and/or subsurface drip irrigation within their irrigation systems have the variable "Implementation of water-saving technologies" equal to 1; the variable is equal to 0 otherwise.

Logistic regression

Because our dependent variable is a dichotomous categorical variable, a logistic specification is recommended (Menard, 2010). Therefore, we conducted logistic regression models to test our hypotheses. The logistic regression computes the coefficients and standard errors of a linear function to predict the logistic transformation of the odds of adoption (natural log of the odds) (Farid et al., 2010):

$$logit(p_i) = x'_i\beta \qquad (4)$$

Where p_i is the probability of participating expressed with a number from 0 to 1, x'_i is the inverse of the vector containing the independent variables (including the constant), and β is a vector with the parameters of the variables. The odds are defined as:

$$odds = \frac{p_i}{1 - p_i} \tag{5}$$

And so, the logit (natural log of the odds) is defined as:

$$logit(p_i) = Ln\left(\frac{p_i}{1-p_i}\right) = x'_i\beta \tag{6}$$

From which it is possible to derive the probability of adoption:

$$Probability\ of\ adoption = p_i = \left(\frac{1}{1 + e^{-x'_i\beta}}\right) \tag{7}$$

Model specification

The factor scores of trust, social networks, and ACAP are used as regressors, together with some control variables regarding farm and farmer characteristics. The control variables have been divided into three main groups: location, human capital, and physical capital. We specified different models with the same regressand (dummy innovation) and different regressors according to the theoretical dimensions that we wanted to investigate. At first, a logistic regression with the factor scores as regressors will be run; secondly, another regression with the addition of the control variables for the location of the farm; then, a regression with the factor scores and controlled for the farmer characteristics; after, a regression with the factor scores and the control variables for the farm characteristics; lastly, a regression with all the previously mentioned variables (Table 2).

Table 2. Regressors per each model.

Logit models. Dependent variable: Implementation of the technology.

Group of predictors	Model a	Model b	Model c	Model d	Model e
Factor scores	x	x	x	x	x
Location		x			x
Human capital			x		x
Physical capital				x	x

Note: On the left column, the groups of predictors are listed. An x in the cell means that the model in that column uses that group of variables as regressors.

Selection of the variables

As shown in Table 1, apart from social capital and ACAP there are four main concepts that are expected to influence innovation. The first concept is human capital. It includes age, experience, education, and agricultural education as indicators. Physical capital includes surface and number of workers. Location is represented by the geographical area. Familiness is represented by whether the farm is a family business.

In the survey, variables related to these indicators were collected. Some indicators were operationalized into one variable only, while others were operationalized into more variables. An example of a single variable per indicator is age, that is operationalized in age in years of the respondent. An instance of more variables per indicator is given by experience, that was operationalized into three variables: years of experience of the respondent within the farm, years of experience in that specific role, and years of experience within the viticultural sector.

Given that some variables bear very similar information, it was decided to select and keep only one variable per indicator. As criteria for the variable selection, two aspects have been considered primarily: the probability density function of the variable, and the collinearity with other variables. Variables with a normal distribution were preferred over variables with different distribution; if a dummy variable is very unbalanced (i.e., almost all the observations were either 0 or 1) the dummy would not be included in the regression. Variables with lower collinearity were preferred over variables with higher collinearity; finally, if two variables were highly correlated, only one would be considered as possible regressor.

Model comparison

To compare different models, we operationalized the McFadden's R-squared (also known as pseudo R-squared), and the count R-squared. The R-squared is not a good indicator being usually low since the true Y can only be 0 or 1. Therefore, the McFadden's R-squared was used:

$$\text{McFadden's R-squared} = 1 - \log L / \log L_0 \tag{8}$$

The count R-squared is the number of correct predictions over the total number of observations. It shows how good a model is at predicting:

$$\text{Count R-squared} = \text{number of correct predictions} / \text{total number of predictions} \tag{9}$$

Besides, we measured the AIC and BIC. AIC and BIC are penalized-likelihood criteria; both information criteria measure fit and penalize for excessive number of parameters. In practice, their difference is the size of the penalty: BIC is stricter.

To evaluate the goodness of fit of the models, the Likelihood Ratio (LR) was run. The LR is a test based on the log-likelihood values of two different models, L being the full model and L_0 being the restricted model:

$$LR = 2(\log L - \log L_0) \sim X^2 (k-1) \tag{10}$$

where k-1 is the number of explanatory variables, logL loglikelihood from full model, $\log L_0$ loglikelihood of model with only an intercept. In this test, H_0: $\beta_2 = \beta_3 = \ldots = \beta_k = 0$ and H_1: not H_0. Therefore, rejecting the null hypothesis means that at least one variable adds some explanatory power to the model.

To assess whether the model has collinearity issues, the variation inflation factor (VIF) was measured. If a predictor has a VIF of 1, it means that it is uncorrelated with other variables. Variables with VIF values of more than 5 are regarded moderately highly correlated whereas values above 10 are considered extremely high.

4. Descriptive statistics

As described in the section 3.2, farms without an irrigation system are excluded from the analysis. Also, subjects with missing data are excluded from the analysis. After checking for these, we found out that 4 observations out of 116 have missing data, and 35 do not have an irrigation system. Therefore, the data analysis was conducted with a subsample of 77 observations. The following chapter includes the descriptive statistics of the items and variables included in the survey.

4.1 Items

The following section includes Table 3, showing the descriptive statistics of the observed variables for the structural equation modeling; per each item, the number of observations, the mean, standard deviation, minimum value, and maximum value are displayed. Table 3 shows the descriptive statistics for the subsample. Appendix 1 includes the descriptive statistics of the full dataset.

4.2 Variables

The following section shows the descriptive statistics of the dependent variable and the possible regressors of the logistic regression; per each item, the number of observations, the mean, standard deviation, minimum value, and maximum value are displayed.

Table 4 shows the descriptive statistics of the dependent variable for the subset that was used for the data analysis. 31% of the farms included in the subsample did not have an efficient irrigation system while the 69% had it. Table 5 displays the descriptive statistics of the independent variables for the subset used for the data analysis. 90% of the interviewed were males, ranging from 24 to 90 years, with an average of 56 years. 87% of the respondents were the farm owners. On average, respondents had 24 years of experience of work with that role, 27 in that company, and 33 in the wine sector. 60% of the interviewed was working full time in the farm, while 9% part time, and 31% were retired. 47% of the respondents finished their studies at high school, while the 13% went to university; 18% of the total took agricultural related studies. The smallest company had 0.30 hectares of vineyards, the largest 290 hectares. The average area planted with vineyard was 17 hectares. Of the vineyards, every farm had an irrigation system and 69% had implemented a drip irrigation system. On average, farms had 1.8 family workers, but some companies had 0 family workers, since they had employees. On average, farms had 2 employees, ranging from 0 to 75. 22% of the farms were smaller than 3 hectares, 31% ranged from 3 to 10 hectares, and 32% from 10 to 30. Almost half of the respondents (47%) considered their farm as an increasing business. 16% had organic production, 32% conducted wine making, 29% bottling, and 57% had other agricultural activities other than grape production. 74% of the companies sold their grapes. 40% of the companies produced in area 1 (Bardolino and Custoza), the Western area, 29% in area 2 (Lessini, Arcole, Soave), the Eastern area, and 39% in area 3 (Valpolicella), the high-priced area. Appendix 1 includes the descriptive statistics about the entire dataset.

Table 3. Descriptive Statistics items for structural equation modeling

	Mean	Std. Dev.	Min	Max	Obs
Trust					
Other companies can rely on me without fearing that I will take advantage of them.	6.01	0.95	4.00	7.00	77
My company will always keep the promises done.	6.03	1.00	4.00	7.00	77
In the case of an informal agreement, I would always stick to the agreement even if there is no contract.	5.96	1.01	3.00	7.00	77
I think that other farmers will damage me if they benefit from it. (R)	2.82	1.65	1.00	7.00	77
The Italian politicians think about their own interests only. (R)	5.45	1.71	1.00	7.00	77
I trust public institutions.	3.60	1.60	1.00	7.00	77
I trust informative agents.	4.17	1.60	1.00	7.00	77
Who sells technologies think to its own interest only. (R)	3.78	1.50	1.00	7.00	77
Social Network					
How many suppliers do you have? *	13.03	27.32	1.00	200.0	77
I spend a considerable amount of time with other farmers.	4.36	1.70	1.00	7.00	77
I have an informal network of suppliers, clients, and competitors.	4.71	1.66	1.00	7.00	77
I always support neighboring farms when they have troubles.	4.91	1.92	1.00	7.00	77
Regarding agricultural activities, I do not communicate with neighboring farmers. (R)	3.05	1.98	1.00	7.00	77
When I participate to agricultural events, I am one of the most Active.	4.42	1.76	1.00	7.00	77
I often meet agricultural professionals and experts.	5.06	1.50	1.00	7.00	77
Absorptive Capacity					
I regularly visit other farms.	4.19	2.01	1.00	7.00	77
I never meet consultants. (R)	3.10	1.73	1.00	7.00	77
I get information on the sector through informal means.	4.18	1.81	1.00	7.00	77
I organize meetings with clients or other parties to collect Information.	3.64	2.13	1.00	7.00	77
My farm is fast to recognize market changes.	4.04	1.53	1.00	7.00	77
I quickly understand new practices to manage the vineyards.	4.62	1.70	1.00	7.00	77
My farm is slow to recognize market changes. (R)	3.95	1.55	1.00	7.00	77
I take notes about new information for future possibilities.	5.17	1.84	1.00	7.00	77
I organize meetings within the farm to discuss about market changes.	2.65	1.75	1.00	7.00	77
I organize meetings within the farm to discuss about new management practices for the vineyards.	2.66	1.65	1.00	7.00	77
The activities of my farm are well defined.	5.83	1.15	1.00	7.00	77
My farm has a clear division of roles and responsibilities.	6.39	0.86	3.00	7.00	77
I constantly consider how to better exploit information.	5.14	1.56	1.00	7.00	77
My farm has difficulties to implement new management practices for the vineyards. (R)	3.77	1.76	1.00	7.00	77

*Note: 1 = strongly disagree, 7 = strongly agree. The first column includes the latent variables and the list of the items that were asked in the questionnaire to measure the corresponding latent variables. Items ending with (R) are reversed questions. If used in the data analysis, the value of the reversed questions has been reversed (e.g. if valued 1, they will get value 7 in the data analysis, if valued 2, they will get 6, etcetera). The item ending with * is the only non-Likert response format question, in which the value is equal to the number of suppliers.*

Table 4. Descriptive Statistics of the Dependent Variable

Water-saving technology	Freq.	Percent
No	24	31.17
Yes	53	68.83
Total	77	100.00

Table 5. Descriptive Statistics of the Independent Variables

Variable	Mean	Std. Dev.	Min	Max	Obs
Age	55.55	15.34	24.00	90.00	77
Years with that role	24.14	15.12	1.00	60.00	77
Years in that company	27.43	17.56	1.00	75.00	77
Years in the wine sector	33.13	19.21	1.00	80.00	77
Vineyard size (Hectares)	17.25	44.38	0.30	290.00	77
Log (Vineyard size)	1.74	1.39	-1.20	5.67	77
Family workers	1.81	1.05	0.00	5.00	77
Employees	2.04	8.86	0.00	75.00	77
Log (Employees+1)	0.42	0.83	0.00	4.33	77
Total workers	3.84	9.08	1.00	78.00	77
Log (Total workers)	0.80	0.81	0.00	4.36	77
Dummy Irrigation	1.00	0.00	1.00	1.00	77
Irrigation (Hectares)	13.64	32.04	0.30	250.00	77
Female	0.10	0.31	0.00	1.00	77
First job	0.60	0.49	0.00	1.00	77
Side job	0.09	0.29	0.00	1.00	77
No job (Retired)	0.31	0.47	0.00	1.00	77
Role as Owner	0.87	0.34	0.00	1.00	77
Role as Manager	0.08	0.27	0.00	1.00	77
Another role	0.05	0.22	0.00	1.00	77
Agricultural Education	0.18	0.39	0.00	1.00	77
Primary school	0.18	0.39	0.00	1.00	77
Secondary school	0.22	0.42	0.00	1.00	77
High school	0.47	0.50	0.00	1.00	77
University (Bachelor or master)	0.13	0.34	0.00	1.00	77
Surface <1 Ha	0.06	0.25	0.00	1.00	77
≥ 1 Surface < 3 Ha	0.16	0.37	0.00	1.00	77
≥ 3 Surface < 10 Ha	0.31	0.47	0.00	1.00	77
≥ 10 Surface < 30 Ha	0.32	0.47	0.00	1.00	77
≥ 30 Surface < 100 Ha	0.12	0.32	0.00	1.00	77
Surface ≥ 100 Ha	0.03	0.16	0.00	1.00	77
Decreasing business	0.19	0.40	0.00	1.00	77
Constant business	0.34	0.48	0.00	1.00	77
Increasing business	0.47	0.50	0.00	1.00	77
Organic	0.16	0.37	0.00	1.00	77
Family business	0.95	0.22	0.00	1.00	77
Successor	0.79	0.41	0.00	1.00	73
Area 1 (Bardolino, Custoza)	0.40	0.49	0.00	1.00	77
Area 2 (Arcole, Durello, Soave, Lessini)	0.29	0.45	0.00	1.00	77
Area 3 (Valpolicella)	0.39	0.49	0.00	1.00	77
Wine making	0.32	0.47	0.00	1.00	77
Bottling	0.29	0.45	0.00	1.00	77
Agricultural activities other than grape production	0.57	0.50	0.00	1.00	77
Livestock	0.06	0.25	0.00	1.00	77
Agritourism	0.06	0.25	0.00	1.00	77
Sale of grape	0.74	0.44	0.00	1.00	77

5. Results of the structural equation modeling

The data analysis of this study is divided in two parts. The first part uses structural equation modeling to test hypotheses 1 and 2 and to compute the factor scores of the latent variables; the second part uses such factor scores as regressors in the estimation of the logit model to test hypotheses 3, 4, and 5. This chapter reports the results of the structural equation modeling, while chapter 6 reports the results of the logistic regressions.

Trust, social network, and absorptive capacity (ACAP) are latent variables (also called factors), thus unobservable. These latent variables can affect other variables that are observable and measurable. Such observed variables (also called items) are described in Table 3. Through structural equation modeling it is possible to compute the factor scores of the factors and to assess the relation among these factors. Structural equation modeling includes two components: a confirmatory factor analysis, and a structural model. Confirmatory factor analysis aims at deriving factors from items.

5.1 Results of the confirmatory factor analysis

The first step of the confirmatory factor analysis is the model specification. Based on the theoretical framework described in chapter 2, a model was specified. In this analysis there are 3 factors: trust, social networks and ACAP. Each factor is assumed to influence some items. Table 6 includes a list of items underneath each factor; the items underneath each factor are the measurable variables that are assumed to be influenced by the factor.

From this list, a selection of the best items was done. Per each factor, a total amount of three items was chosen. The arbitrary choice of having three items was motivated by two aspects: stability of the estimates of the population, and reliability of the items. The stability of the population factor (i.e., less variability across different samples) is linked to the sample size over number of variables ratio; larger samples have more stable solutions. Given that the sample size cannot be changed, it was decided to limit the number of observed variables, thus keeping the ratio to a value ranging between 5 and 10. The reliability of the items depends on the number of items per factor; it was decided to keep three items per factor to increase the reliability of the items and to better represent the complexity of complex concepts such as trust, social network, and ACAP.

Firstly, the selection of the best items was based on the validity of the items. The validity of the items was examined by checking the factor loadings of each item per each factor. The larger the factor loading, the stronger the connection between the item and the factor. The choice of the items was clear-cut: each item with a factor loading lower than 0.6 was dropped. Through this selection, three out of eight items measuring trust, five out of seven items measuring social network, and eleven out of fourteen items measuring absorptive capacity were selected. Table 6 reports the factor loadings of all the items, while Table 7 shows the items with a factor loading higher than 0.6.

Table 6. Factor analysis results with all the variables.

	Factor loading	N
Trust		
Other companies can rely on me without fearing that I will take advantage of them.	0.7900	77
My company will always keep the promises done.	0.8345	77
In the case of an informal agreement, I would always stick to the agreement even if there is no contract.	0.7378	77
I think that other farmers will damage me if they benefit from it. (R)	0.4106	77
The Italian politicians think about their own interests only.	0.1210	77
I trust public institutions.	0.1053	77
I trust informative agents.	0.4207	77
Who sells technologies thinks to its own interest only. (R)	0.4028	77
Social Network		
How many suppliers do you have?	0.6244	77
I spend a considerable amount of time with other farmers.	0.8032	77
I have an informal network of suppliers, clients, and competitors.	0.8155	77
I always support neighboring farms when they have troubles.	0.6914	77
Regarding agricultural activities, I do not communicate with neighboring farmers. (R)	0.4954	77
When I participate to agricultural events, I am one of the most Active.	0.6970	77
I often meet agricultural professionals and experts.	0.6104	77
Absorptive Capacity		
I regularly visit other farms.	0.7680	77
I never meet consultants. (R)	0.5746	77
I get information on the sector through informal means.	0.6453	77
I organize meetings with clients or other parties to collect information.	0.7720	77
My farm is fast to recognize market changes.	0.8339	77
I quickly understand new practices to manage the vineyards.	0.7758	77
My farm is slow to recognize market changes. (R)	0.7883	77
I take notes about new information for future possibilities.	0.7789	77
I organize meetings within the farm to discuss about market changes.	0.7794	77
I organize meetings within the farm to discuss about new management practices for the vineyards.	0.8028	77
The activities of my farm are well defined.	0.5598	77
My farm has a clear division of roles and responsibilities.	-0.0175	77
I constantly consider how to better exploit information.	0.7916	77
My farm has difficulties to implement new management practices for the vineyards. (R)	0.6811	77

Note: The first column includes the list of the items that were asked in the questionnaire to measure the latent variables. Items ending with (R) are reversed questions. If used in the data analysis, the value of the reversed questions has been reversed (e.g. if valued 1, they will get value 7, if valued 2, they will get 6, etcetera).

From Table 7 it is possible to notice that the factor trust has 3 items, but social networks and ACAP have 5 and 11 respectively. Therefore, to reduce the items to a total of 3 per factor, some selection was done. The item "how many suppliers do you have?", since it was the only item based on a different response format, was dropped. The item "My farm is slow to recognize market changes" was dropped, as it was the reversed question of the item "My farm is fast to recognize market changes", which was included. The items "I organize meetings within the farm to discuss about market changes" and "I organize meetings within the farm to discuss about new management practices for the vineyards" did not seem appropriate to the dataset, as most farms are run by one or two people only. The remaining items were selected based on the size of the factor loadings. Table 8 shows the factors and the corresponding three items, based on the last selection.

Table 7. Factor analysis results with the variables from the first selection.

	Factor loading	N
Trust		
Other companies can rely on me without fearing that I will take advantage of them.	0.8280	77
My company will always keep the promises done.	0.8752	77
In the case of an informal agreement, I would always stick to the agreement even if there is no contract.	0.6713	77
Social Network		
How many suppliers do you have?	0.6851	77
I spend a considerable amount of time with other farmers.	0.7684	77
I have an informal network of suppliers, clients, and competitors.	0.7556	77
When I participate to agricultural events, I am one of the most active.	0.7671	77
I often meet agricultural professionals and experts.	0.6885	77
Absorptive Capacity		
I regularly visit other farms.	0.7623	77
I get information on the sector through informal means.	0.6357	77
I organize meetings with clients or other parties to collect information.	0.7749	77
My farm is fast to recognize market changes.	0.8353	77
I quickly understand new practices to manage the vineyards.	0.7785	77
My farm is slow to recognize market changes.	0.7884	77
I take notes about new information for future possibilities.	0.7754	77
I organize meetings within the farm to discuss about market changes.	0.7890	77
I organize meetings within the farm to discuss about new management practices for the vineyards.	0.8146	77
I constantly consider how to better exploit information.	0.7824	77
My farm has difficulties to implement new management practices for the vineyards. (R)	0.6722	77

Note: The first column includes the list of the items that were asked in the questionnaire to measure the latent variables. Items ending with (R) are reversed questions. If used in the data analysis, the value of the reversed questions has been reversed (e.g. if valued 1, they will get value 7, if valued 2, they will get 6, etcetera).

At this stage, a reliability check was done. Reliability examines the degree to which measurement scales are error free. The reliability of the factors was examined using Cronbach's alpha. Every alpha was above the threshold 0.7: 0.851 for trust, 0.840 for social network, and 0.833 for ACAP (Table 8).

5.2 Results of the structural equation model

This section includes the steps and the results of the structural model. Based on hypotheses 1 and 2, the model was specified. The structural model is shown in Figure 3. Trust and social networks are exogenous factors that influence ACAP, the endogenous factor. Each factor influences three corresponding items (Figure 3). Secondly, the model was checked to be identified. A model is identified when the number of parameters in the model is lower than the number of values in the variance-covariance matrix. The number of values in the matrix is found by using equation 1**.** The number of observed variables in the model is 9, therefore there are 45 values in the variance-covariance matrix. The number of parameters is equal to 21, respectively 10 standard errors, and 11 coefficients. Therefore, the model is identified.

Table 8. Factor analysis results with the final selected items.

	Factor loading	N
Trust (Cronbach's alpha = 0.8508)		
Other companies can rely on me without fearing that I will take advantage of them.	0.8280	77
My company will always keep the promises done.	0.8752	77
In the case of an informal agreement, I would always stick to the agreement even if there is no contract.	0.6713	77
Social Network (Cronbach's alpha = 0.8396)		
I spend a considerable amount of time with other farmers.	0.8301	77
I have an informal network of suppliers, clients, and competitors.	0.7654	77
When I participate to agricultural events, I am one of the most active.	0.7178	77
Absorptive Capacity (Cronbach's alpha = 0.8325)		
My farm is fast to recognize market changes.	0.7784	77
I quickly understand new practices to manage the vineyards.	0.7928	77
I constantly consider how to better exploit information.	0.7099	77

Note 1: Next to each factor, the corresponding Cronbach's alpha is shown. Values above 0.7 are considered good.

Note 2: The first column includes the list of the items that were asked in the questionnaire to measure the latent variables. Items ending with (R) are reversed questions. If used in the data analysis, the value of the reversed questions has been reversed (e.g. if valued 1, they will get value 7, if valued 2, they will get 6, et cetera).

Next, the model can be identified. The extraction method to be used is different according to the type of distribution of the observed variables. The differences between the assumptions in the extraction methods are included in the section 3.4.1. To select the proper extraction procedure, tests on multivariate normality of the items were run. All the tests for multivariate normality (Mardia's multivariate kurtosis test, Mardia's multivariate skewness test, Henze–Zirkler's consistent test, Doornik–Hansen omnibus test) reject the null hypothesis of multivariate normality, p-value of 0.000 (Table 9). The items do not appear to be normally distributed. Therefore, maximum likelihood method cannot be used, as it assumes multivariate normality of the observed variables. Due to the small sample size, a model estimated with asymptotic distribution free method would not converge to an optimal solution. The quasi-maximum likelihood method relaxes the normality assumption when estimating the standard errors (Satorra & Bentler, 1994). Thus, the model was estimated using a quasi-maximum likelihood method (Figure 4).

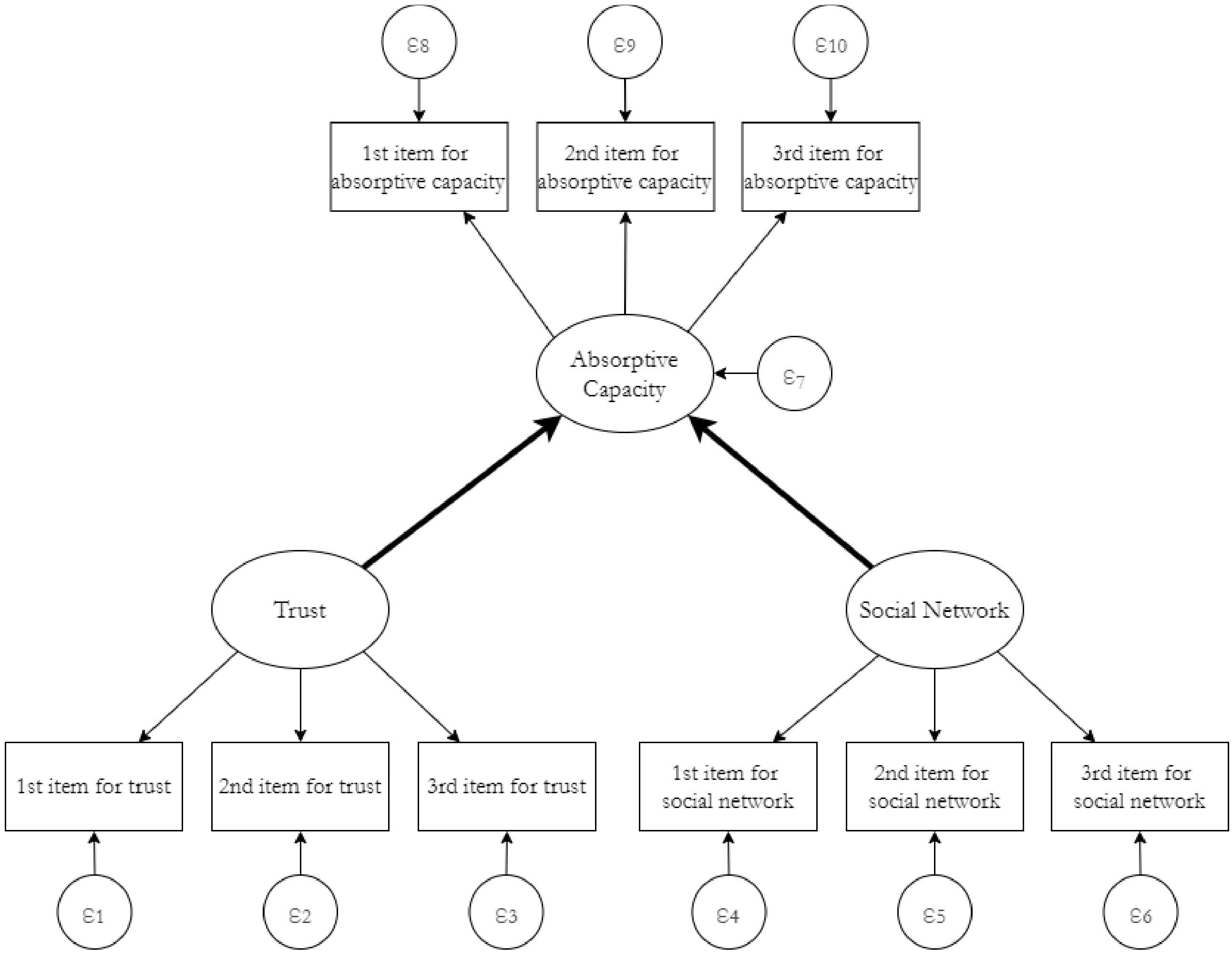

Figure 3. Hypothesized structural equation model. The bolded lines show the structural component; the thin lines show the measurement component. Circles represent latent variables; rectangles represent measured variables. The items included in the model correspond to the one included in Table 8. ε is the error associated with the variable.

Table 9. Tests on multivariate normality

Test	Degrees of freedom	Chi-squared	p-value
Mardia's multivariate kurtosis	4495	5689.882	.000
Mardia's multivariate skewness	1	14.453	.000
Henze–Zirkler	1	67.004	.000
Doornik-Hansen	58	199.799	.000

Note: null hypothesis of multivariate normality; alternative hypothesis of non-normality.

At this stage, the model can be tested. The first test that is going to be assessed is the estimated model vs saturated model test. It suggests the goodness of fit of the model. Given that the method of estimation used was the quasi-maximum likelihood method, the test that was run is the Satorra-Bentler scaled test. This test is the equivalent of a likelihood ratio test of the estimated model vs the saturated model. A significant chi-squared indicates that the model does not fit the relations among the items. The Satorra-Bentler scaled test of the model is: $\chi2(25)=61.23$, $p<0.01$. The chi-squared is significant; thus, the saturated model explains the relations among the items better than the estimated model.

In addition, the parameter estimates of the structural model can be tested. Both the estimates of the coefficients of trust ($\beta = 0.238$, s.d.=0.101, $p < 0.05$) and social network ($\beta = 0.509$, s.d.=0.090, $p < 0.01$) are positive and statistically significantly different from zero (Table 10). According to the model, hypotheses 1 and 2 are proven: social network and trust are positively correlated to absorptive capacity.

5.3 Factor scores

The last step in the structural equation modeling is the computation of factor scores. Factor scores are needed as regressors in the logistic regression. A brief review on different computation methods was presented in section 3.4.1. The method that was chosen for the computation is a refined method: regression factor score. Regression factor scores estimates a least squares regression approach to predict factor scores. The regressand of the regression are the factor scores. Factor scores computed in this way are standardized to a mean of zero. Table 11 shows the descriptive statistics for the factor scores.

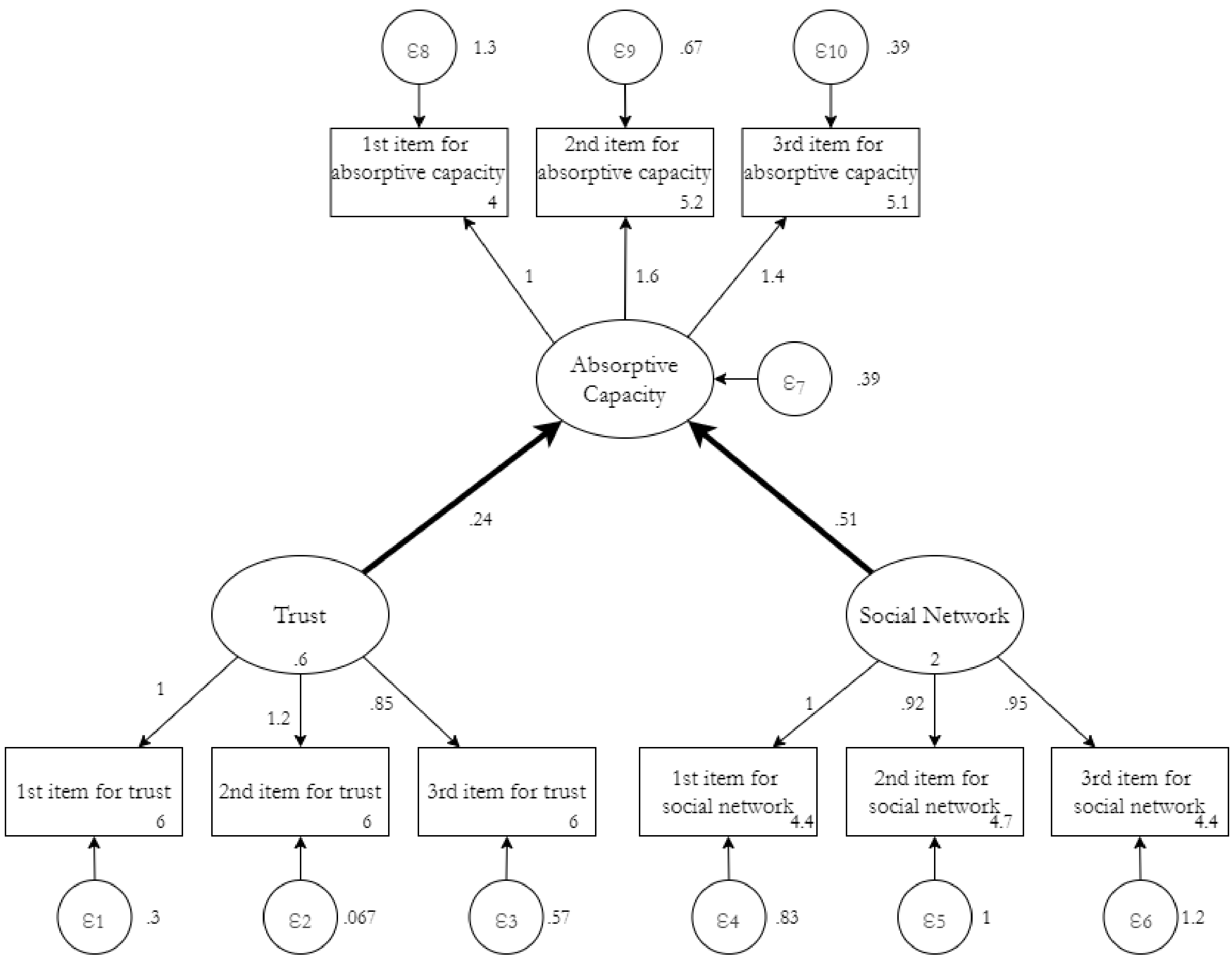

Figure 4: Hypothesized structural equation model. The bolded lines show the structural component; the thin lines show the measurement component. Circles represent latent variables; rectangles represent measure variables. Chi-square(25)=61.23; p<0.01.

Table 10. Results of the structural model

	Structural model
Absorptive Capacity	
Trust	0.238** (0.101)
Social Network	0.509*** (0.090)

*Note: Absorptive Capacity is the latent endogenous variable; Trust and Social Networks are latent exogenous variables. Values without parentheses are the coefficients; values within brackets are the standard errors. * p<0.10, ** p<0.05, *** p<0.01*

Table 11. Descriptive statistics of the factor scores

Variable	Mean	Std. Dev.	Min	Max	Obs
Trust	.000	.753	-1.601	.783	77
Social Network	.000	.490	-1.124	.907	77
Absorptive Capacity	.000	1.498	-3.384	2.851	77

6. Results of the Logistic Regression

The logistic regressions aimed at testing hypotheses 3, 4, and 5. This chapter summarizes the results of the logistic regressions. The first section describes the selection of the variables. The second section shows the results of the logistic regressions.

6.1 Selection of the regressors and model specification

The regressors used for the logistic regressors are the factor scores of social network, trust and ACAP, and the control variables.

Section 2.6 explores which characteristics of the farmer and the farm are expected to influence innovation. Per each of the concepts included in Table 1**,** a set of indicators was selected. These indicators are age, experience, education, agricultural education, farm's surface, number of workers, location, and family business. Each indicator was measured by at least one variable.

Age was measured as respondent's age. Experience was measured as years of work with that role, years of work in that company, and years of work in the wine sector of the respondent. For education, a categorical variable with the educational level was used (equal to 0 if the respondent had taken primary education only, 1 if secondary education, 2 if high school, and 3 if higher). Agricultural education is a dummy variable equal to 1 if the respondent had taken agricultural studies. The surface of the farm was operationalized into two variables: total surface (in categories from 0 to 5, in which 0 if the total surface <1 Ha, 1 if ≥ 1 total surface < 3 Ha, 2 if ≥ 3 surface < 10 Ha, 3 if ≥10 surface <30 Ha, 4 if ≥ 30 surface < 100 Ha, 5 if surface ≥ 100 Ha) and vineyard surface (in hectares). The number of workers was also operationalized into two variables: number of employees, and number of total workers (which is equal to employees plus family workers). The geographical area includes three different areas: called areas 1, 2, and 3. The family business is a dummy variable equal to 1 if the farm is a family business (Table 12).

Table 12. Variables that were considered as possible regressors.

Concept	Indicator	Variables
Human capital	Age	Age
	Experience	Years with that role
		Years in that company
		Years in the wine sector
	Education	Education (= 0 if primary ed., 1 if secondary ed., 2 if high school, 3 if higher level)
	Agricultural education	Agricultural Education
Physical capital	Size (surface)	Vineyard size
		Farm size (= 0 if surface <1 Ha, 1 if ≥ 1 surface < 3 Ha, 2 if ≥ 3 surface < 10 Ha, 3 if ≥10 surface <30 Ha, 4 if ≥ 30 surface < 100 Ha, 5 if surface ≥ 100 Ha)
	Size (number of workers)	Employees
		Total workers
Location	Location	Area 1 (Bardolino, Custoza)
		Area 2 (Arcole, Soave, Lessini)
		Area 3 (Valpolicella)
Familiness	Family business	Family business

As explained in section 3.4.2, to select the regressors, the probability distribution of the variables and the collinearity among variables were considered. The probability distribution of the control variables can be seen in Appendix 2, where the histograms are presented. The collinearity is shown in a collinearity table in Appendix 3.

The following paragraph motivates the choice of the regressors based on collinearity and probability density function. For what concerns the variables for the location group, the three location dummies were chosen; none of them presented high correlation with other variables and each dummy is well represented in the sample. Regarding the variables in the farmer characteristic group, age was chosen as it was shown to be normally distributed and uncorrelated to other variables. Moreover, the variables "years with this company", "years in the sector", and "years with that role" were shown to be strongly correlated, so only one was chosen; to select the variable that would have been used, the normality distribution of these variables was tested; to test it, the Shapiro-Francia normality test was chosen, as it showed to be a powerful test in detecting deviation from normality regardless the sample sizes (Mbah & Paothong, 2015). The null hypothesis of the test is normality; rejecting the null hypothesis implies proving that the distribution of the variable is not normal. "years with this company", "years in the sector", and "years with that role" were tested. The test rejected the null hypothesis of normality for "years with that role" and "years with this company", while failed to reject it for "years in the sector" at p=0.05 (Table 13). Therefore, "years in the sector" was chosen as regressor. The discrete variable for education and the dummy for agricultural education did not show any collinearity issues, therefore were selected. Lastly, the variables in the farm characteristic group were chosen. The logarithmic transformation of vineyard size showed a strong correlation to farm size, therefore it was decided to keep one of this only; it was preferred to use the logarithmic transformation of vineyard size as it is a continuous variable, while farm size is an ordinal data, i.e., there is no proportionate interval between the measurements. Furthermore, the logarithmic transformation of "employees" plus one and "total workers" showed correlation therefore one of the two was chosen; the log of "total workers" was chosen, as it gives more information about the total number of people in the company, so it could be a better proxy of the size of the farm compared to the number of employees only. The variable "family business" is equal to 1 in 95% of the cases, so it was chosen not to use it in the regression, as there was not enough variability.

Table 13. Shapiro-Francia W' test for normality distribution

Variables	**Obs**	**W'**	**z**	**Prob> z**
Years with this company	77	0.959	2.133	0.016
Years with this role	77	0.962	1.970	0.024
Years in the sector	77	0.968	1.631	0.051

Note: W' is the Shapiro–Francia test statistic. Null hypothesis of normality. Alternative hypothesis non-normality.

The correlation between the factor scores was also computed (**Errore. L'origine riferimento non è stata trovata.**). Trust does not have a strong correlation with social network and ACAP. However, social network and ACAP are highly correlated. For this reason, it was decided to run two different sets of regressions, one in which the components of social capital (social network and trust) are used as regressors, one in which ACAP is the regressor.

Table 14. Correlation between the factor scores

Variables	(1)	(2)	(3)
(1) Trust	1.00		
(2) Social Network	0.30	1.00	
(3) ACAP	0.40	0.84	1.00

Note: the highlighted cell indicates that the correlation between the variables is equal or above 0.8.

Two sets of five logistic regressions have been run. All the models are logistic regression regressing the dummy innovation. The only difference between the two sets is the use of ACAP instead of trust and social network as regressor. The first set of regressions is here described: the first model regresses the dependent variable with the factor scores of trust, and social network; the second regression adds the dummies of the areas as regressors; the third regression includes control variables about the human capital; the fourth regression uses control variables about physical capital; the last regression combines all the previously mentioned control variables (Table 15). The second set of regressions uses ACAP instead of social network and trust (Table 16).

Table 15. First set of regression models. Logit models. Dependent variable: Implementation of the technology. Predictors: Social networks and trust

Group of variables	Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Social capital	Social network	x	x	x	x	x
	Trust					
Location	Area 1					
	Area 2		x			x
	Area 3					
Farmer characteristics	Age					
	Years in the sector			x		x
	Education					
	Agricultural education					
Farm characteristics	Log(Vineyard size)				x	x
	Log(Total workers)					

Table 16. Second set of regression models.

Logit models. Dependent variable: Implementation of the technology. Predictors: Absorptive capacity

Group of variables	Variables	Model 6	Model 7	Model 8	Model 9	Model 10
ACAP	ACAP	x	x	x	x	x
Location	Area 1					
	Area 2		x			x
	Area 3					
Farmer characteristics	Age					
	Years in the sector			x		x
	Education					
	Agricultural education					
Farm characteristics	Log(Vineyard size)				x	x
	Log(Total workers)					

6.2 Regressions results

The first set of regressions aimed at testing hypotheses 3 and 4, while the second set of regressions intended to test hypothesis 5.

The results of the first set of regressions are shown in Table 17. Hypothesis 3 was proven by models 1 and 3 in which social network influences the implementation of water-saving technologies. All the other models did not prove the hypothesis. None of the models proved hypothesis 4: in the sample trust does not significantly influence the implementation of water-saving technologies.

Model 1 regressed the dummy innovation with social network and trust; the model correctly classified 70% of farmers' innovation; according to the model, farmers' innovation was predicted by social network ($\beta = 0.389$, s.d.=0.204 , $p < 0.1$). Model 2 regresses innovation with social network by controlling for the location of the farm; 78% of farmers' innovation was correctly classified by the model; farmers' innovation was not predicted by social network or trust, but by area 1 only (β = -2.746, s.d.=1.656 , p < 0.1). Model 3 controls for the farmers' characteristics; the model predicts 79% of the innovations; social network (β = 0.584, s.d.=0.258 , p < 0.05), age (β = -0.317, s.d.=0.159 , p < 0.05), and age squared (β = 0.003, s.d.=0.001 , p < 0.05) are statistically significantly predicting innovation. Model 4 controls for farms' characteristics; the model predicts 68% of the innovations; no parameter was significantly different from 0. Model 5 controls for all the groups; the model predicts 88% of innovations. Area 1 (β = -6.387, s.d.=2.410 , p < 0.01), age (β = -0.549, s.d.=0.288 , p < 0.1), age squared (β = 0.005, s.d.=0.003, p < 0.1), education (β = -1.247, s.d.=0.663, p < 0.1), agricultural education (β = 1.817, s.d.= 1.056, p<0.1) and the logarithmic transformation of total workers (β = 2.756, s.d.=1.394, p < 0.1) were statistically predicting innovation.

Table 17. Results from the first set of regressions.

Logit model. Dependent variable: Implementation of the technology. Predictors: Social networks and trust

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Predictors					
Social network	0.389*	0.404	0.584**	0.137	0.366
	(0.204)	(0.265)	(0.258)	(0.244)	(0.387)
Trust	-0.0750	-0.280	0.0229	0.0170	0.105
	(0.359)	(0.478)	(0.373)	(0.375)	(0.597)
Area 1		-2.746*			-6.387***
		(1.656)			(2.410)
Area 2		-0.444			-2.224
		(1.755)			(2.130)
Area 3		1.171			-0.992
		(1.328)			(1.615)
Age			-0.317**		-0.549*
			(0.159)		(0.288)
Age squared			0.003**		0.005*
			(0.001)		(0.003)
Years in the sector			-0.008		0.018
			(0.025)		(0.039)
Education			-0.100		-1.247*
			(0.358)		(0.663)
Agricultural education			0.425		1.817*
			(0.778)		(1.056)
Log(Vineyard size)				0.109	0.216
				(0.283)	(0.464)
Log(Total workers)				0.759	2.756*
				(0.569)	(1.394)
Constant	0.836***	2.118	9.167**	0.127	18.950*
	(0.256)	(1.688)	(4.660)	(0.482)	(9.482)
N	77	77	77	77	77
Pseudo R-squared	0.042	0.343	0.109	0.082	0.532
Count R-squared	0.701	0.779	0.792	0.675	0.883
AIC	97.51	74.80	101.1	97.72	70.70
BIC	104.50	88.86	119.90	109.40	101.20
Likelihood ratio test	4.04	32.75***	10.40	7.83*	50.85***

*Note: Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Among the models, model 5 showed the best performances in terms of pseudo R-squared (0.577), count R-squared (0.883), and AIC (66.41); model 2 showed the best performance in terms of BIC (88.86). A likelihood ratio test was performed on each model. In such test, the null hypothesis is that all the parameters are equal to zero; the alternative hypothesis is that at least one is not different from zero. The tests on model 1, and 3 failed to reject the null hypothesis. The tests on models 2, 4, and 5 rejected the null hypothesis and proved the alternative hypothesis (respectively p<0.01, p<0.1, p<0.01).

The results of the second set of regressions are shown in Table 18. None of the models proved hypothesis 5: in this sample, ACAP does not significantly influence the implementation of water-saving technologies.

Table 18. Results from the second set of models

Logit model. Dependent variable: Implementation of the technology. Predictors: Absorptive capacity

	Model 6	**Model 7**	**Model 8**	**Model 9**	**Model 10**
Predictors					
Absorptive capacity	0.289 (0.250)	0.261 (0.339)	0.519 (0.368)	-0.069 (0.295)	0.426 (0.567)
Area 1		-2.866* (1.631)			-6.482*** (2.448)
Area 2		-0.515 (1.699)			-2.242 (2.137)
Area 3		0.963 (1.278)			-1.227 (1.652)
Age			-0.287* (0.154)		-0.550* (0.299)
Age squared			0.003* (0.001)		0.005* (0.003)
Years in the sector			-0.001 (0.024)		0.0180 (0.0395)
Education			-0.114 (0.362)		-1.268* (0.668)
Agricultural education			0.457 (0.759)		1.699 (1.039)
Log(Vineyard size)				0.164 (0.272)	0.300 (0.462)
Log(Total workers)				0.896 (0.602)	2.781* (1.426)
Constant	0.806*** (0.249)	2.217 (1.655)	8.511* (4.532)	-0.067 (0.453)	18.89* (9.830)
N	77	77	77	77	77
Pseudo R-squared	0.014	0.323	0.068	0.079	0.527
Count R-squared	0.688	0.805	0.740	0.675	0.883
AIC	98.22	74.66	103.10	96.04	69.22
BIC	102.90	86.38	119.50	105.40	97.35
Likelihood ratio test	1.33	30.89***	6.45	7.51*	50.32***

*Note: Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Model 6 regressed the dummy innovation with ACAP; the model correctly classified 69% of farmers' innovation; according to the model, the parameter of ACAP was not significantly different from zero. Model 7 controlled the regression with the location dummies; the model predicted 81% of the observations; Area 1 (β=-2.886, s.d.=1.631, $p < 0.1$) was statistically predicting innovation. Model 8 controlled the regression by using the variables related to farmers' characteristics; that model correctly classified 74% of innovation; the parameters of age (β=-0.287, s.d.=0.154, $p<0.1$) and age squared (β=0.003, s.d.=0.001, $p<0.1$) were statistically different from zero. Model 9 regressed innovation with ACAP controlling with the variables related to farms' characteristics; 68% of the observations were correctly classified; none of the parameters was statistically significantly different from zero. Finally, Model 10 regressed innovation with ACAP controlling with all the previously mentioned variables; the model correctly classified 88% of the observations; Area 1 (β=-6.482, s.d.= 2.448, $p<0.01$), age (β=-0.549, s.d.= 0.299, $p<0.1$), age squared (β=-0.0048, s.d.= 0.0026, $p<0.1$), education (β=-1.268, s.d.= 0.668 $p<0.1$), and the logarithmic transformation of the total workers were statistically predicting innovation (β=2.781, s.d.= 1.426, $p<0.1$).

Among the models of the second set, model 10 showed the best performances in terms of pseudo R-squared (0.527), count R-squared (0.883), and AIC (69.22); model 7 showed the best performance in terms of BIC (86.38). A likelihood ratio test was performed on each model. In such test, the null hypothesis is that all the parameters are equal to zero; the alternative hypothesis is that at least one is not different from zero. The tests on model 6, and 8 failed to reject the null hypothesis. The tests on models 7, 9, and 10 rejected the null hypothesis and proved the alternative hypothesis (respectively $p<0.01$, $p<0.1$, $p<0.01$).

7. Discussion

Using survey data, a structural equation model and different logistic regressions were developed to investigate the factors influencing the implementation of water-saving technologies adopted on grape producing farms in the Verona wine province. This chapter includes the discussion of the results, a sensitivity analysis with different regressions and the limitations of the study.

7.1 Discussion of the results

This section includes a discussion of the results of the models displayed in Table 10, Table 15 and Table 16.

7.1.1 Correlation between social networks and ACAP

The results from the structural equation modelling (SEM) suggests that social network is positively correlated to ACAP (Table 10); farmers' social network plays a positive role in developing ACAP. As outlined by Cohen & Levinthal (1990), the development of broad and active networks may improve individuals' awareness of others' knowledge, increasing the ACAP of individuals and of the company itself. If a company creates close relationships with external knowledge sources that creates or amplifies information channels and company's ACAP benefits. Regarding the agricultural sector, Tepic et al. (2012) found a correlation between farmers' social network and ACAP.

Specifically, the items related to social network that were used in the survey were "I spend a considerable amount of time with other farmers", "I have an informal network of suppliers, clients, and competitors", and "When I participate to agricultural events, I am one of the most active participants".

The first item refers to what Putnam (2000) defined as bonding social capital, so networks among individuals sharing similar characteristics. The second and third items measure to a certain degree bonding capital, as they refer to networks within the agricultural community, but also bridging capital, which are defined as outward-looking ties across different groups (Putnam, 2000), e.g. farmers and scientists, or farmers and technology providers. Zahra & George (2002) investigated in detail the type of network that a company needs to develop ACAP; firms exposing to more diverse and complementary sources of knowledge have a larger opportunity to develop their ACAP (Zahra & George, 2002). Bridging social capital seems to better correspond to diverse and complementary sources of knowledge than bonding social capital. Due to the design of the study, it is not possible to infer whether bridging social capital helps developing ACAP more than bonding social capital; however, it is not excluded, and further research could help covering this gap.

7.1.2 Correlation between trust and ACAP

From the results of the SEM, it seems that trust is positively correlated to ACAP (Table 10). By looking at the nature of the items that measure trust, it is possible to make some considerations; the items that were used in the factor analysis for trust are the following: "other companies can rely on me without fearing that I will take advantage of them", "my company will always keep the promises done", and "in the case of an informal agreement, I would always stick to the agreement even if there is no contract". From the items, one can notice that the three items only relate to trust between farmers; none of the items bears information about trust between farmers and other parties (e.g. farmer communities, or technology providers). Moreover, the three items are bearing a similar aspect of the same concept, that is farmers' perception on how they are trusted by other farmers. Fisher (2013) argued that farmers trusting their information sources are more likely to assimilate and interpret the information and to transform it into knowledge. From the results, it is confirmed that trust among farmers facilitate the increase of ACAP; however, no inference can be done related to the role of trust between farmers and other information sources; Zahra & George (2002) argued that it is the diversity of the source of knowledge that influences ACAP; our study cannot prove that trust in different information sources might have a role in developing ACAP and therefore further research is required.

7.1.3 Correlation between social networks and implementation of water-saving technologies

The results of the first set of logistic regressions (Table 17), in which social network and trust were used as regressors, do not provide a clear answer to the research question number 3. Models 1 and 3 confirmed that social network is statistically correlated to the implementation of water-saving technologies. However, models 1 and 3 present bad fit compared to models 2, and 5. Moreover, models 1 and 3 were the only models that failed to reject the null hypothesis of the likelihood test.

In addition, the relationship pointed out by the logistic regression might be spurious; specifically, model 2 controlled the regression with the geographical area of the farm; farmers from area 1 (Bardolino and Custoza) present a negative mean value of the factor score of social network (-0.28), while farmers from area 2 (Arcole, Soave, Lessini) and 3 (Valpolicella) have positive values of the scores (0.36 and 0.18 respectively) (Appendix 4). Thus, the relationship highlighted by models 1 and 3 might be partially explained by a possible spurious relation between social network and innovation in which some characteristics of the geographical areas are the confounders.

7.1.4 Correlation between trust and implementation of water-saving technologies

The models did not find any correlation between trust and implementation of water-saving technologies (Table 17). Simply put, in this sample trust is not directly linked to implementation of water-saving technologies, while the literature would suggest that implementation of technologies would be facilitated by trust.

A possible explanation could be related to the type of trust that was used to calculate the factor score of the latent variable. Hunecke et al. (2017) reported that farmers' main source of information are extension agents. Genius et al. (2014) noticed that the information provided by extension services, through visits by extension agents, are more effective than the one obtained by peer farmers in increasing the implementation of irrigation technologies in cases in which the innovation is already strongly present. In the sample, 69% of the farms implemented the water-saving technology, showing that such innovation is strongly present in the territory. Moreover, as described previously, to compute the factor scores trust was measured by using items that relate to trust between farmers only. Therefore, our study lacks an analysis on the extent to which trust towards extension agents influence technology adoption. The sensitivity analysis assesses this issue.

7.1.5 Correlation between ACAP and implementation of water-saving technologies

The last set of logistic regressions (Table 18) uses ACAP and the control variables as regressors for innovation. In this sample, ACAP does not influence the implementation of water-saving technologies. ACAP has been described as the capability to adapt and transform externally generated knowledge into the firms' operations (Micheels & Nolan, 2016). In the data analysis, that items that has been used to compute ACAP's factor score are: "My farm is fast to recognize market changes", "I quickly understand new practices to manage the vineyards", and "I constantly consider how to better exploit information". The first two components measure the ability to assimilate information and internalize it creating knowledge, while the last item refers to the exploitation ability, that is the capability to incorporate knowledge into the farm operations. However, these items measure only 2 components of the 4 that composes ACAP (acquisition of information, assimilation of information, transformation of information, and exploitation of information). Therefore, the results might be driven by the fact that the factor score of ACAP only represents a part of the latent variable. The sensitivity analysis covers this aspect.

7.1.6 Correlation between control variables and implementation of water-saving technologies

As already described in the literature and substantiated here, some control variables have an influence on innovation. From models 3, 5, 8, and 10, age was shown to have an influence on the implementation of water-saving technologies. More specifically, age has a quadratic relationship with the implementation of water-saving technologies: young and old farmers implement more technologies than farmers with an age in between. Our results seem to be in line with a part of the literature. Torbett et al. (2007) found that older farmers, i.e., farmers over 50 years old, were implementing more technologies than the rest of the farmers. In a different study, Paustian & Theuvsen (2017) found that younger farmers, being motivated and having a long planning horizon, are more willing to adopt innovations.

As highlighted by Pierpaoli et al. (2013), the geographical area is often a significant determinant of innovations. From our results we can see that farmers from area 1 implement less technologies than farmers from areas 2 and 3, confirming that the geographical area can be a relevant factor. Area 1 is the Western part of the province, which includes the locations of Bardolino and Custoza. This could suggest that there might be some structural differences among this area and the rest of the province. One point of attention might be the price of the grape: grapes produced in Bardolino and Custoza are among the cheapest grapes in the province (Camera di commercio di Verona, 2020), therefore the dummy for the geographical area might be a rough proxy for farmer's income. Part of the sensitivity (section 7.2.2) analysis digs more deeply into this issue.

It has been observed that innovation happens across different sizes of farms (Micheels & Nolan, 2016). The authors argued that not all the technologies are scale dependent and innovation often depends on more factors than the physical capital of the farm. Our results are in line with that. The results from models 4 and 9 shows that the vineyard surface and the number of total workers do not explain innovation. Moreover, the count R-squared are lower than the ones of models 1 and 6 (i.e., the models in which the factor scores are the only regressors), showing that including the physical capital variables worsens the predictive power of the model.

Läpple et al. (2015) argued that farmers that took agricultural related studies may have greater awareness about agricultural innovations. The results from model 5 are in line with this argument since the dummy variable for agricultural education has a positive effect on the adoption of efficient irrigation systems.

The level of education is considered an important factor for technology adoption: farmers that have higher educational level may implement more technologies (Pierpaoli et al., 2013). However, in our sample educational level is linked to a lower implementation of technology adoption. When discussing the effect of education, it is important to consider that the variable for educational level is assumed to be an interval variable (i.e., interval between successive ranks is equal) and contains 4 different categories: 0=primary school, 1=secondary school, 2=high school, 3=higher level (Table 19). By using this variable in the logistic regression, we are assuming that the difference from primary school to secondary school and the difference from secondary school to high school, and so on, is the same. However, there is no certainty about that. The sensitivity analysis (7.2.1) includes a more solid approach to regress with this kind of variable.

Table 19. Categorical variable for education.

Variable	Categories
Education	0=primary school
	1=secondary school
	2=high school
	3=higher education

Education has been included in the data anaalysis as an interval variable (i.e. interval between successive ranks is equal).

7.2 Sensitivity analysis

The following section contains a sensitivity analysis. The models included in Table 15 and Table 16 have been modified to verify whether the results are consistent. The first change regards the variable for education; the categorical variable has been substituted with three dummy variables. The second change regards the geographical variable; instead of considering three areas (West, centre, and east) only high-cost (Area 3) and low-cost (Area 1 and 2) wine area has been considered. Finally, different methods to compute factor scores have been applied, to assess if a change in the computation method leads to the same results.

7.2.1 Education

The first sensitivity analysis regards a change in the variable for educational level. As explained in the discussion of the results, the variable for educational level is categorical and contains 4 different categories: 0=primary school, 1=secondary school, 2=high school, 3=higher level. By using this variable as an interval variable, we are assuming that the difference from primary school to secondary school and the difference from secondary school to high school, and so on, is the same. However, there is no certainty about that.

Micheels & Nolan (2016), for instance, found that the number of new technologies adopted depends on whether the farmer has done some high school and some technical school. However, farmers that took a university program do not have a different likelihood of adopting new technologies (Micheels & Nolan, 2016). Therefore, to verify if there are differences among the effects of the levels of education, we have substituted the variable for education with three dummy variables: secondary school, high school, and university. Table 20 and Table 21 show the results of models 3, 5, 8, and 10 (i.e., the same models described in Table 15 and Table 16) and models 3.1, 5.1, 8.1, and 10.1 in which education is substituted with the three dummy variables. From Table 20 and Table 21 it is possible to notice that the results are consistent even if education is changed into three dummy variables. By comparing each model with the corresponding one, there are no substantial changes in the estimated parameters.

7.2.2 Geographical areas

The second sensitivity analysis regards a change in the variable for geographical areas. The case study we are considering includes three main geographical areas: area 1, which includes wines from the west of the Verona province, area 2, which includes wines from the east of the province, and area 3, with wines from the centre. However, there is also a strong difference in prices among the wines, and more interestingly for the study, there is a substantial difference in the price of the grape. Grapes from area 1 and 2 are sold at about 0.40-0.50€/Kg, while grapes from area 3 at 1.60-1.90 €/Kg (Camera di commercio di Verona, 2020). Therefore, another classification could be high-price and low-price areas. To verify if this is consistent with our results, models 2, 5, 7, and 10 have been modified. The only geographical variable is a dummy variable equal to 1 if the farm is operating in area 3 (the high-priced area).

Table 20. Results from the sensitivity analysis in which the variable for education is changed: models 3 and 5. Logit model. Dependent variable: Implementation of the technology. Predictors: Social networks and trust

	Model 3	**Model 3.1**	**Model 5**	**Model 5.1**
Predictors				
Social network	0.584**	0.627**	0.366	0.356
	(0.258)	(0.272)	(0.387)	(0.410)
Trust	0.0229	-0.010	0.105	0.131
	(0.373)	(0.380)	(0.597)	(0.609)
Area 1			-6.387***	-6.462***
			(2.410)	(2.457)
Area 2			-2.224	-2.320
			(2.130)	(2.148)
Area 3			-0.992	-0.969
			(1.615)	(1.620)
Age	-0.317**	-0.361**	-0.549*	-0.612*
	(0.159)	(0.175)	(0.288)	(0.356)
Age squared	0.003**	0.003**	0.005*	0.005*
	(0.001)	(0.002)	(0.003)	(0.003)
Years in the sector	-0.008	-0.010	0.018	0.012
	(0.025)	(0.025)	(0.039)	(0.041)
Agricultural education	0.425	0.494	1.817*	2.040*
	(0.778)	(0.819)	(1.056)	(1.214)
Education	-0.100		-1.247*	
	(0.358)		(0.663)	
Secondary school		0.551		-0.639
		(0.881)		(1.365)
High school		0.043		-2.539*
		(0.872)		(1.519)
University		-0.236		-3.815*
		(1.193)		(2.176)
Log(Vineyard size)			0.216	0.253
			(0.464)	(0.489)
Log(Total workers)			2.756*	2.882*
			(1.394)	(1.475)
Constant	9.167**	9.974**	18.95*	20.35*
	(4.660)	(4.931)	(9.482)	(10.87)
N	77	77	77	77
Pseudo R-squared	0.109	0.116	0.532	0.535
Count R-squared	0.792	0.792	0.883	0.883
AIC	101.10	104.50	70.70	74.41
BIC	119.90	127.90	101.20	109.60
Likelihood ratio test	10.40	11.06	50.85***	51.14***

Intercept includes: Primary school; No agricultural education.

*Note: Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table 21. Results from the sensitivity analysis in which the variable for education is changed: models 8 and 10. Logit model. Dependent variable: Implementation of the technology. Predictors: Absorptive capacity

	Model 8	Model 8.1	Model 10	Model 10.1
Predictors				
Absorptive capacity	0.519	0.526	0.426	0.399
	(0.368)	(0.369)	(0.567)	(0.591)
Area 1			-6.482***	-6.540***
			(2.448)	(2.511)
Area 2			-2.242	-2.286
			(2.137)	(2.155)
Area 3			-1.227	-1.177
			(1.652)	(1.682)
Age	-0.287*	-0.301*	-0.550*	-0.596*
	(0.154)	(0.165)	(0.299)	(0.361)
Age squared	0.003*	0.003*	0.005*	0.005*
	(0.001)	(0.001)	(0.003)	(0.003)
Years in the sector	-0.001	-0.002	0.018	0.013
	(0.024)	(0.024)	(0.040)	(0.041)
Agricultural education	0.457	0.573	1.699	1.943
	(0.759)	(0.800)	(1.039)	(1.224)
Education	-0.114		-1.268*	-1.268*
	(0.362)		(0.668)	(0.668)
Secondary school		0.270		-0.732
		(0.866)		(1.336)
High school		-0.205		-2.645*
		(0.879)		(1.533)
University		-0.136		-3.839*
		(1.196)		(2.176)
Log(Vineyard size)			0.300	0.315
			(0.462)	(0.488)
Log(Total workers)			2.781*	2.935*
			(1.426)	(1.514)
Constant	8.511*	8.702*	18.89*	19.890*
	(4.532)	(4.677)	(9.830)	(11.090)
N	77	77	77	77
Pseudo R-squared	0.068	0.071	0.527	0.529
Count R-squared	0.740	0.714	0.883	0.883
AIC	103.10	106.70	69.22	72.96
BIC	119.50	127.80	97.35	105.80
Likelihood ratio test	6.45	6.80	50.32***	50.59***

Intercept includes: Primary school; No agricultural education.

*Note: Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table 22 and Table 23 show the results of models 2, 5, 7, and 10 (i.e., the same models described in Table 15 and Table 16) and models 2.2, 5.2, 7.2, and 10.2, in which the only geographical dummy is area 3. From Table 22 and Table 23 it is possible to notice that in the modified models (2.2, 5.2, 7.2, and 10.2) the dummy variable area 3 is always statistically significantly larger than 0 ($p<0.01$). Overall, by comparing each model with the corresponding one, there are no substantial changes in the parameters. Model 2.2 reports a weak statistically significance of the parameter for social network ($p<0.10$). Model 5.2 does not find any significance in the log of total workers. Model 10.2 does not find any effect of age and age squared on the implementation of the technology.

Table 22. Results from the sensitivity analysis in which operating or not in area 3 is the only geographical variable: models 2 and 5. Logit model. Dependent variable: Implementation of the technology. Predictors: Social networks and trust

	Model 2	**Model 2.2**	**Model 5**	**Model 5.2**
Predictors				
Social network	0.404 (0.265)	0.439* (0.240)	0.366 (0.387)	0.388 (0.308)
Trust	-0.280 (0.478)	-0.152 (0.240)	0.105 (0.597)	0.105 (0.445)
Area 1	-2.746* (1.656)		-6.387*** (2.410)	
Area 2	-0.444 (1.755)		-2.224 (2.130)	
Area 3	1.171 (1.328)	2.565*** (0.813)	-0.992 (1.615)	2.799*** (0.992)
Age			-0.549* (0.288)	-0.312* (0.182)
Age squared			0.005* (0.003)	0.003* (0.002)
Years in the sector			0.018 (0.039)	-0.014 (0.030)
Agricultural education			1.817* (1.056)	1.263 (0.899)
Education			-1.247* (0.663)	-0.927* (0.475)
Log(Vineyard size)			0.216 (0.464)	0.133 (0.338)
Log(Total workers)			2.756* (1.394)	0.993 (0.833)
Constant	2.118 (1.688)	0.181 (0.303)	18.95* (9.482)	9.081* (5.334)
N	77	77	77	77
Pseudo R-squared	0.343	0.204	0.532	0.303
Count R-squared	0.779	0.766	0.883	0.766
AIC	74.80	84.06	70.70	88.61
BIC	88.86	93.44	101.20	114.40
Likelihood ratio test	32.75***	19.49***	50.85***	28.94***

*Note: Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table 23. Results from the sensitivity analysis in which operating or not in area 3 is the only geographical variable: models 7 and 10. Logit model. Dependent variable: Implementation of the technology. Predictors: Absorptive capacity

	Model 7	Model 7.2	Model 10	Model 10.2
Predictors				
Absorptive capacity	0.261	0.254	0.426	0.262
	(0.339)	(0.392)	(0.567)	(0.466)
Area 1	-2.866*		-6.482***	
	(1.631)		(2.448)	
Area 2	-0.515		-2.242	
	(1.699)		(2.137)	
Area 3	0.963	2.487***	-1.227	2.676***
	(1.278)	(0.791)	(1.652)	(0.950)
Age			-0.550*	-0.280
			(0.299)	(0.187)
Age squared			0.005*	0.003
			(0.003)	(0.002)
Years in the sector			0.018	0.016
			(0.040)	(0.030)
Education			-1.268*	-0.928*
			(0.668)	(0.480)
Agricultural education			1.699	1.296
			(1.039)	(0.890)
Log(Vineyard size)			0.300	0.208
			(0.462)	(0.327)
Log(Total workers)			2.781*	1.058*
			(1.426)	(0.843)
Constant	2.217	0.150	18.89*	8.102*
	(1.655)	(0.295)	(9.830)	(5.478)
N	77	77	77	77
Pseudo R-squared	0.323	0.174	0.527	0.285
Count R-squared	0.805	0.714	0.883	0.779
AIC	74.66	84.91	69.22	88.33
BIC	86.38	91.94	97.35	111.80
Likelihood ratio test	30.89***	16.64***	50.32***	27.21***

*Note: Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

7.2.3 Different computation of factor scores

This section aims at assessing the consistency of the results in the case the factor scores are computed differently, either by a different method or by different items.

Change in methods for computing factor scores

The third sensitivity analysis aims at assessing whether the results are sensitive to the method used for computing the factor scores of the latent variables. All the previous models have been run with factor scores computed with the regression factor scores method, which is a refined method. This section runs the same models (i.e., the ones described in Table 15 and Table 16) by using factor scores computed using a sum score method. Sum score method is a computational method for factor scores that involves summing the values of the items loading on a factor (Distefano et al., 2009):

$$\text{Factor score}_{ji} = \frac{\sum_{i=1}^{n} \text{item}_{ji}}{n} \quad (11)$$

Where j is a vector from 1 to 3 with the factor scores, i is the vector with the items of each factor score, and n is the number of items per factor score.

Table 24 and Table 25 show the results of the models in which the factor scores were computed by using a sum score method. The items used for computing such factor scores are the ones included in Table 8. Table 24 shows the results of the modified versions of the models in Table 17. By comparing each model with the corresponding one, there are no substantial changes in the parameters. Table 25 includes the modified models of Table 18. By comparing the results of Table 25 with Table 18, it is noticeable that by changing the factor scores, part of the parameters changes. Overall, the parameters of the control variables do not present any substantial change, however model 6.3 and 8.3 reports significance of the parameter for absorptive capacity. That suggests the importance of choosing the right computational method.

Change in items for computing factor scores: all the items

This part of the analysis aims at checking whether the results are sensitive to the choice of the items. To compute factor scores, the data analysis in chapter 5 used 3 items per latent variable (Table 8) that were selected from a larger list of items (Table 6). Table 26 and Table 27 show the result of the models in which the factor scores were computed by using a sum score method. All the items included in Table 6 except one were used. The only item that was not used is the one related to the question "*How many commercial contacts do you have?"*, as it was measured on a different response format (not a Likert-response format). Table 26 reports the results of the modified versions of the models included in Table 17. By comparing each model with the corresponding one, there are no substantial changes in the parameters; the regressions calculate similar parameters for social network, trust, and the control variables. Table 27 includes the results of the modified versions of the models in Table 18. Overall, the parameters of the control variables do not present any substantial change, however model 6.4 and 8.4 reports significance of the parameter for absorptive capacity. This is consistent with the results of models 6.3 and 8.3.

Table 24. Results from the sensitivity analysis in which the factor scores are calculated with sum score method. Logit model. Dependent variable: Implementation of the technology. Predictors: Social networks and Trust

	Model 1.3	**Model 2.3**	**Model 3.3**	**Model 4.3**	**Model 5.3**
Predictors					
Social network [1]	0.351*	0.387	0.515**	0.132	0.325
	(0.180)	(0.239)	(0.223)	(0.219)	(0.341)
Trust [1]	-0.0105	-0.306	0.015	0.095	0.053
	(0.306)	(0.420)	(0.325)	(0.321)	(0.545)
Area 1		-2.662*			-6.267***
		(1.664)			(2.404)
Area 2		-0.356			-2.119
		(1.769)			(2.139)
Area 3		1.325			-0.880
		(1.357)			(1.646)
Age			-0.311**		-0.532*
			(0.155)		(0.282)
Age squared			0.003**		0.005*
			(0.001)		(0.002)
Years in the sector			-0.009		0.017
			(0.025)		(0.039)
Education			-0.054		-1.230*
			(0.355)		(0.656)
Agricultural education			0.497		1.882*
			(0.783)		(1.069)
Log(Vineyard size)				0.096	0.194
				(0.288)	(0.468)
Log(Total workers)				0.775	2.772**
				(0.563)	(1.387)
Constant	-0.675	2.115	6.521	-1.025	16.610*
	(1.814)	(2.812)	(4.573)	(1.863)	(9.343)
N	77	77	77	77	77
Pseudo R-squared	0.044	0.346	0.111	0.085	0.532
Count R-squared	0.701	0.792	0.727	0.649	0.883
AIC	97.33	74.44	100.90	97.47	70.71
BIC	104.40	88.51	119.70	109.20	101.20
Likelihood ratio test	4.22	33.10***	10.64	8.08*	50.84***

*Note: 1=sum score method was used to compute the latent variables. To compute the latent variables, the items included in Table 8 were used. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table 25. Results from the sensitivity analysis in which the factor scores are calculated with sum score method. Logit model. Dependent variable: Implementation of the technology. Predictor: Absorptive capacity

	Model 6.3	Model 7.3	Model 8.3	Model 9.3	Model 10.3
Predictors					
Absorptive capacity[1]	0.319* (0.181)	0.290 (0.238)	0.601** (0.270)	0.070 (0.215)	0.393 (0.437)
Area 1		-2.745* (1.631)			-6.339*** (2.408)
Area 2		-0.441 (1.713)			-2.164 (2.111)
Area 3		1.082 (1.292)			-1.053 (1.611)
Age			-0.344** (0.169)		-0.561* (0.304)
Age squared			0.003** (0.001)		0.005* (0.003)
Years in the sector			-0.003 (0.025)		0.0203 (0.040)
Education			-0.239 (0.378)		-1.333* (0.696)
Agricultural education			0.426 (0.770)		1.627 (1.058)
Log(Vineyard size)				0.140 (0.278)	0.242 (0.469)
Log(Total workers)				0.784 (0.582)	2.825* (1.423)
Constant	-0.644 (0.836)	0.795 (1.896)	7.316 (4.592)	-0.269 (0.859)	17.450* (9.256)
N	77	77	77	77	77
Pseudo R-squared	0.034	0.333	0.104	0.079	0.529
Count R-squared	0.649	0.805	0.714	0.649	0.883
AIC	96.33	73.74	99.66	95.99	68.96
BIC	101.00	85.46	116.10	105.40	97.09
Likelihood ratio test	3.22*	31.81***	9.89	7.56*	50.58***

*Note: 1=sum score method was used to compute the latent variables. To compute the latent variables, the items included in Table 8 were used. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table 26: Results from the sensitivity analysis in which the factor scores are calculated with all the items and non-refined methods. Logit model. Dependent variable: Implementation of the technology. Predictors: Social networks and trust

	Model 1.4	**Model 2.4**	**Model 3.4**	**Model 4.4**	**Model 5.4**
Predictors					
Social network [1]	0.412**	0.471*	0.533**	0.222	0.401
	(0.203)	(0.270)	(0.251)	(0.252)	(0.430)
Trust [1]	-0.234	-0.456	-0.179	-0.222	-0.270
	(0.330)	(0.437)	(0.349)	(0.342)	(0.569)
Area 1		-3.113*			-6.380***
		(1.691)			(2.432)
Area 2		-0.614			-2.036
		(1.768)			(2.127)
Area 3		0.860			-1.212
		(1.327)			(1.694)
Age			-0.257*		-0.479*
			(0.147)		(0.283)
Age squared			0.002*		0.004*
			(0.001)		(0.002)
Years in the sector			-0.013		0.015
			(0.025)		(0.039)
Education			-0.052		-1.217*
			(0.355)		(0.655)
Agricultural education			0.351		1.798*
			(0.769)		(1.049)
Log(Vineyard size)				0.023	0.112
				(0.307)	(0.497)
Log(Total workers)				0.840	2.953**
				(0.557)	(1.408)
Constant	-0.012	2.388	5.854	0.208	16.230*
	(1.643)	(2.631)	(4.347)	(1.674)	(8.668)
N	77	77	77	77	77
Pseudo R-squared	0.046	0.355	0.097	0.088	0.531
Count R-squared	0.714	0.792	0.740	0.675	0.896
AIC	97.13	73.66	102.30	97.11	70.83
BIC	104.20	87.72	121.00	108.80	101.30
Likelihood ratio test	4.42	33.89***	9.26	8.43*	50.72***

*Note:[1]=a non-refined method was used to compute the latent variables. To compute the latent variables, the items included in Table 6 were used, except from the item "How many commercial contacts do you have?". Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table 27: Results from the sensitivity analysis in which the factor scores are calculated with all the items and non-refined methods. Logit model. Dependent variable: Implementation of the technology. Predictors: Absorptive capacity

	Model 6.4	Model 7.4	Model 8.4	Model 9.4	Model 10.4
Predictors					
Absorptive capacity[1]	0.441** (0.216)	0.493 (0.301)	0.761** (0.307)	0.153 (0.270)	0.729 (0.560)
Area 1		-3.009* (1.672)			-6.823*** (2.485)
Area 2		-0.666 (1.754)			-2.427 (2.103)
Area 3		0.913 (1.313)			-1.412 (1.616)
Age			-0.322** (0.162)		-0.566* (0.292)
Age squared			0.003** (0.001)		0.005* (0.003)
Years in the sector			-0.012 (0.025)		0.021 (0.041)
Education			-0.219 (0.373)		-1.371* (0.699)
Agricultural education			0.578 (0.772)		1.792* (1.058)
Log(Vineyard size)				0.115 (0.282)	0.205 (0.483)
Log(Total workers)				0.737 (0.581)	2.839** (1.423)
Constant	-1.104 (0.945)	0.237 (1.939)	5.966 (4.542)	-0.542 (1.000)	16.310* (9.079)
N	77	77	77	77	77
Pseudo R-squared	0.046	0.347	0.119	0.081	0.541
Count R-squared	0.636	0.779	0.740	0.636	0.883
AIC	95.15	72.39	98.19	95.77	67.85
BIC	99.84	84.11	114.60	105.10	95.98
Likelihood ratio test	4.40**	33.15***	11.36	7.78*	51.70***

*Note:[1]=a non-refined method was used to compute the latent variables. To compute the latent variable, the items included in Table 6 were used. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Change in items for computing the factor scores of trust

As addressed in the section 7.1.4, the research does not find any significant correlation between trust among farmers and the implementation of the water-saving technology. This part of the sensitivity analysis aims at investigating the effect of other types of trust on innovation.

Table 28 shows the results of the models in which the factor score for trust was computed by using a sum score method including only items concerning trust between farmers and the government and farmers and information agents (that is the 5th, 6th, 7th, and 8th item included in Table 6). The factor score for social network was computed through a sum score method including the items of Table 8. Overall, the parameters of the control variables do not present any substantial change compared to models 1, 2 ,3, 4, and 5 from Table 17. The parameter of trust is not statistically significantly different from 0.

Table 28. Results from the sensitivity analysis in which the factor score for trust is calculated using items regarding trust in the government and trust in information agents. Logit model. Dependent variable: Implementation of the technology. Social network and trust

	Model 1.5	Model 2.5	Model 3.5	Model 4.5	Model 5.5
Predictors					
Social network [1]	0.369**	0.356*	0.517**	0.184	0.353
	(0.178)	(0.230)	(0.215)	(0.212)	(0.331)
Trust [1]	-0.186	-0.173	-0.126	-0.221	-0.162
	(0.232)	(0.279)	(0.248)	(0.237)	(0.356)
Area 1		-2.768*			-6.312***
		(1.646)			(2.429)
Area 2		-0.503			-2.087
		(1.737)			(2.145)
Area 3		1.108			-0.936
		(1.308)			(1.674)
Age			-0.303*		-0.499*
			(0.155)		(0.289)
Age squared			0.003**		0.004*
			(0.001)		(0.003)
Years in the sector			-0.013		0.018
			(0.025)		(0.039)
Education			-0.034		-1.243*
			(0.359)		(0.662)
Agricultural education			0.508		1.958*
			(0.778)		(1.087)
Log(Vineyard size)				0.023	0.158
				(0.307)	(0.469)
Log(Total workers)				0.840	2.874**
				(0.557)	(1.402)
Constant	-0.142	1.199	6.806	0.157	16.470*
	(1.074)	(2.101)	(4.397)	(1.081)	(8.952)
N	77	77	77	77	77
Pseudo R-squared	0.051	0.345	0.114	0.093	0.534
Count R-squared	0.675	0.792	0.779	0.701	0.883
AIC	96.67	74.60	100.70	96.67	70.51
BIC	103.70	88.67	119.40	108.40	101.00
Likelihood ratio test	4.88*	32.95***	10.89	8.88*	51.04***

*Note:[1]=a non-refined method was used to compute the latent variables. To compute the factor score of social network, the items included in Table 8 were used. To compute the factor score of trust, the 5th, 6th, 7th, and 8th items included in Table 6 were used. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

7.3 Limitations

While our results suggest that social network and trust could influence ACAP, and that social network could affect the implementation of water-saving technologies in the Verona wine province, we also understand that the research has certain limitations. This section aims at addressing the main ones.

7.3.1 Sample size

This part of the limitations addresses the issues related to the sample size of the research, that are internal and external validity.

External validity

The study aimed at generalizing the results to the entire population of grape farms in the Verona wine province. O′Leary (2004) reported that to represent a population of about 5000 cases, a sample of at least 357 subjects is necessary. The population of PDO grape farms in Verona includes 5405 cases, while our sample has 77 usable subjects. According to O′Leary (2004) our sample cannot represent the entire population, therefore the external validity is low.

Internal validity

Beside generalizing the results, it is important to discuss whether the results are internally valid. Statistical analyses are suspected to produce problematic results if the ratio between number of events and independent variables is not large enough (Concato et al., 1993). In logistic regressions, the number of events is defined as the number of observations of the least represented category in the binary dependent variable (e.g. farmers with the technology versus farmers without the technology) (Peduzzi et al., 1996); a sample might have a very large number of observations but too little variability in the binary dependent variable (e.g. too few farmers implemented the technology). Therefore, it is crucial to consider the distribution of the dependent variable when analysing the sample size.

To maintain the validity of the model, at least 10 events per independent variable are necessary (Peduzzi et al., 1996); values below that threshold can lead to misleading associations, and concerns about accuracy and precision of the regression coefficients. In a Monte Carlo study, Peduzzi et al. (1996) found that too few observations per independent variable (ratio<10) in logistic regressions can lead to paradoxical associations (i.e. significance in the wrong direction). In our study, the number of events is equal to 24 (24 farms without the water-saving technology), which would mean that no more than two independent variables shall be used in the model for the estimates to be valid.

From Table 29 and Table 30 it is possible to notice that the number of events per dependent variables are below the desired threshold of 10 in each model in which some control variables have been used (i.e., every model except for models 1 and 6).

To have a stronger internal validity, our sample shall have around 390 usable observations [3]. In reality, the usable observations are 77. That means that the results might be biased and that some estimates could be misleading. For instance, models 5 and 10 detected a significantly negative relationship between education and implementation of technologies; in our sample, farmers with lower education implemented the efficient irrigation system more than farmers with higher education. This could be an example of misleading association, since several authors reported the opposite, arguing that educational level is one of the drivers of technology adoption in agriculture (Hunecke et al., 2017; Pierpaoli et al., 2013).

[3] In the sample, 24 farms out of 77 do not have the technology (31%). To have valid results, it is required to have at least 10 events per independent variable. The model with the largest number of independent variables is model 5. It contains 12 independent variables, that would require at least 120 events for valid results. If we assume that 31% of the farms that were interviewed do not have the water-saving technology, it means that the sample should include approximately 386 usable observations (120/0.31 = 386).

Table 29. Number of events per number of independent variables for the first set of models

	Model 1	Model 2	Model 3	Model 4	Model 5
Number of events per variable	12	4.8	3.4	6	2

Note: computed as number of events over number of independent variables, where number of events corresponds to the number of observations in the least represented category of the binomial dependent variable (equal to 24 farms without the water-saving technology).

Table 30. Number of events per number of independent variables for the second set of models

	Model 6	Model 7	Model 8	Model 9	Model 10
Number of events per variable	24	6	4	8	2.2

Note: computed as number of events over number of independent variables, where number of events corresponds to the number of observations in the least represented category of the binomial dependent variable (equal to 24 farms without the water-saving technology).

7.3.2 Selection bias

The sampling procedure was randomized, as 400 farms were randomly selected from the entire population. However, during the steps of the data collection, some selection biases might have occurred.

The first step after selecting the subjects was retrieving the phone number of the farm and/or the farmer. To do so, farm websites, phone books, and web search engines were used. Out of 400 farms in the sample, it was possible to retrieve the phone number of 197 subjects. This has possibly leaded to some selection biases. Farms with a website might be overrepresented, as it was easier to find the phone number of such farms. People who only have mobile phones tend to be younger (Blumberg & Luke, 2016). In our research, most of the respondents were contacted on a phone number that was found on the Italian phone book. The Italian phone book includes landline phone numbers only. Therefore, this suggests that younger farmers might be underrepresented as they might not have their phone numbers on the public phone book.

As defined by Rousseau et al. (1998, p.395), trust is "the intention to accept vulnerability based upon positive expectations of the intentions or behaviour of another". In other words, people that trust others have positive expectations of others' intensions. During the data collection process, some of the contacted farmers did not want to take the survey as they did not want to give any personal data to a stranger (the interviewer). Therefore, farmers with low trust might be underrepresented, as they might have been part of those that did not want to take part of the study.

7.3.3 Other limitations

The survey did not include some variables that might have given important information. The year of adoption of the technology was not included in the questionnaire. In fact, some subjects might have the technology since more time than others. The introduction of some relevant policies or subsidies might have stimulated or constrained farmers towards the adoption of such technology. With this regard, the current study assumes that the likelihood of adoption of the technology is the same every year.

Income is a factor that has been shown to influence the adoption of technologies (Pierpaoli et al., 2013). However, this research does not control for income. Profitability can be perceived as sensitive information, and questions on profitability are often associated with high non-response rates (Galobardes & Demarest, 2003). Therefore, information on farms' profitability was meant to be collected from the online database Orbis[4]. However, while retrieving the information from this database, we realized that several farms are not included in the database and information about financial aspects are missing often. Therefore, it was not possible to include this information in the study.

The information about human capital, social capital, and ACAP were collected regarding the respondent. Even though the respondents were supposed to be people responsible for the strategic decisions concerning investments in grape production (section 3.2), there is no certainty that all the respondents had decision power for what concerns the implementation of technologies within the farm. For example, 13% of the respondents were not the owners of the farm (Table 5), suggesting that part of the survey might have been addressed to the wrong people.

It is important to be aware that the variable for education is categorical, but it was used as an interval variable (i.e., interval between successive ranks is equal); that means that we assumed that a difference between primary school and secondary school is valued one, as well as the difference between secondary school and high school, and so on. A more solid approach would have been to regress by using the dummy variables of all the educational levels, as it was done in the sensitivity analysis (section 7.2.1); however, the choice of keeping one single categorical variable was driven by the need of keeping the number of regressors low, being the sample size low. One might express a similar argument about Likert response format items. These items produce ordinal variables that do not satisfy the interval data assumption. However, as explained more in depth in section 3.3, this is not an issue in this research as the data-analysis was based on multi-item measurement scales, which are robust to the interval data assumption.

Finally, the supposed effect of social network on implementation of technologies was detected by models 1 and 3 only. However, stronger models, i.e., models that have a larger pseudo R-squared and smaller AIC and BIC, such as models 2 and 5 do not detect any statistical significance.

8 Conclusions

The objective of this research was to help improving the knowledge about social capital, absorptive capacity (ACAP), and innovation by exploring the determinants that influence grape farmers to innovate in water-saving technologies. A survey was taken in the Verona wine province. The survey generated 77 usable observations for the data analysis. A structural equation model and a logit model were developed to answer the research questions.

[4] Orbis is a database owned by Bureau van Dijk that contains financial information on approximately 400 million companies across the world (https://www.bvdinfo.com/en-gb/our-products/data/international/orbis).

8.1 Conclusions on the research questions

8.1.1 Research questions 1 and 2

Research questions 1 and 2 investigated the relationships between trust, social network, and ACAP. The study confirms that farmers with larger social networks and higher level of trust has higher ability to assimilate information and exploit it for commercial ends.

8.1.2 Research questions 3

Research questions 3, 4, and 5 investigated the effects of trust, social network, and ACAP on the implementation of water-saving technologies.

The study suggests that social network may be positively correlated to the implementation of water-saving technologies. Farmers with larger networks (with other farmers, suppliers, clients, and farmer associations) have higher access to information as there is a spillover effect from peers and other parties; therefore, they may have higher chances to implement water-saving technologies.

Changing the computational method for calculating the factor score of social networks, and changing the items to compute it, leads to consistent results, supporting the theory. However, the models that found significance in the parameter of social networks are the weakest models (in terms of pseudo R squared, AIC and BIC). Such models are models 1 and 3 from Table 17. Therefore, a largest sample would be necessary to have more clarity about it.

8.1.3 Research questions 4

None of the models in Table 17 found significance in the parameter of trust. In the discussion we argued that these results might be driven by the fact that trust's factor score was computed using items that regards trust between farmers only. Therefore, different types of trust might play a role. However, the sensitivity analysis shows that, even by changing the types of trust used to compute the factor scores (Table 26, Table 28), the results are consistent.

The explanation that we gave to the lack of effect of trust on the implementation of the water-saving technology is that, by being a strongly present technology (69% of the farms in the sample already implemented it), drip irrigation and subsurface irrigation are technologies that are supposed to be well known by farmers. Therefore, it is not a technology that requires high level of trust as farmers are probably not skeptical about it. Including the time dimension in the study might have shown a correlation between early adoption of the technology and trust.

8.1.4 Research questions 5

The research does not seem to support the idea that innovation is influenced by ACAP. However, in the current study innovation is intended as the implementation of an efficient irrigation system. Such system is already highly implemented in the Verona wine province, since 53 farms out of 77 in our sample has it. Therefore, it is reasonable to assume that the applicability of such technology is commonly known within the territory. Being ACAP the capability to adapt and transform knowledge, its effect on the adoption of a commonly known technology might be limited.

The sensitivity analysis showed that the estimated effect of ACAP is dependent on the method factor scores are computed. With a sum score method, ACAP seems to influence the implementation of the technology (Table 25). We argue that being refined methods generally considered to have higher validity, the results shown in Table 16 shall be more valid and so we conclude that ACAP does not seem to have an effect on the implementation of a highly implemented technology in the Verona wine province. Perhaps ACAP had an influence in the early adoption of the water-saving technology, but as this study does not consider the time in which the technology was implemented, it is not possible to conclude anything about it.

8.2 Conclusions on the control variables

The study finds that, according to the geographical area where the farm is operating, the likelihood of technology adoption is different. Farmers from area 1 (Bardolino and Custoza) may invest less than farmers from the other areas. The sensitivity analysis shows that farms that operate in area 3 (Valpolicella) have implemented the water-saving technology more than farms that are not operating in this area (Table 22, Table 23). We argue that the value of the grape, which is considerably higher in Valpolicella compared to the other areas, might play a role in facilitating the investments of the technology. However, information about farms' income lacks and therefore no inference can be done about it.

Agricultural education is positively correlated to the implementation of the technology. Farmers with an agricultural background are more aware of agricultural innovations and therefore they may be keener to implement it.

However, the sample size of the study is small, as it contains 77 usable subjects. That increases the chances of having misleading associations and decreases the accuracy and precision of the regression coefficients. One example of a paradoxical association found by the research is that higher educational levels are linked to lower likelihood of implementation of the technology.

8.3 Implications of the study

The Verona wine province, as different areas in Italy and the world, is experiencing water scarcity as a product of large water consumption (urban and agricultural) and climate change effects (reduction of water supply). Under this scenario, researchers have identified drip irrigation systems and subsurface irrigation systems as irrigation technologies that can effectively reduce the water use, compared to other irrigation techniques.

Our research showed that large and active networks between farmers and other peers and/or other parties might have a role in promoting the implementation of drip and subsurface irrigation systems, through the facilitation of information diffusion. However, our study did not find any relation between trust and innovation. This suggests that, taking a social capital framework, social networks might have a larger role than trust in explaining implementation of strongly established technologies in the viticultural sector. Building on this, efforts to enhance agricultural innovations shall be built on programs that fortify social abilities not only considering technical capabilities.

The study finds that ACAP is not a key factor in influencing technology implementation in the Verona wine province. Human capital seems to be more relevant. The research indicates that farmers that took agricultural related studies are more open to agricultural innovations, since they are more aware about technologies. Policies that aim to enhance agricultural innovations shall focus their efforts on farmers that do not have any agricultural background in their studies, bridging the gap between the technology and the possible adopters.

However, readers must consider the limitations of the study when utilizing the information included in the report. Small sample size, selection bias, and lack of information about time and income are among the main limitations of this research (section 7.3).

8.4 Suggestions for future research

The study has focused on the implementation of efficient irrigation systems. Besides drip and subsurface irrigation systems, there are several technologies that can help reducing the inputs of the agricultural systems. Some of these technologies have a very low implementation rate. An example is the use of decision support systems (DSSs). DSSs are software that provides the timing for pesticide applications on the basis of plant disease models (Pertot et al., 2017). Even though their use has been associated to a strong decrease of quantities of active substances compared to common spraying practices (Bouma, 2007; Shtienberg, 2013), their implementation is still low (Rose et al., 2016). From our full sample, only 4 farms out of 116 were using a DSS (Appendix 5). Therefore, focusing on studying which are the drivers and barriers to DSSs implementation could be an interesting topic for future research.

Finally, future research shall be conducted in a way that reduces limitations. Sample size should be appropriate to the type of analysis that will be done, and to the number of variables that want to be tested. As a rule of thumb, in logistic regressions there should be at least 10 number of events per independent variable, where the number of events corresponds to the number of observations in the least represented category of the binomial dependent variable. Future studies shall try to obtain the contacts (phone numbers and/or email addresses) of the full sample to try to reduce the selection biases. Direct contacts of the farms/farmers could be obtained by governmental organizations, such as AVEPA[5] for the Verona wine province. It shall be taken into account that such organizations can require long waiting times before providing the required data. Information about the year in which the technology was implemented, as well as the income of the farm, might provide insights about other factors influencing the implementation of the technology.

[5] AVEPA (https://www.avepa.it/) is an Italian institution responsible for distributing the agricultural subsidies and funds to farmers located in Veneto.

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Appendix

Appendix 1. Descriptive statistics of the full dataset

Table 31. Descriptive statistics of the items from the survey

Variable	Mean	Std. Dev.	Min	Max	Obs
Trust					
Other companies can rely on me without fearing that I will take advantage of them.	5.96	1.05	3.00	7.00	112
My company will always keep the promises done.	6.02	1.08	3.00	7.00	112
In the case of an informal agreement, I would always stick to the agreement even if there is no contract.	5.90	1.06	3.00	7.00	112
I think that other farmers will damage me if they benefit from it. (R)	2.74	1.68	1.00	7.00	112
The Italian politicians think about their own interests only. (R)	5.49	1.70	1.00	7.00	112
I trust public institutions.	3.57	1.69	1.00	7.00	112
I trust informative agents.	4.21	1.55	1.00	7.00	112
Who sells technologies think to its own interest only. (R)	3.86	1.49	1.00	7.00	112
Social Network					
How many suppliers do you have?	10.04	23.03	1.00	200.0	114
I spend a considerable amount of time with other farmers.	4.22	1.60	1.00	7.00	112
I have an informal network of suppliers, clients, and competitors.	4.55	1.68	1.00	7.00	112
I always support neighboring farms when they have troubles.	4.78	1.95	1.00	7.00	112
Regarding agricultural activities, I do not communicate with neighboring farmers. (R)	3.21	2.01	1.00	7.00	112
When I participate to agricultural events, I am one of the most Active.	4.11	1.74	1.00	7.00	112
I often meet agricultural professionals and experts.	4.71	1.69	1.00	7.00	112
Absorptive Capacity					
I regularly visit other farms.	3.82	1.97	1.00	7.00	112
I never meet consultants. (R)	3.40	1.82	1.00	7.00	112
I get information on the sector through informal means.	4.08	1.83	1.00	7.00	112
I organize meetings with clients or other parties to collect Information.	3.21	2.01	1.00	7.00	112
My farm is fast to recognize market changes.	3.90	1.55	1.00	7.00	112
I quickly understand new practices to manage the vineyards.	4.42	1.70	1.00	7.00	112
My farm is slow to recognize market changes. (R)	4.04	1.56	1.00	7.00	112
I take notes about new information for future possibilities.	5.06	1.86	1.00	7.00	112
I organize meetings within the farm to discuss about market changes.	2.37	1.61	1.00	7.00	112
I organize meetings within the farm to discuss about new management practices for the vineyards.	2.39	1.56	1.00	7.00	112
The activities of my farm are well defined.	5.71	1.21	1.00	7.00	112
My farm has a clear division of roles and responsibilities.	6.24	1.13	1.00	7.00	112
I constantly consider how to better exploit information.	5.00	1.60	1.00	7.00	112
My farm has difficulties to implement new management practices for the vineyards. (R)	4.06	1.86	1.00	7.00	112

*Note: 1 = strongly disagree, 7 = strongly agree. The first column includes the latent variables and the list of the items that were asked in the questionnaire to measure the corresponding latent variables. Items ending with (R) are reversed questions. If used in the data analysis, the value of the reversed questions has been reversed (e.g. if valued 1, they will get value 7 in the data analysis, if valued 2, they will get 6, etcetera). The item ending with * is the only non-Likert response format question, in which the value is equal to the number of suppliers.*

Table 32. Descriptive Statistics Dependent Variables

Variable	Categories	Count	Percentage
Dummy Drip Irrigation	No	62	53.45
	Yes	54	46.55

Table 33. Descriptive Statistics of the Independent Variables

Variable	Mean	Std. Dev.	Min	Max	Obs
Age	56.98	15.18	24.00	90.00	116
Years with that role	23.87	15.63	1.00	60.00	116
Years in that company	26.39	17.42	1.00	75.00	116
Years in the wine sector	31.83	19.03	1.00	80.00	116
Vineyard size (Ha)	12.53	36.76	0.30	290.00	116
Log (Vineyard size)	1.39	1.34	-1.20	5.67	116
Family workers	1.68	1.05	0.00	5.00	116
Employees	1.45	7.26	0.00	75.00	116
Log (Employees+1)	0.33	0.72	0.00	4.33	116
Total workers	3.13	7.48	1.00	78.00	116
Log (Total workers)	0.66	0.76	0.00	4.36	116
Dummy Irrigation	0.69	0.46	0.00	1.00	116
Irrigation	9.10	26.83	0.00	250.00	116
Female	0.11	0.32	0.00	1.00	116
First job	0.54	0.50	0.00	1.00	116
Side job	0.16	0.36	0.00	1.00	116
Retired	0.30	0.46	0.00	1.00	116
Owner	0.86	0.35	0.00	1.00	116
Manager	0.09	0.29	0.00	1.00	116
Another role	0.04	0.20	0.00	1.00	116
Agricultural Education	0.17	0.38	0.00	1.00	116
Primary school	0.17	0.38	0.00	1.00	116
Secondary school	0.28	0.45	0.00	1.00	116
High school	0.44	0.50	0.00	1.00	116
University (Bachelor or master)	0.10	0.31	0.00	1.00	116
<1 hectare	0.09	0.28	0.00	1.00	116
1-3 hectares	0.22	0.42	0.00	1.00	116
3-10 hectares	0.33	0.47	0.00	1.00	116
10-30 hectares	0.26	0.44	0.00	1.00	116
30-100 hectares	0.09	0.28	0.00	1.00	116
>100 hectares	0.02	0.13	0.00	1.00	116
Decreasing business	0.17	0.38	0.00	1.00	116
Constant business	0.43	0.50	0.00	1.00	116
Increasing business	0.40	0.49	0.00	1.00	116
Organic	0.13	0.34	0.00	1.00	116
Family business	0.96	0.20	0.00	1.00	116
Successor	0.73	0.45	0.00	1.00	111
Area 1 (Bardolino, Custoza)	0.33	0.47	0.00	1.00	116
Area 2 (Arcole, Soave, Lessini)	0.33	0.47	0.00	1.00	116
Area 3 (Valpolicella)	0.40	0.49	0.00	1.00	116
Wine making	0.25	0.43	0.00	1.00	116
Bottling	0.22	0.42	0.00	1.00	116
Agricultural activities	0.59	0.49	0.00	1.00	116
Livestock	0.06	0.24	0.00	1.00	116
Agritourism	0.04	0.20	0.00	1.00	116
Sale of grape	0.79	0.41	0.00	1.00	116

Appendix 2. Histograms of the variables for the observations used in the data analysis.

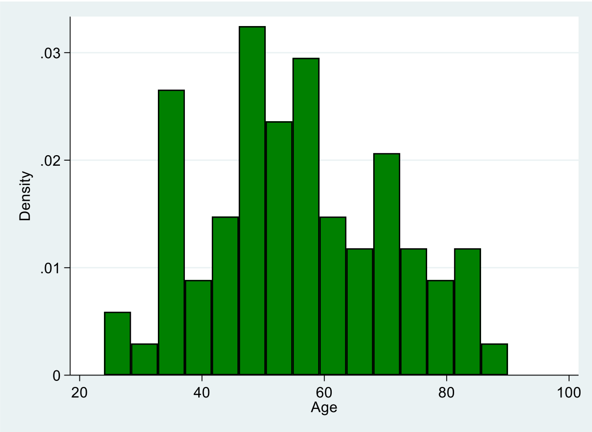

Figure 5. Age

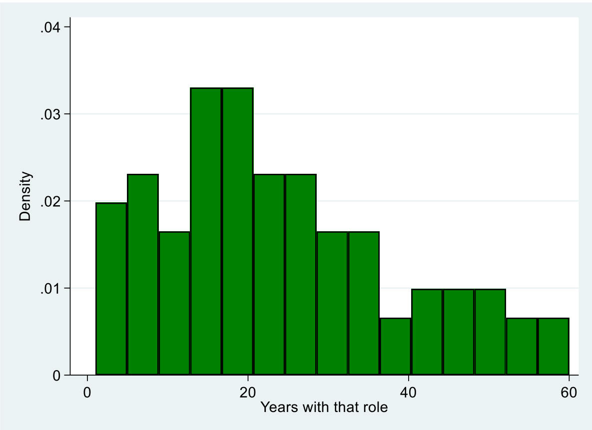

Figure 6. Years with that Role

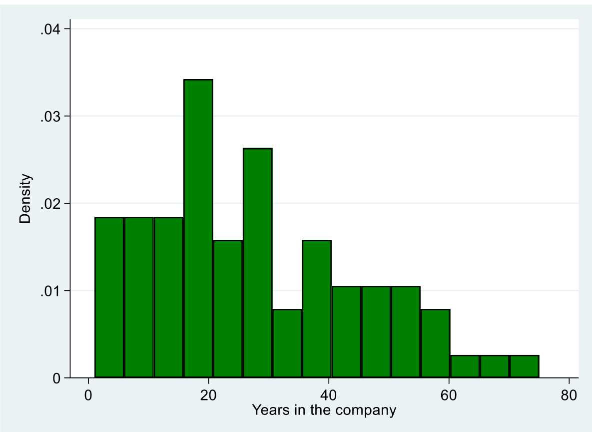

Figure 7. Years in the Company

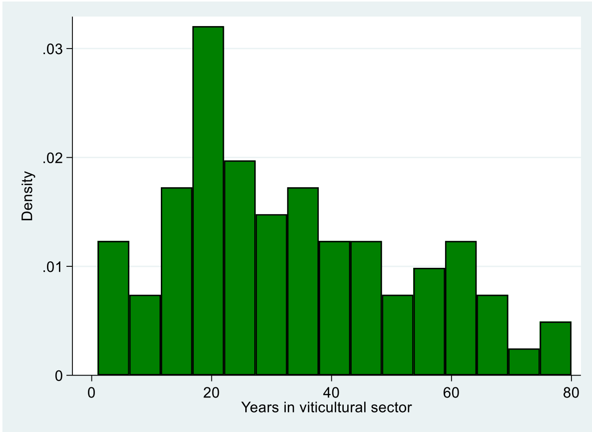

Figure 8. Years in the Viticultural Sector

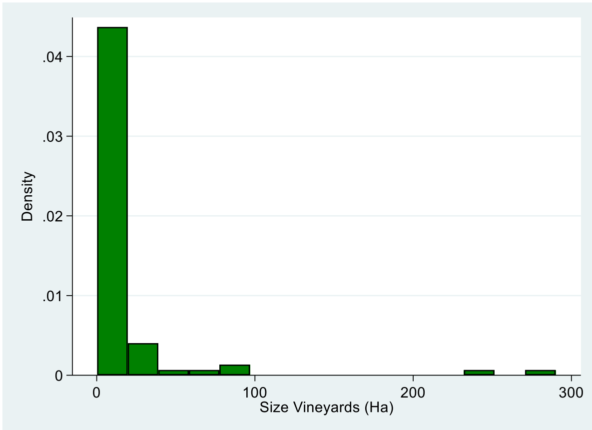

Figure 9. Vineyard size (Ha)

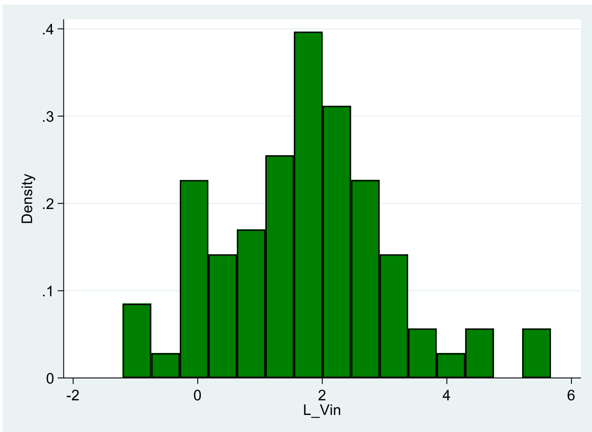

Figure 10. Logarithmic Transformation of Vineyard Size

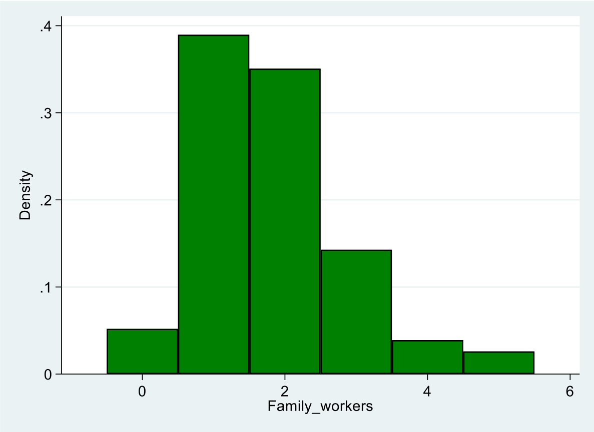

Figure 11. Number of Family Workers

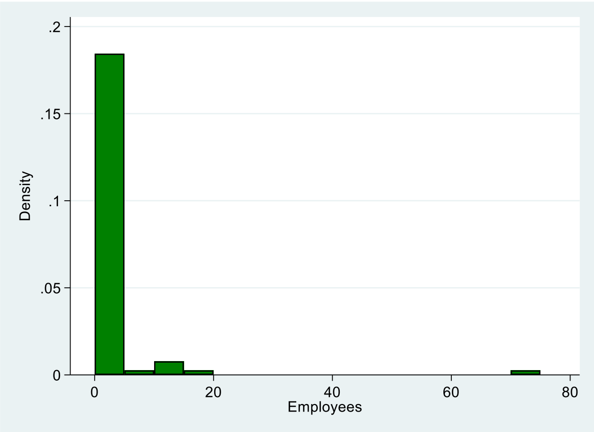

Figure 12. Number of Employees

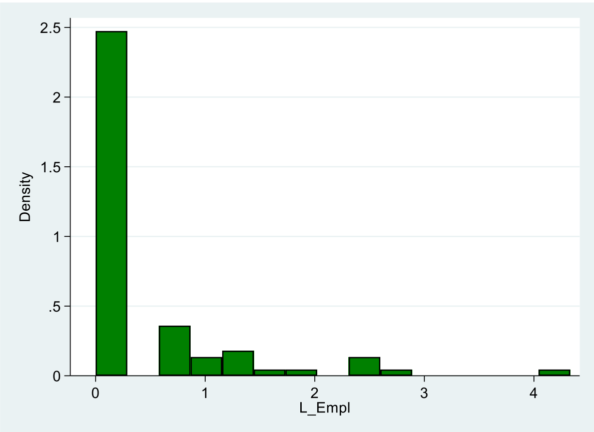

Figure 13. Logarithmic Transformation of Employees + 1

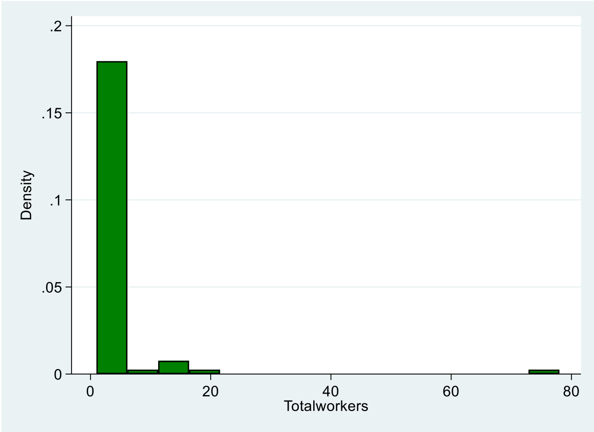

Figure 14. Number of Total Workers

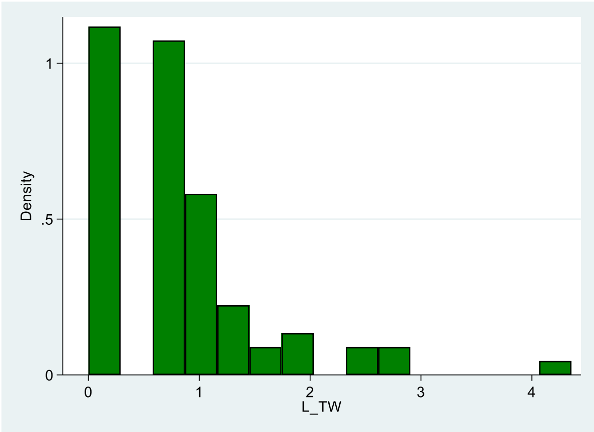

Figure 15. Logarithmic Transformation of Total workers

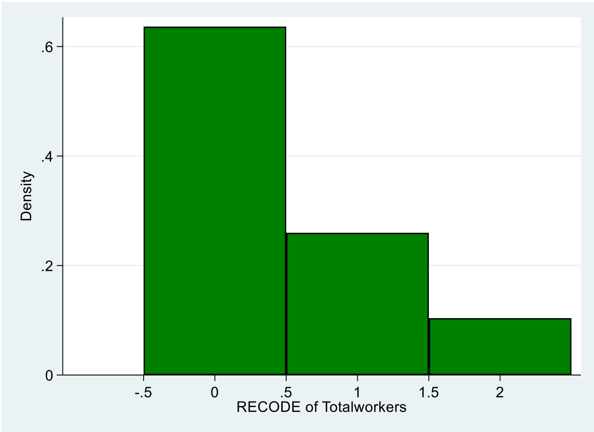

Figure 16. Recode of Total Workers in Categories

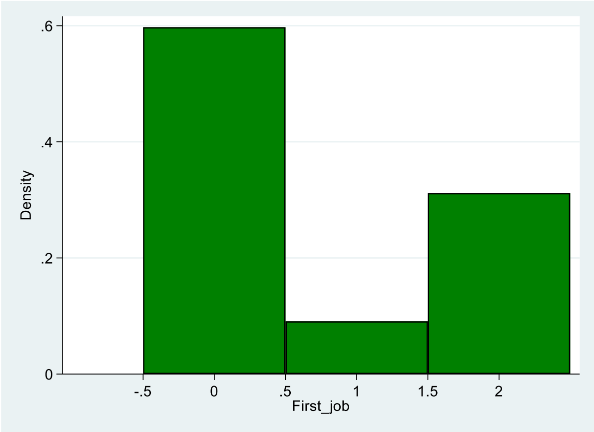

Figure 17. Job Type

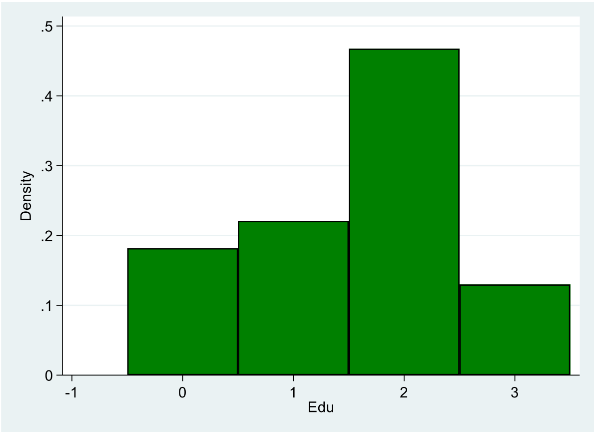

Figure 18. Education

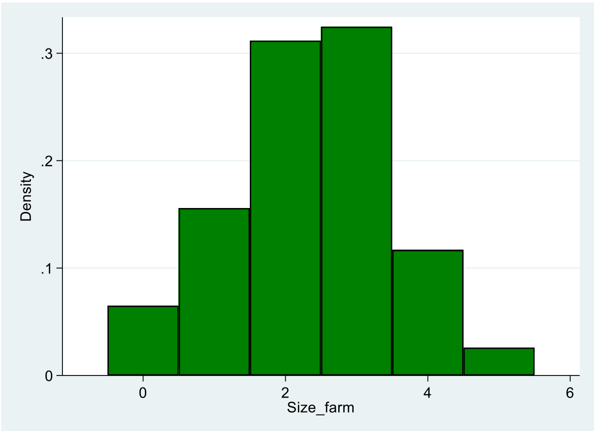

Figure 19. Farm Size

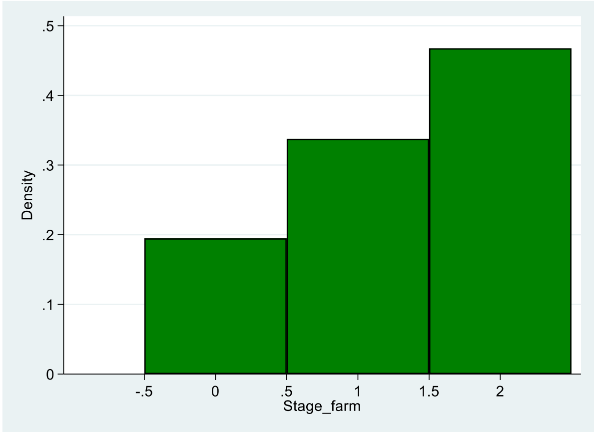

Figure 20. Stage of the Farm Life Cycle

Appendix 3. Correlation coefficients

This section presents the correlation coefficients of the variables included in the models shown in chapter 6.

Table 34. Pairwise correlations

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Area 1	1.00															
(2) Area 2	-0.52	1.00														
(3) Area 3	-0.55	-0.27	1.00													
(4) Age	0.06	-0.22	0.07	1.00												
(5) Years with that role	0.12	-0.21	0.05	0.69	1.00											
(6) Years in that company	0.04	-0.13	0.07	0.72	0.84	1.00										
(7) Years in that sector	0.19	-0.24	-0.02	0.82	0.79	0.83	1.00									
(8) Farm size	0.00	-0.07	0.15	-0.41	-0.06	-0.15	-0.19	1.00								
(9) L(Vineyard size)	-0.07	0.01	0.16	-0.42	-0.07	-0.17	-0.22	0.91	1.00							
(10) L(Employees+1)	-0.19	-0.03	0.26	-0.27	-0.13	-0.22	-0.20	0.60	0.71	1.00						
(11) L(Total workers)	-0.10	-0.09	0.26	-0.41	-0.19	-0.29	-0.28	0.68	0.75	0.85	1.00					
(12) Education	-0.08	-0.09	0.22	-0.53	-0.41	-0.54	-0.51	0.35	0.32	0.37	0.49	1.00				
(13) Agricultural education	0.09	0.00	-0.03	-0.14	-0.04	-0.05	-0.08	0.15	0.07	-0.05	0.04	0.27	1.00			
(14) Decreasing company	0.13	-0.09	-0.12	0.17	0.06	0.16	0.17	-0.26	-0.26	-0.25	-0.24	-0.25	0.02	1.00		
(15) Constant company	0.14	-0.03	-0.23	0.30	0.24	0.25	0.23	-0.31	-0.35	-0.32	-0.39	-0.21	0.02	-0.35	1.00	
(16) Increasing company	-0.24	0.10	0.32	-0.42	-0.28	-0.36	-0.35	0.51	0.53	0.50	0.56	0.40	-0.04	-0.46	-0.67	1.00

Note: The dark blue cells highlight the correlations above 0.8.

Appendix 4. Factor scores per geographical areas

Table 35. Descriptive Statistics of social network in different geographical areas

Geographical areas	Mean	Std. Dev.	Min	Max	Obs
Area 1 (Bardolino, Custoza)	-0.28	1.39	-2.90	2.19	31
Area 2 (Arcole, Soave, Lessini)	0.36	0.93	-1.38	2.22	22
Area 3 (Valpolicella)	0.18	1.50	-3.19	2.22	30

Appendix 5. Farms using a decision support system within the full sample

Table 36. Descriptive Statistics of decision support system

Variable	Categories	Count	Percentage
Decision support system	No	112	96.55
	Yes	4	3.45

Appendix 6. Original questionnaire in Italian

Questionario:

Buongiorno, sono Marco Tosoni, studente di economia agraria all'università di Cremona. Per conto dell'università sto svolgendo uno studio che include le aziende viticole della provincia di Verona. Avrei bisogno di parlare con il titolare dell'azienda, o con una persona che ha potere decisionale sugli investimenti legati alla viticoltura.

Qual è il suo ruolo nell'azienda?

Proprietario

Manager

Altro (specificare)

Indipendentemente dall'azienda, da quanti anni svolge questo ruolo?

Da quanti anni lavora in questa azienda?

Da quanti anni lavora nel settore viticolo?

La sua azienda, oltre a coltivare vigneti, quali altre attività svolge?

Imbottigliamento

Vinificazione

Altro (specificare)

Vendi l'uva?

Ora le dirò una serie di frasi. Vorrei che mi rispondesse con un valore da 1 a 7 in base a quanto è d'accordo con le affermazioni, dove 1 significa 'Totalmente in disaccordo' e 7 significa 'Totalmente d'accordo'. (Se non capiscono, gli viene spiegato nuovamente)

Le aziende possono contare sulla mia azienda senza paura che io me ne approfitti, anche se se ne presentasse l'occasione; *(FA)*

Chi sta al governo italiano, pensa solo ai propri interessi; (R) *(FI)*

Mi fido degli agenti informativi; *(FINF)*

Spendo una quantità considerevole di tempo in occasioni sociali con gente di altre aziende agricole; *(NI)*

Supporto sempre le aziende agricole vicine quando hanno dei problemi; *(NI)*

Quando partecipo ad eventi sull'agricoltura, di solito sono tra i partecipanti più attivi; *(NF)*

Visito regolarmente altre aziende agricole; *(ACQ)*

In generale, la mia azienda manterrà sempre le promesse fatte ad altre aziende; *(FA)*

La nostra azienda è veloce nel riconoscere cambiamenti di mercato (e.g. competizione, regolamentazioni); *(ASS)*

Il modo in cui le attività della nostra aziende sono eseguite è ben definito; *(SFR)*

Prendo nota e conservo le nuove conoscenze che acquisisco per future possibilità; *(TR)*

Raccolgo informazioni sul settore attraverso mezzi informali (e.g. pranzi e chiacchierate con amici agricoltori); *(ACQ)*

Immagina che la tua azienda abbia fatto un accordo informale con un'altra azienda. Sei sicuro che farai quello che avete specificato nell'accordo anche se non è stato stipulato alcun contratto; *(FA)*

Ho una rete di conoscenze informale tra clienti, fornitori e concorrenti; *(NI)*

La nostra azienda organizza incontri periodici per discutere di cambiamenti di mercato; *(TR)*

Considero costantemente come sfruttare meglio le informazioni; *(SFR)*

Penso che altri agricoltori, se ne traessero beneficio, mi danneggerebbero. (R) *(FA)*

La nostra azienda è lenta nell'interpretare cambiamenti di mercato. (R) *(ASS)*

Chi vende tecnologie pensa solo al proprio interesse. (R) *(FINF)*

Mi incontro spesso con professionisti e esperti in agricoltura. *(NF)*

Ho fiducia nelle istituzioni pubbliche. *(FI)*

Riguardo al lavoro in campo, non comunico con gli agricoltori che lavorano vicino a me. (R) *(NI)*

La nostra azienda organizza incontri con clienti o altre parti per raccogliere informazioni; *(ACQ)*

La nostra azienda ha una chiara divisione di ruoli e responsabilità; *(SFR)*

Nuove opportunità di gestione del vigneto sono capite velocemente; *(ASS)*

Non incontro mai consulenti; (R) *(ACQ)*

La nostra azienda organizza incontri periodici per discutere di nuovi sistemi di gestione del vigneto. *(TR)*

La nostra azienda ha difficoltà nell'implementare nuovi sistemi di gestione del vigneto. (R) *(SFR)*

Ora le farò una serie di domande sull'azienda e su di lei e poi abbiamo finito.

Quanti fornitori ha la tua azienda? *(GN)*

Quanto grande è l'azienda (in ettari)?

- < 1
- ≥ 1 < 3
- ≥ 3 < 10
- ≥ 10 < 30
- ≥ 30 < 100
- ≥ 100

Quanti ettari di vigneti?

Che forma di allevamento avete? (percentuale)

- Guyot
- Tendone
- Pergola
- Altro (specificare)

Quanti ettari di vigneto sono irrigati?

- Quanti sono irrigati per scorrimento?
- Quanti sono irrigati per aspersione?
- Quanti sono irrigati a goccia?
- Quanti sono irrigati per irrigazione ipogea?

La produzione o parte di essa è biologica?

- Se si, quanti ettari sono certificati biologici?

Quale irroratrice per pesticidi utilizza in vigneto? (più scelte sono accettabili)

- Irroratrice portata
- Irroratrice trainata
- Irroratrice a tunnel
- Altro (specificare)

La sua azienda utilizza un DSS per gestire i vigneti (Sistema informatico di supporto alle decisioni)?

- SI / NO

Qual è la sua qualifica?

Scuola primaria

Secondaria di primo grado

Secondaria di secondo grado

Università o più alta

Se ha fatto la secondaria di secondo grado o ha un'educazione maggiore, era una scuola/università specializzata in agricoltura e/o viticoltura?

Età

Sesso

Negli ultimi anni, la superficie aziendale è stata costante o è cambiata? Se è cambiata, è aumentata o diminuita?

Quali di queste uve producete? (Più opzioni sono accettabili)

Arcole

Bardolino

Custoza

Durello

Soave

Valpolicella

Che macchine e attrezzature avete in azienda agricola?

Fresa

Cimatrice

Vendemmiatrice

Potatrice

La sua è una azienda familiare?

Se sì, quanti familiari lavorano in azienda?

Se si, è presente un successore?

Quanti lavoratori dipendenti ci sono in azienda?

Key:

(R): Reversed-coded question

FA: Fiducia per gli agricoltori

FI: Fiducia nelle istituzioni

FINF: Fiducia negli agenti informativi

GN: Grandezza del network

NI: Network informale

NF: Network formale

ACQ: Acquisizione delle informazioni

ASS: Assimilazione delle informazioni

TR: Trasformazione delle informazioni

SFR: Sfruttamento delle informazioni

Appendix 7. Translation of the questionnaire

Survey:

Hello, I am Marco Tosoni, student of agricultural economics at the university of Cremona. On behalf of the university, I am running a study that includes the grape producing farms of the province of Verona. I would like to talk to the owner of the farm, or to a person that has decisional power on the farm's investment linked to the grape production.

What is your role in the company?

Owner

Manager

Other (please specify)

Since when do you have that role?

How many years have you worked in this company?

How many years have you worked in the viticultural sector?

Besides grape production, which activity does your company do?

Wine making

Wine bottling

Other (specify)

Do you sell the grape?

Now I am telling you some sentences. Please, reply to these sentences with a discrete value on a scale from 1 to 7 based on how much you agree or disagree with it, in which 1 means "I strongly disagree", and 7 is "I strongly agree". (If they do not understand, the explanation is given again)

Other companies can rely on me without fearing that I will take advantage of them. (TF)

The Italian politicians think about their own interests only. (R) (TG)

I trust informative agents. (TI)

I spend a considerable amount of time with other farmers. (IN)

I always support neighboring farms when they have troubles. (IN)

When I participate to agricultural events, I am one of the most Active. (FN)

I regularly visit other farms. (ACQ)

My company will always keep the promises done. (TF)

My farm is fast to recognize market changes. (ASS)

The activities of my farm are well defined. (EXP)

I take notes about new information for future possibilities. (TR)

I get information on the sector through informal means. (ACQ)

In the case of an informal agreement, I would always stick to the agreement even if there is no contract. (TF)

I have an informal network of suppliers, clients, and competitors. (IN)

I organize meetings within the farm to discuss about market changes. (TR)

I constantly consider how to better exploit information.(EXP)

I think that other farmers will damage me if they benefit from it. (R) (TF)

My farm is slow to recognize market changes. (R) (ASS)

Who sells technologies think to its own interest only. (R) (TI)

I often meet agricultural professionals and experts. (FN)

I trust public institutions. (TG)

Regarding agricultural activities, I do not communicate with neighboring farmers. (R) (IN)

I organize meetings with clients or other parties to collect information. (ACQ)

My farm has a clear division of roles and responsibilities. (EXP)

I quickly understand new practices to manage the vineyards. (ASS)

I never meet consultants. (R) (ACQ)

I organize meetings within the farm to discuss about new management practices for the vineyards. (TR)

My farm has difficulties to implement new management practices for the vineyards. (R) (EXP)

Please, answer to the following questions:

How many suppliers do you have? (NS)

How large is the farm (in hectares)?

< 1

$\geq 1 < 3$

$\geq 3 < 10$

$\geq 10 < 30$

≥ 30 < 100

≥ 100

How many hectares of vineyards are there?

What is the type of vineyard? (in percentage)

Guyot

Tendone

Pergola

Other (please specify)

How many hectares are irrigated?

How many with basin irrigation?

How many with sprinklers?

How many with drip irrigation?

How many with subsurface irrigation?

Is the production or part of it organic?

What type of pesticide sprayer does your farm have?

Carried sprayer

Pulled sprayer

Tunnel sprayer

Other (please specify)

Does your company use a DSS to manage the vineyards?

YES/NO

What is your level of education?

Primary school

Secondary school

High school

Higher

If you took high school or have a higher education, was your study focused on agriculture and/or viticulture?

Age

Sex

In the last years, has the farm surface been constant or did it change? If it changed, did it increase or decrease?

Which of these grapes do you produce? (More options are valid)

Arcole

Bardolino

Custoza

Durello

Soave

Valpolicella

Other (specify)

Which machinery and equipment do you have in the farm?

Tillage equipment

Hedge trimmer

Pruning machine

Harvester

Is it a family business?

If so, how many familiars work in the company?

If so, is there a successor?

How many employees are there?

Key:

(R): Reversed-coded question

TF: Trust in farmers

TG: Trust in government

TI: Trust in information agent

NS: Network size

IN: informal Network

FN: Formal Network

ACQ: Acquisition of information

ASS: Assimilation of information

TR: Transformation of information

EXP: Exploitation of information