Econometric analysis of agricultural production

New primal perspectives

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To my wife, Yunfei

Abstract

This thesis seeks to rebuild and extend the primal approach in production analysis by: a) developing a new paradigm for agricultural production analysis that acknowledges the relevance of the agronomic aspects of the production processes; b) defining factor demand in agricultural production from a primal, technical perspective. The theory and approach developed are used to address aspects of environmental and economic sustainability of agriculture in the Netherlands.

This research advocates that production models should respect and incorporate prior knowledge into production analysis. The research recognizes that inputs used in agricultural production have distinct functionalities and this must be accounted for explicitly in the model. Input functionality is first defined as productive inputs, damage-abating inputs, and inputs that have both functionalities. Then the research further generalizes this distinction by defining a dichotomy of growth inputs and facilitating inputs. Growth inputs are directly involved in the biological process of crop growth and include land, seed, fertilizer, and water; facilitating inputs help create or alter growth conditions, under which growth inputs take effect, and include labor, capital, and pesticides. Based on this dichotomy, a conceptual framework is developed. The framework connects agronomy and economics, presenting a new paradigm for production analysis. The empirical analyses use data from Dutch arable farms. Test results reject the traditional translog model, in favor of the new model proposed in this research.

Next, the research addresses input demand from a primal, technical perspective. A capital requirement model is proposed, and the factors that affect the capital requirement in production are investigated. Using the capital requirement model, this research defines a concept of excess capital and finds excess capital widely exists in Dutch arable farming. The presence of excess capital implies mismeasurement and simultaneity of capital in production. Its implications in econometric analysis of production are demonstrated with a production frontier model. Results show that models not addressing these problems would yield biased and inconsistent efficiency estimates.

In addition to the separate studies of product supply and input demand, this research further combines the two aspects and conducts an analysis on the total factor productivity growth in Dutch agriculture, focusing on the impacts of capital structure, investment, and governmental subsidies.

Keywords: Agricultural production, production function, asymmetric specification, growth inputs, facilitating inputs, input requirement, excess capital, endogeneity, productivity growth, capital structure

Preface

I have a new colleague who just started his PhD recently. Knowing I am finishing up, he asked me if I look back, what advice I would give to help him finish his PhD in three years. I was amazed by the question - that was exactly my plan at the beginning: I was just as enthusiastic and ambitious as he is right now. Without reservation, I proudly presented him my “wisdom”, concluding that it is possible *if* he, as an econometrician, allows a relatively large standard error. My PhD program takes more than four years even if I deduct the time I spent on post-doctoral research proposals in the later stage. It could easily take another half a year if I chose to finish one more article. But I decided it’s time to put an end to it.

The content of this research also deviated dramatically from the original plan. The proposed project was “Bioeconomic modeling of conventional and organic farming systems.” In this thesis, however, only the first article reflects part of the original plan. The rest of the work reorients to a more fundamental research on production, with an emphasis on theory and methodology. Under the basic theme of agricultural production analysis, the decision on what to write next was a rather dynamic process, open to any interesting ideas popped up during the writing of the previous articles. The present research is thus a result of a dynamic optimization process, constantly updated with new ideas and interests and subject to new constraints.

Looking back at my work, I very much appreciate the freedom I had in my research, for which I have to thank my supervisors Prof. Alfons Oude Lansink, Prof. Ada Wossink, and Dr. Martin van Ittersum for allowing me to go on my own way. I would like to thank Alfons for many basic things I learned from him that are important for a scientific researcher, from scientific writing to the structural way of thinking. I am also grateful for his support for my education program in the Netherlands Network of Economics (NAKE), where I could draw on the top-class resources of Dutch universities and received an all-round training in economics. I am deeply indebted to Ada for all the help and encouragement she gave me during these years. She was always available for help, responsive to my questions, and she has been a very good co-author. And I would like to thank Martin for his contribution with his unique perspective and expertise from a different discipline. I thank him for his sharpness in spotting the weakness in the writing, and I learned from him to be precise in science.

This research would not have been possible without the cooperation from the Agricultural Economics Research Institute (LEI) in The Hague. I sincerely thank LEI for its permission to use its data, and Johan Bremmer for making the data available for this research.

I would like to thank Prof. Subal Kumbhakar for inviting me to the State University of New York (SUNY) at Binghamton and for the fruitful collaboration. My two-month stay at SUNY Binghamton contributed not only to my academic research, but also to my understanding of life and friendship, for which I have to thank warm-hearted Wang Dan for helping me settle down there. I especially want to thank my friends Shu Liangcai and Xu Andong for the great time we had together. Liangcai and Andong, thank you for the great "lunch seminars" and those philosophical, spiritual conversations.

My six years in Holland not only built up my knowledge and research capability, but also exposed me to a different culture and many beautiful things. I especially want to thank Matthias and Noortje, Chen Le, Heiko and Tunde, Sandra, and Sebastien for all the beautiful time we spent together, and for the multicultural experience and perspectives we shared with each other. I would also like to thank my roommates in Asserpark for opening a special window of Dutch culture and mentality to me. I owe many thanks to Huibert for his help with many things, for instance, correcting my Dutch pronunciation. I wouldn't be surprised if somebody tells me that I speak Dutch with some Zeeland accent. As one of the few international students in the department when I started my PhD, Cesare helped me in many respects. Cesare, thank you and your wife Marta for sharing your international experience in Holland. Also, I thank Tanya for being helpful on many practical issues about life in Holland.

I also want to thank Lan, both as a colleague and as a friend, for all the help she gave me and my wife during the years. I appreciate very much the help from Zhang Rong, Dongshan and Zhang Fang. I thank them for always being ready to help. There are many more people I would like to thank but could not list all of them, including all my friends and previous colleagues back in China. 感谢我所有的朋友及生活中帮助过我的人，他们使我的生活更有内容，也更加美好。

My most special thanks are reserved for my wife Yunfei, to whom this book is dedicated. She witnessed and shared every difficult and happy moment of my research. She lets me know life is not only about research. She gives me a home and is the sunshine of my life. 我把我最高的敬意献给我的家庭，没有他们的培养、牺牲与奉献精神我无法完成今天的学业。他们的爱与期待激励着我不断前行。

Guan Zhengfei
Delft, October 2005

Contents

Chapter 1

General Introduction

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1. Introduction

Agricultural production has a range of stakeholders in society as it directly relates to environment, food safety, farm income, governmental subsidies and many other issues. In Western Europe, environmental and economic sustainability of agriculture have been subject to much discussion and have attracted the attention of producers, policy makers, the general public, and academia, particularly in the context of globalization, environmental movements, EU enlargement, and WTO trade negotiation on the liberalization of agriculture. One of the concerns, for example, is the impact of farming practice and input use, particularly pesticide and fertilizer use, on the environment and food safety, which has stimulated the introduction of alternative forms of farming (e.g. organic agriculture). The new perspective and context of agricultural production generate a need for scientific research to facilitate the decision making of different stakeholders.

In the economics literature, research on agricultural production is extensive. However, the theory of production economics is still far from well equipped to deal with empirical issues. When studying agricultural production, economists tend to turn to *behavioral assumptions* rather than to proven *biophysical facts* of the production process per se. The standard assumptions that underlie most empirical production analyses are profit maximization and cost minimization. These two basic assumptions form the foundation of the dual approach in production economics. However, reality often rejects these assumptions, as evidenced by Lin, Dean, and Moore (1974), Ray and Bhadra (1993), Pope and Chavas (1994), Driscoll et al., 1997, Tauer and Stefanides (1998), to mention a few. When behavioral assumptions do not hold, imposing these assumptions in product supply and factor demand studies results in biased estimates. On the other hand, even if behavioral assumptions prove consistent with empirical observations, the dual approach may still not be desirable. Mundlak (1996, pp.431) pointed out that “estimates based on duality, unlike direct estimators of the production, do not utilize all the available information and therefore are statistically inefficient and the loss in efficiency may be sizeable.” A further problem with the dual approach is that it is demanding in terms of information on prices. Price information, however, is often unavailable at the firm level, in which case it is impossible to estimate the product supply and factor demand functions. Even if the information *is* available, prices may show little variation across firms in a competitive market. This complicates the estimation of the product supply and factor demand functions with the dual approach, particularly when cross-sectional data are used.

Based on these observations, the research presented in this thesis studies agricultural production with a reconceptualized primal approach that is consistent with underlying agronomic processes. The general practice of the existing primal approach is to specify output as a function of inputs using a flexible functional form, such as a quadratic or translog function, without considering the underlying agronomic process of how inputs affect outputs and what the functionality of each input is in this process. For example, labor and fertilizer, two basic inputs in agricultural production, are assumed to affect crop yield in the same way as can be seen from the symmetric treatment of the two inputs in generic production models (e.g., quadratic or translog functions). The symmetric treatment of inputs disregards the fact that fertilizer is directly involved in the biological process of crop growth whereas labor plays an entirely different role. In this sense, the generic production models are over-simplistic. Studies using these models ignore fundamental agronomic aspects of agricultural production and therefore would not yield much useful insight.

Compared to product supply analysis, the primal approach on the factor demand side is not widely used in the empirical literature, mainly for two reasons. First, the factor demand study in the traditional primal approach requires as a precondition that the production technology is known and the production function be explicitly specified (Beattie and Taylor, 1993, pp. 237-241). This seems to suggest that factor demand is not directly relevant in its own right and makes study of factor demand dependent on the study of product supply. Second, the primal study of factor demand further requires behavioral assumptions and price information, in which sense it is not much different from the dual approach. The factor demand derived under these assumptions is a normative concept, imputing how much input *should* be used in the production to maximize profit or minimize cost given certain prices and the state of technology, instead of studying how much is actually needed or used. However, this latter technical perspective provides useful information on input requirement and resource use in production. In agricultural production in particular, the technical requirements on resources or factors of production, such as capital, labor, fertilizer or pesticide, affect production cost, farm income and environment, and therefore have a direct impact on environmental and economic sustainability of agriculture. Hence, factor demand study from a primal, technical perspective is of particular interest and relevance to various stakeholders of agricultural production in the current socio-economic context.

In addition to the respective analyses of product supply and factor demand, agricultural production can also be studied from the perspective of total factor productivity growth, combining both input and output aspects of production. Total factor productivity growth is an important indicator of the economic sustainability which addresses the total factor productivity changes over time. Under the pressure of competition from outside Western Europe (due to EU enlargement and WTO trade negotiation), productivity growth is a particularly relevant issue to be addressed when studying the economic sustainability of the agricultural sector. An empirical analysis of productivity growth and factors that affect productivity growth has therefore policy relevance in the current context.

2. Objective of the study

This thesis rethinks on the traditional primal approach in production analysis and seeks to rebuild and extend the primal. The theory and approach developed will then be used to address aspects of environmental and economic sustainability of agriculture. More specifically:

a) This research aims to develop a new paradigm for production analysis, which acknowledges the relevance of the agronomic aspects of agricultural production. The new paradigm recognizes the differing roles of inputs in the production process and incorporates prior agronomic knowledge into the production model.
b) Using the theoretical model, the research compares and tests the difference in the production processes of conventional and organic farming systems, with a particular focus on crop damage control process and environmental impacts of agricultural production.
c) The research further defines the factor demand in agricultural production from a primal, technical perspective, studying capital requirement in the production process.
d) Finally, this research addresses aspects of economic sustainability of agricultural production by analyzing productivity growth and the factors that affect productivity growth of Dutch arable farms, with a focus on the role of capital structure, investment, and governmental subsidies.

3. Outline of the thesis

Chapter 2 starts from the environmental concerns of the society related to agriculture, of which pesticide use is one of the main issues. This chapter proposes a theoretical model that distinguishes between the damage-abating and productive role of inputs. Pesticide is considered as a damage-abating input. Land, fertilizer, and other miscellaneous variable inputs are productive inputs. Capital and labor are used for both productive (e.g. sowing and harvesting) and damage-abating activities (e.g. machinery or manual weeding). Next, an empirical model reflecting these distinctions is tested against the traditional symmetric model. The model is used for the comparison of the production technologies used in conventional and organic farming systems, focusing on their damage control processes.

Chapter 3 further develops the concept of asymmetric functionality of inputs. This chapter recognizes that differences in inputs used in agricultural production are broader than damage-abating vs. productive as proposed by previous studies (e.g., Lichtenberg and Zilberman, 1986). Examples are the differences between labor and fertilizer, seed and machinery, water and other inputs. This chapter proposes a more general concept, distinguishing growth inputs and facilitating inputs. Growth inputs include land, seed, fertilizer, and water and are directly involved in the biological process of crop growth; facilitating inputs include labor, machinery, and pesticide and help create or alter growth conditions under which growth inputs can take effect. Based on this dichotomy, a general conceptual framework is proposed. The framework integrates agronomic principles into the economic analysis of agricultural production. The robustness of the new concept and theoretical model are tested using crop-level data on potato production in the Netherlands.

Chapters 2 and 3 focus on the product supply side of production. Chapter 4 proceeds to address the factor demand side. This chapter defines a factor demand model from a primal, technical perspective, focusing on the capital in agricultural production. The factors that affect the technical requirement of capital are investigated. Based on the capital requirement model, this chapter further defines a concept of excess capital. The implications of excess capital on empirical analysis of production are analyzed.

Chapters 2-4 address product supply and factor demand in farm production. Chapter 5 analyzes the economic sustainability of agriculture for the case of productivity growth of Dutch arable farming. This chapter investigates factors that affect productivity growth and discusses policy implications. The impacts of subsidization, investment, and access to credit market are analyzed.

Chapter 6 reviews the previous chapters and opens a general discussion on the theoretical, methodological, and empirical issues. Main results and conclusions are presented, with suggestions for future research.

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Chapter 2

Damage Control Inputs: A Comparison of Conventional and Organic Farming Systems

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Abstract

The economic literature on pest control exclusively assumes a non-negative marginal product of pesticides based on a monotonic non-decreasing function of damage abatement, which may bias pesticide productivity estimates. This paper proposes a specification that allows for a negative marginal product of pesticides and a damage-abating role for labour and machinery. Pesticide productivity is found to be lower than previously reported. Conventional farms are found to rely substantially on pesticides and machinery for damage abatement, while organic farms mainly rely on machinery use and changes in cultural practices. Productivity analyses based on the asymmetric specification suggest pesticides are used optimally in conventional farming, which contrasts with results in previous literature.

Keywords: Production function, asymmetric specification, damage control, conventional farming, organic farming

1. Introduction

As public awareness is growing regarding food safety and environmental problems in the food production chain, governments are facing the challenge of designing policies to re-orient agriculture toward safer and more sustainable practices. One of the major concerns relates to pesticide use in agricultural production, which has stimulated the introduction of organic agriculture. Organic farming differs greatly from conventional agriculture in production process and in chemical input use. Insights into these differences are important for designing policies to promote sustainable farming systems. For example, information on the productivity of pest control inputs in different systems can be used as a reference to design an appropriate level of taxes on pesticide use or subsidies on alternative cultural practices. The information can also assist farmers in making decisions about changing towards more sustainable farming systems. The empirical economics literature, however, has paid little attention to the distinctive production processes, particularly the damage control process, in conventional and organic farming systems.

Damage control inputs used in agricultural production include pesticides, resistant crop varieties, natural predators and all types of cultural practices (e.g., rotation, tillage) (Wossink and Rossing, 1998). In particular, pesticide use has received much attention in the economics literature. This line of study has mainly focused on the correct specification of production functions for the purpose of the estimation of pesticide productivity. Lichtenberg and Zilberman (1986) were the first to propose an output damage-abatement function in the econometric estimation of pesticide productivity. Damage abatement is defined as the proportion of the destructive capacity of the damaging agent eliminated by applying a given level of a control input. The abatement function was applied by Babcock et al. (1992), Carrosco-Tauber and Moffit (1992), Lin et al. (1993) and Chambers and Lichtenberg (1994). Carpentier and Weaver (1997) defined an input damage-abatement function, a more general treatment. An empirical application was successfully carried out by Oude Lansink and Carpentier (2001). However, a major limitation of these studies is that a specific input is considered to be *either* damage-reducing *or* productivity-increasing. In reality, productive inputs such as labour and machinery are *also* used for damage abatement. In organic farming, for example, mechanical and manual weeding may serve as alternatives to pesticides. Thus, capital and labour serve as both productivity-increasing and damage-reducing inputs; ignoring their dual role in empirical studies may bias estimates of the productivity of pesticides.

The literature uses different specifications for the damage-abatement function, such as Pareto, exponential, logistic or Weibull distributions (Lichtenberg and Zilberman, 1986). These specifications impose explicit or implicit restrictions on the parameters in order to ensure that the value of the damage-abatement function lies within the interval [0,1]. The explicit bounds may undermine the statistical inference of the bounded parameters and affect the estimates of other parameters. Of more concern is the implicit assumption of non-negative marginal productivity of damage control inputs implied by non-decreasing damage-abatement functions, which actually motivates the bound restrictions seen in the literature. This assumption, however, is by no means realistic. Pesticide use can well have negative agronomic effects, including phytotoxicity (manifested as damaged crops and especially likely to occur in the case of over-dosage of herbicides), resistance, adaptation,[1] the development of secondary pest, and changes in output quality (Oskam et al., 1992; Wossink and Rossing, 1998).

This paper intends to make three contributions to the literature. First, we propose a damage-abatement specification that allows for negative productivity of pesticides. The new specification effectively constrains the value of the abatement function on the interval [0, 1] without imposing restrictions on parameters. Second, the proposed specification is further generalised to address the damage-abating role of labour and machinery. The resulting asymmetric model is then tested against the traditional translog production model. Third, we compare the damage-abatement processes in conventional and organic farming systems.

The remainder of the paper is structured as follows. Section 2 presents the theoretical model of damage control production. Section 3 introduces the background of the case study in Dutch arable farming followed by model specifications, estimation method and data description. Results are analysed in section 4 and conclusions presented in section 5.

2. Model of damage control production

Production theory assumes that the relationship between multiple outputs and multiple inputs is reflected by the concept of a *transformation function.* With some additional assumptions (*e.g.* free disposal of inputs and exclusion of technical inefficiency) and aggregation of all outputs, the input-output relationship is often reduced to a *production function* (Chambers, 1988, pp. 7-8) in which one output depends on multiple inputs: $y = f(X)$. In the traditional specification of the production function, all inputs in the vector X are treated symmetrically, i.e. they are assumed to contribute to the output in the same way.

[1] After some years of soil treatment the chemicals used are decomposed by micro-organisms before they can become active.

Pest control processes have a special feature with important consequences for the functional specification. This distinctive feature is that pest control inputs act indirectly on output (Lichtenberg and Zilberman, 1986). In crop production**,** inputs such as land, fertilisers and machinery are generally viewed as productive inputs and pesticides as damage-abating inputs. The concept of damage-abating inputs was first introduced into the agricultural economics literature by Hall and Norgaard (1973) and Talpaz and Borosh (1974). Lichtenberg and Zilberman (1986) suggested the damage-abating role should be explicitly taken into account in the specification of the production function through an asymmetric treatment:

(1) $$y = G(x, D(z))$$

where *D(z)*is the damage-abatement effect achieved with the use of damage-abating inputs *z*. The damage-abatement effect is defined on the interval of [0, 1]. This specification may take a simple linear form:

(2) $$y = g_1(x) + g_2(x) \cdot D(z)$$

where $g_1(x)$ represents the minimum output; *D(z)* works as a scaling factor, and $g_1(x) + g_2(x)$ is the maximum output, *i.e.,* the *potential output* from productive inputs *x,* free of damage from diseases or pests. The potential output level is obtained when all growth conditions (availability of water, nutrients) are optimal and assuming no growth-reducing factors by the incidence of pests and diseases (van Ittersum and Rabbinge, 1997). In many cases, the minimum output is zero, and the specification reduces to:

(3) $$y = g(x) \cdot D(z)$$

When *D(z)* takes the value of 1, the specification yields the potential output given by $g(x)$, the *production function* of regular "productive" inputs *x*. A value of zero for *D(z)* implies maximum damage and output reduces to zero[2].

In conventional production systems, damage-abating inputs mainly include pesticides for chemical pest control. In organic farming, damage-abating inputs more likely include labour and machinery for mechanical and manual pest control and for additional

[2] Carpentier and Weaver (1997) proposed a less restrictive input-oriented specification, in which the damage-abatement inputs determine the effective use of productive inputs instead of scaling down output: $x_i^e(z) = D_i(z) \cdot x_i$. In empirical applications, however, the non-linear functional form in x^e makes estimation difficult, if not impossible.

management time. So as to accommodate labour and machinery as damage abating inputs, we extend equation (3) as follows:

(4) $$y = g(x_p, x_s; R) \cdot d(x_s, z)$$

where x_p denotes the purely productive inputs, x_s denotes the inputs that have both productive and damage abating roles, and *R* denotes the rotation system, measured by the share of root crops. The rotation system *R* distinguishes differences in crop mixes and is included in the model because of its impact on the production level, given the level of inputs.

Recent systems of pest control aim at improving the accuracy and timing with which pesticides are applied. They promote benign substitutes such as less harmful pesticides or biological controls such as resistant varieties. In organic systems, the emphasis is usually more on preventive instead of curative pest control by means of changes in planting date, tillage and rotation and other cultural practices. In general, low-input and organic systems of pest control pay more attention to the production environment as characterised by soil type, weather and their interaction (Wossink *et al.*, 2001). Therefore, the damage-abatement process may differ significantly from that in conventional farming system. Pesticides are generally assumed to play a major role in damage abatement in conventional farming systems, whereas labour and machinery are *a priori* expected to be important for damage abatement on organic farms. These hypotheses are tested with empirical data in this study.

The robustness of the theoretical model proposed in (4) can be examined in the following testing framework:

(5) $$y = g(x_p, x_s, z; R) \cdot d(x_s, z)$$

Within this framework, two hypotheses can be tested: a) parameters of the *z*-terms in function *g(.)* are zero, and b) the value of $d(x_s, z)$ is equal to 1. If a) is rejected while b) is not, the test favours the symmetric model. On the contrary, if condition a) is not rejected while b) is rejected, the test favours the asymmetric model. Both models are rejected if neither condition holds. The testing framework also allows for assessing the role of labour and capital. If labour and capital in model (5) are irrelevant in the damage-abatement process, the coefficients of variable x_s in $d(x_s, z)$ will be zero and these terms drop out. Furthermore, the testing framework in (5) allows for testing the sign of the marginal product of pesticides.

3. Application

3.1 Background

Since the early 1980s, research has been carried out in the Netherlands to develop new farming systems for field crops. This technical development has brought different possibilities to the farmer for reducing the input of pesticides. These projects had significant consequences, particularly for pesticide policy. A Long-Term Crop Protection Plan was approved in 1991 in the Netherlands, according to which pesticide use was to be halved by the year 2000 compared to the average national use over the period 1984-1988. No specific tax or quota was imposed; rather, the Dutch farmers' organisation (*Landbouwschap*, meanwhile renamed *LTO-Nederland)* signed a covenant with the government in May 1993 that committed them to achieve the reduction goals, specifically those for the crop farming sector (responsible for about 70 per cent of total pesticide use). In the covenant, agribusiness and farmers' unions agreed to help finance and implement the Long-Term Crop Protection Plan *if* the government dropped its plan to tax pesticides and postponed the ban of a large number of particularly environmentally hazardous pesticides to the year 2000 (Oskam *et al*., 1998, pp. 132). Applicator training and certification became required for all applicators and since 1996 application equipment testing has been required for all equipment. Since 1993, soil sterilants may only be applied under a license obtained from a specific government agency and can at most be applied once every four years on any given plot of land (Wossink and Feitshans, 2000).

The overall target for the year 2000 of a 50 per cent reduction in pesticide use was achieved (Nefyto, 2002) by reducing the use of soil sterilants, in particular. Soil sterilants are broad-spectrum chemicals that kill all types of soil pests and are particularly used to control soil nematodes. Before the 1990s, soil sterilants made up approximately 50 per cent of pesticide use in the Netherlands (Oskam *et al*., 1998, pp. 8). By 1995 the sale of soil sterilants had already dropped by 77 per cent, reflecting a shift to non-chemical pest control practices, particularly changes in rotation and selection of resistant cultivars. Since the pesticide reduction target was achieved in 2000, a further reduction programme has been working toward a 90 per cent reduction by 2010 by means of a certification programme for farms.

This Dutch case study offers a unique opportunity to analyse changes in the use of control inputs in crop production. The significant reduction in pesticide use in the arable farming sector was made possible by replacing chemical control by mechanical methods (particularly in weed control) and biological control methods (resistant cultivars, rotation) in the conventional production system. Meanwhile, the switch by some farmers to an organic system also contributed to the reduction. Due to the most recent reduction plan and changing consumers' perceptions, organic farming is becoming a potentially attractive option for many field crop growers.

3.2. Model Specification

3.2.1 Production function

The empirical application of model (4) requires the specification of functional forms for the production function $g(.)$ and for the damage-abatement function $D(.)$. In the literature, the Cobb-Douglas specification is commonly used for the production function for ease of estimation (Headley, 1968; Carrasco-Tauber and Moffit, 1992; Babcock *et al*., 1992; Carpentier and Weaver, 1997; Saha *et al*., 1997) However, the Cobb-Douglas specification restricts *a priori* all elasticities of substitution to be 1. The translog function does not impose such *a priori* restrictions. This study adopts the more flexible translog as the empirical specification of *g(.)*.

3.2.2 Damage-abatement function

Different specifications for the damage-abatement function are available in the literature. This section begins by discussing a number of existing approaches and problems associated with these approaches. Next, a new specification is introduced to address these problems, followed by a discussion of the properties of the new specification.

To address the output-reducing nature of damage abatement, the value of the abatement function has to be constrained to the [0, 1] interval. Specifications that satisfy this condition include the Pareto, exponential, logistic and Weibull distribution. The exponential specification defined in the literature (Lichtenberg and Zilberman, 1986; Carrasco-Tauber and Moffitt, 1992; Oude Lansink and Carpentier, 2001) usually takes the following form:

$$(6) \qquad D = 1 - \exp(-\beta_0 - \beta_1 z), \beta_0 \geq 0, \beta_1 \geq 0$$

In this specification, traditionally only pesticides (denoted by z) are considered as damage-abating. However, labour and machinery (denoted by x_2 and x_3) can easily be included:

$$(7) \qquad \begin{array}{l} D = 1 - \exp(-\beta_0 - \beta_1 z - \beta_2 x_2 - \beta_3 x_3) \\ \beta_0 \geq 0, \beta_1 \geq 0, \beta_2 \geq 0, \beta_3 \geq 0 \end{array}$$

The parameters of the abatement function are restricted to be non-negative in order to constrain the value of function (6) and (7) to lie within the interval [0,1] as defined by damage abatement[3]. The explicit bounds may undermine the statistical inference of the bounded parameters. When the constraints do become binding, they may well affect other parameter estimates, such as the parameters of the regular inputs in the production function. The exact statistical implication is unclear and beyond the scope of this study.

Saha *et al*. (1997) used a simpler specification $D = \exp(-A)$, where A is a linear function. These authors did not impose explicit restrictions on the parameters of the function. If labour and machinery are included in the specification, it is written as:

$$D = \exp(-A) = \exp[-(\beta_0 + \beta_1 z + \beta_2 x_2 + \beta_3 x_3)] \tag{8}$$

If the Cobb-Douglas or translog functional form is used for the production function *g(.)* in model (4), the overall model becomes additive in parameters after taking logarithms of both sides of the model. With this specification, some of the problems in the estimation of non-linear models (such as non-convergence) are effectively avoided. However, the value of the abatement function may run well beyond the upper limit of 1, which in fact violates the definition of damage abatement. This can result in parameter estimates that have no clear interpretation.

Specifications (6) and (7) suffer from a further drawback: the functions are monotonically increasing. The marginal effects of the damage abatement - $\partial D/\partial z$, $\partial D/\partial x_2$ and $\partial D/\partial x_3$ - are non-negative. The assumption of non-negative marginal product is generally acceptable for productive inputs. For pesticides, however, this is not plausible as overuse may well damage crop growth. The existing literature on pesticides use has ignored this fact and generally imposes non-negativity with monotonic abatement functions.

To avoid the problem of sign restrictions, to restrict the value of abatement within a sensible region and to allow for both positive and negative marginal product of pesticides, we propose the following specification with respect to the role of pesticides in damage abatement:

$$D = \exp(-A) = \exp[-(\beta_0 + \beta_1 z)^2] \tag{9}$$

Thus *A(.)* is defined as $(\beta_0 + \beta_1 z)^2$. This function has a minimum of zero when $\partial A/\partial z = 0$, i.e., at the point where $z_m = -\beta_0/\beta_1$. The damage-abatement process is illustrated in Figure

[3] The restriction on the sign of parameters is also implied in specifications based on the Pareto, logistic and Weibull distributions.

1[4]. The value of function *A(.)* in the upper panel first decreases with *z*; it reaches its minimum of zero at z_m and then increases. Translated into the abatement function *D=exp(-A)* in the lower panel, damage abatement first increases with *z*; the value of 1 is reached at z_m and then the function decreases.

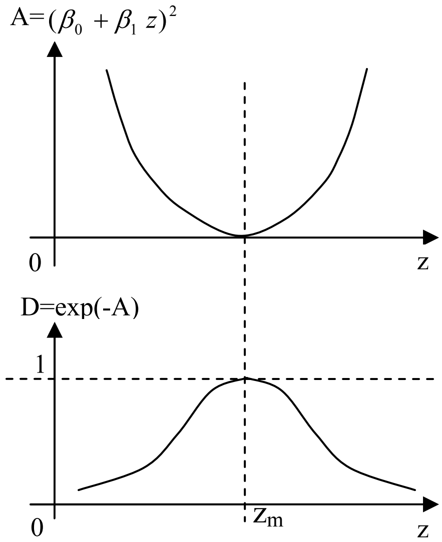

Fig. 1 Damage abatement function

This specification is appealing as it characterises the damage-abatement process of pest control without imposing explicit bounds on the parameters in the nonlinear model. The illustrated process of damage abatement conceptually differs from frequently used models of non-negative marginal product (see Fox and Weersink, 1995).

Equation (9) can be extended to accommodate labour and machinery in the abatement function:

$$D = \exp(-A) = \exp[-(\beta_0 + \beta_1 z + \beta_2 x_2 + \beta_3 x_3)^2] \tag{10}$$

where x_2 and x_3 represent labour and machinery. The function addresses the damage abatement from the use of labour and machinery. Furthermore, it allows interactions[5] among the damage-abating inputs.

3.2.3 Overall Model Specification

[4] It is worth noting that there is no sign restriction for β_0 and β_1. When β_0 and β_1 have the same sign, z_m is negative which implies a negative marginal product at any positive quantity of pesticide use.

[5] We thank a referee for drawing our attention to the issue of interactions between damage-abatement inputs.

With the production function $g(.)$ and damage-abatement function $D(.)$ defined, the overall model specification to be estimated in model (4) is as follows:

$$(11)\qquad \ln(y) = \left[c + \sum_{i=1}^{N-1} c_i + \sum_{t=91}^{99} d_t + \sum_{k=1}^{5} \alpha_k \ln(x_k) + \frac{1}{2}\sum_{k=1}^{5}\sum_{j=1}^{5} \alpha_{kj} \ln(x_k)\ln(x_j) + \gamma_0 \cdot R \right] - (\beta_0 + \beta_1 z + \beta_2 x_2 + \beta_3 x_3)^2 + e$$

All α, β, γ, c and d are parameters to be estimated. The arguments x_k are productive input use, with k = 1 for land, 2 for labour, 3 for capital, 4 for fertiliser and 5 for miscellaneous inputs. Pesticides are denoted as z, which is aggregated over fungicides, herbicides and other pesticides. R is the percentage of major root crops (potatoes, sugar beets and onions) in the total area. This variable reflects the impact of differences in rotational system on production. Individual farm effects are captured by the farm dummy c_i. The subscript i indexes each farm and N is the number of farms. The year dummy, d_t, captures yield differences across years as agricultural production is subject to dramatic yield variations from year to year, mainly due to weather conditions[6]. Finally, e denotes a disturbance term representing factors that are not accounted for in the specification such as measurement errors and other stochastic events.

The traditional translog production function treating all damage-abatement and productive inputs symmetrically is given by:

$$(12)\qquad \ln(y) = \left[c + \sum_{i=1}^{N-1} c_i + \sum_{t=91}^{99} d_t + \sum_{k=1}^{5} \alpha_k \ln(x_k) + \frac{1}{2}\sum_{k=1}^{5}\sum_{j=1}^{5} \alpha_{kj} \ln(x_k)\ln(x_j) + \gamma_0 \cdot R \right] + \beta_{10}\ln(z) + \sum_{k=1}^{5} \beta_{1k}\ln(z)\ln(x_k) + \frac{1}{2}\beta_{20}\ln(z)\ln(z) + e_1$$

The difference between the specifications in (11) and (12) is the treatment of the damage-abating inputs. The theoretical model (4) and its empirical specification given by (11) incorporate agronomic insights in the functions of inputs in agricultural production, and therefore may better represent the underlying production technology. The traditional translog specification given by (12) does not distinguish between productive and damage-abating inputs. The choice between specification (11) and (12) can be determined by an encompassing test[7] in the following framework:

[6] Accounting for weather effects also addresses the potential endogeneity problem which is likely to occur when pesticide and fertiliser use are affected by weather.

[7] Model 0 "encompasses" model 1 if the features of model 1 can be explained by model 0 whereas the reverse is not true (Mizon and Richard, 1986).

$$(13) \quad \ln(y\ ) = \left[c + \sum_{i=1}^{N-1} c_i + \sum_{t=91}^{99} d_t + \sum_{k=1}^{5} \alpha_k \ln(x_k) + \frac{1}{2} \sum_{k=1}^{5} \sum_{j=1}^{5} \alpha_{kj} \ln(x_k) \ln(x_j) + \gamma_0 \cdot R \right]$$
$$+ \beta_{10} \ln(z) + \sum_{k=1}^{5} \beta_{1k} \ln(z) \ln(x_k) + \frac{1}{2} \beta_{20} \ln(z) \ln(z) - (\beta_0 + \beta_1 z + \beta_2 x_2 + \beta_3 x_3)^2 + e_0$$

If the parameters $\beta_0, \beta_1, \beta_2, \beta_3$ are jointly zero while $\beta_{10}, \beta_{1k}, \beta_{20}$ are jointly non-zero, then the traditional specification in (12) is not rejected, implying that the translog function remains an acceptable specification. However, if the parameters $\beta_{10}, \beta_{1k}, \beta_{20}$ are jointly zero and $\beta_0, \beta_1, \beta_2, \beta_3$ are jointly non-zero, then it suggests the asymmetric specification in (11) is a better representation of the technology.

3.3 Estimation

Specification (12) is a fixed-effect log-linear model. The least squares dummy variable (LSDV) approach was used in the estimation. The asymmetric model in (11) and the testing framework in (13) involve nonlinear models, and for these equations the nonlinear least squares (NLS) estimator was used (Greene, 2003, pp. 166-169). The estimation of the nonlinear model (11) and (13) was based on the linearised regression model derived from the first-order Taylor series approximation. In the linearised model, pseudo-regressors were computed from the first derivatives of non-linear model with respect to the corresponding parameters. The pseudo-regressor of the parameter β_0 was computed as:

$$(14) \qquad w_{\beta_0} = \frac{\partial \ln y}{\partial \beta_0^0} = 2\left(\beta_0^0 + \beta_1^0 z_1 + \beta_2^0 z_2 + \beta_3^0 z_3\right)$$

where $\beta_0^0, \beta_1^0, \beta_2^0, \beta_3^0$ are true parameter values, which were solved for iteratively. Similarly, the pseudo-regressor associated with parameters β_1, β_2, β_3 are:

$$(15) \qquad w_{\beta_k} = \frac{\partial \ln y}{\partial \beta_k^0} = 2\left(\beta_0^0 + \beta_1^0 z_1 + \beta_2^0 z_2 + \beta_3^0 z_3\right) z_k$$

where k=1,2, and 3.

The pseudo-regressors associated with dummies, percentage of potato acreage, and log-linear terms are just the original regressors. The disturbance terms in equations (11), (12) and (13) were assumed to be independently and identically distributed random variables with mean zero and variance of finite constants. The disturbances were assumed to be uncorrelated with regressors, in the log-linear case, or the pseudo-regressors, in the nonlinear case. The statistical inference of NLS estimators is based on asymptotic approximations; no particular distributions are required (see Greene, 2003, pp. 164). Likewise, no normality is assumed for the error term e_1 in (12) in order to make the comparison between linear and nonlinear regressions consistent.

3.4 Data

The production technology and damage-abatement process were studied using accountancy data (FADN data from the Agricultural Economics Research Institute (LEI)) of conventional and organic cash crop farms in the Netherlands. Panel data are available over the period 1990-1999 from 405 conventional farms (1746 observations) and 28 organic farms (133 observations)[8]. The panel is unbalanced. On average, farms stay in the sample for 4 to 5 years.

One output and six inputs were distinguished. The output consists of potatoes, sugar beet, onions and cereals. The inputs were classified as purely productive inputs, shared inputs or damage-abating inputs. The productive inputs include land, fertiliser and miscellaneous inputs. Land is measured in hectares. Fertiliser includes both organic manure and chemical fertiliser. Miscellaneous inputs are aggregated over seed, feed, contract work, energy, storage and delivery. Shared inputs include labour and capital. Labour is measured in quality-corrected man-years and includes family labour as well as hired labour. The quality correction of labour was performed by the Agricultural Economics Research Institute (LEI). Capital includes capital invested in machinery, equipment and buildings. The damage-abating input is pesticides. For organic farms, the use of organic pesticides derived from natural origin with a low toxicity is allowed, although many farms use only negligible amounts of these organic pesticides.

The output, fertiliser, pesticides, capital, and miscellaneous inputs were deflated to 1990 prices (prices were obtained from the LEI/CBS[9]). Tornqvist price indices were calculated for capital and miscellaneous inputs. The price indices vary over the years but not over the farms, implying that differences in the composition of inputs and quality differences are reflected in the quantity (Cox and Wohlgenant, 1986).

Summary statistics of the data used in this research are presented in Appendix A. A simple comparison shows that organic farms use much less pesticides and fertiliser (manure) and they are more labour intensive than conventional farms.

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[8] The percentages of arable acreage and arable revenue are over 90 per cent for conventional farms whereas they are both 66.7 per cent for organic farms. The number of purely arable organic farms is limited; most organic farms operate mixed farming systems in order to obtain manure supplies.

[9] CBS denotes the Central Bureau of Statistics.

4. Results

4.1 Comparison of asymmetric and traditional specifications

The robustness of the asymmetric specifications was tested using the testing framework in (13). Tests were performed with conventional and organic farms, respectively, in order to examine the applicability of the asymmetric model under different circumstances.

With the conventional farms, parameters $\beta_0, \beta_1, \beta_2, \beta_3$ of the damage abatement function in the asymmetric specification were highly significant with a *p*-value of 0.000 for the Wald test statistic. Besides, $\beta_{10}, \beta_{1k}, \beta_{20}$ were all zero at the 5 per cent significance level. A further joint test yielded a *p*-value of 0.435, and thus the null hypothesis was not rejected. As a result, the non-nested test did not reject the asymmetric specification, suggesting that the asymmetric specification better represents the production technology of conventional farms. The same procedure was performed with the organic farm sample. The null hypothesis that parameters $\beta_0, \beta_1, \beta_2, \beta_3$ are jointly zero was strongly rejected (p=0.000), the same hypothesis for $\beta_{10}, \beta_{1k}, \beta_{20}$ was not rejected (p=0.38). This provides strong evidence in favour of the asymmetric specification.

The tests performed for the two data sets lead to the same conclusion: the asymmetric model is able to explain the features of the translog model, but the reverse does not hold. For comparison purposes, both the asymmetric and the translog model were estimated, and the results are presented in Table 1. Farm fixed effects are not presented due to space limitations. These results are available from the authors upon request.

Although the adjusted *R*-squared of the asymmetric model is only slightly improved[10], results show that the asymmetric model performs much better than the translog model. In the conventional sample, for example, 40 per cent of the slope parameters of the asymmetric model are significant while only 21 per cent are significant for the translog model (at the 5 per cent significance level). This result was expected *a priori* since the number of parameters is smaller in the asymmetric model than in the translog model. Also, this result suggests that the restrictions imposed by the asymmetric model better represent the underlying production technology.

[10] Adjusted *R*-squared: 0.9671 vs. 0.9670 for the conventional sample, and 0.9729 vs. 0.9722 for the organic sample.

Table 1. Estimated coefficients of production functions

	Conventional				Organic			
	asymmetric		Traditional		asymmetric		Traditional	
Parameter	estimate	P-value	estimate	P-value	estimate	P-value	estimate	P-value
Intercept	1.093	0.329	1.089	0.320	-7.667	0.192	-7.670**	0.008
Year dummies								
1991	-0.0076	0.590	-0.0050	0.722	-0.043	0.477	-0.034	0.584
1992	-0.0101	0.531	-0.0066	0.685	-0.062	0.356	-0.063	0.368
1993	0.192**	0.000	0.196**	0.000	0.191*	0.012	0.201**	0.009
1994	0.139**	0.000	0.143**	0.000	0.074	0.316	0.120	0.117
1995	-0.019	0.317	-0.014	0.460	-0.0027	0.972	0.021	0.794
1996	-0.058**	0.003	-0.054**	0.007	0.074	0.338	0.082	0.301
1997	0.095**	0.000	0.097**	0.000	0.237**	0.003	0.267**	0.001
1998	-0.032	0.148	-0.034	0.126	-0.105	0.189	-0.099	0.227
1999	-0.218**	0.000	-0.214**	0.000	0.038	0.654	0.062	0.492
Productive inputs								
r0	0.638**	0.000	0.622**	0.000	-0.183	0.438	0.037	0.870
α1	0.733	0.136	0.411	0.424	-0.058	0.971	-2.325	0.163
α2	0.347	0.261	0.277	0.336	-0.222	0.848	0.611	0.499
α3	0.812*	0.027	0.117	0.584	15.958*	0.031	-1.150	0.167
α4	0.510*	0.021	0.474*	0.036	0.807**	0.001	0.717**	0.002
α5	0.268	0.199	-0.014	0.955	1.096	0.079	1.078	0.093
α11	-0.163	0.315	-0.040	0.818	-0.116	0.814	0.539	0.317
α12	-0.113	0.116	-0.129	0.077	-0.165	0.491	-0.195	0.448
α13	0.067	0.294	0.048	0.463	0.347*	0.025	0.358*	0.036
α14	-0.112	0.119	-0.093	0.207	-0.253**	0.000	-0.202**	0.005
α15	0.134*	0.048	0.182*	0.016	-0.107	0.577	-0.201	0.346
α22	0.091	0.266	0.032	0.531	0.155	0.677	0.474	0.051
α23	0.040	0.374	0.057	0.177	0.360	0.080	0.162	0.393
α24	0.078	0.051	0.068	0.112	-0.018	0.477	-0.0050	0.855
α25	-0.019	0.677	-0.046	0.352	-0.365**	0.005	-0.295*	0.037
α33	-0.176	0.087	0.035	0.433	-4.769*	0.022	-0.079	0.737
α34	-0.076*	0.043	-0.094*	0.016	-0.012	0.800	-0.027	0.609
α35	-0.129**	0.001	-0.106**	0.009	0.092	0.495	0.063	0.674
α44	-0.046	0.422	-0.047	0.444	0.029	0.056	0.011	0.515
α45	0.101*	0.019	0.119*	0.018	0.050	0.212	0.040	0.373
α55	-0.047	0.466	-0.0044	0.952	-0.114	0.607	0.0024	0.992
Damage abatement inputs								
β0	1.316**	0.000			4.797**	0.000		
β1	-0.0028**	0.005			-0.0016	0.377		
β2	0.027	0.471			-0.012	0.482		
β3	-0.0011**	0.002			-0.0048**	0.000		
β10			0.344	0.158			0.171	0.073
β01			-0.106	0.140			-0.035*	0.029
β02			0.034	0.489			-0.0034	0.750
β03			0.036	0.393			-0.015	0.317
β04			-0.00011	0.998			0.0019	0.766
β05			-0.083	0.156			0.022	0.112
β20			0.114	0.065			0.013	0.092

"Asymmetric" refers to model (10) and "traditional" refers to model (11) in the text.

r_0 root crop share; α_1 to α_5 denote land, labour, capital, fertiliser, and miscel. inputs, respectively; a_{11} to α_{55} denote corresponding cross terms; β_0 to β_3, damage abatement in asymmetric model; β_{10} to β_{20} damage abatement in traditional model.

(*) and (**) indicate that the estimate is significantly different from zero at the 5(1) per cent significance level respectively.

The significant coefficients of capital in the asymmetric models indicate that capital does play a role in the damage-abatement process. Comparing the asymmetric model with the translog one, the estimates and significance level of the parameters α_1 to α_{55} also changed. Some of these changes, such as the parameter α_3 of the log-linear term of capital, are obviously not minor changes. However, the statistical inference based on the translog model is not reliable since the model is rejected in the encompassing tests. Consequently, empirical analyses (e.g., marginal product) based on the translog are biased. Further analyses are based on the asymmetric model.

4.2 Production technologies of conventional and organic farming systems

The tests of the asymmetric concept in the preceding section were based on two separate samples; thus an implicit assumption is that the two farming systems use different production technologies. The validity of this assumption was examined by testing the equality of coefficients from the regressions of two samples. For the traditional specification, results for the *Chow* test (Chow, 1960) yielded a *p*-value of 0.000, which strongly rejects the hypothesis of identical technologies. A Wald test for the asymmetric specification was performed with the conventional farms and the organic farms combined in the same model through a dummy variable, where the intercept *c* and slope parameters of the organic farms are allowed to vary. Again the hypothesis of identical technology was rejected with a *P* value of 0.000.

Thus, conventional and organic farms use different production technologies. Damage abatement may play an important role in this difference. In the estimation results (Table 1) of the asymmetric model, the significant parameter β_1 confirms that pesticides indeed play an important damage-abating role in conventional farming. Moreover, conventional farms rely substantially on capital use for crop protection; machinery may be used for mechanical weeding and/or to facilitate application of pesticides. As expected, organic farming does not rely on pesticides for damage abatement, as is confirmed by the insignificant estimate of pesticide. Capital has a significant contribution in the damage-abatement process of organic farms. These results confirm the hypothesis presented in Section 2. However, in contrast to *a priori* expectations, labour does not contribute to damage abatement either on conventional farms or on organic farms. A Wald test of the joint significance of parameters $\beta_0, \beta_1, \beta_2, \beta_3$ shows that the null hypothesis is rejected for both farming systems (*p*=0.000), which indicates that there exist yield reductions from non-optimal production conditions (like infestation from weeds and pests), and that input use plays a significant role in damage abatement.

Besides input use, the two farming systems also have non-input damage-abatement means, particularly in organic farms. To protect crops from damage, control measures in organic farming include resistant crop varieties, natural predators and different cultural practices. The use of crop varieties that are resistant to disease, pests and weeds reduces the dependence on pesticide use. Changes in tillage and planting/harvesting date and other preventive strategies further reduce the input demand for the damage-abatement process. These elements are not directly modelled in this study, but are captured in the farm specific dummy, which reflects the heterogeneity among farms. Indeed, about 60 per cent of the farm dummies are significant at the 5 per cent significance level. In addition to the aforementioned crop protection means, farmers usually change their rotation regimes as a preventive measure to reduce disease incidence or pest pressure. For example, in conventional farms, farmers usually grow potatoes in a given plot every 4 years whereas this is reduced to once every 6 or 7 years under the organic farming regime. To some extent this practice can be a crucial control method in organic farming. An examination of the data shows that the major root crop[11] area for organic farms is only 31 per cent while that of conventional farms amounts to 53 per cent. A lower percentage of root crops results in lower pesticide use.[12] Meanwhile, a longer rotation cycle reduces the disease pressure and thus contributes to organic production. Root crops are generally considered as profitable crops, a decrease in area usually causes revenue loss as is evidenced by the significant positive coefficient of root crop area in conventional farms. Hence, the insignificant (negative) coefficient in organic farms actually suggests the benefit of a longer rotation regime.

Compared to organic farming, conventional farming exhibits an overall negative time trend observed from fixed year effects. The year 1993 and 1994 witnessed a prominent increase in production and thereafter a decline in production dominates the trend. The decline may suggest better weather conditions in the first years and/or worse weather conditions in more recent years. The year effect might also signal a decrease in land productivity over time in conventional farming as a consequence of intensive farming practices. The Dutch policy in recent years of "spray-free buffer strips" in field crops may have reduced output as well.

4.3 Analysis of Marginal Product and Elasticities

Analysis of marginal product and elasticities yields important insight into the productivity of individual inputs and economy of scale in the arable farming sector. The value of the marginal product (VMP) is the shadow price of individual inputs[13]. The VMP estimates

[11] Major root crops are defined as potato, sugar beet and onion in the study according to area planted and their contribution to income.

[12] Root crops have higher pesticide requirements and this is verified by the data. Major root crops account for 71 per cent of pesticide use (52 percentage points for potatoes) in conventional farms and 51 per cent in organic farms. Meanwhile, root crops account for 57 per cent of fertiliser application on conventional farms and only 17 per cent on organic farms.

[13] The value of marginal product (or shadow price) is the marginal product times price of output.

computed at the sample mean for the asymmetric specification are presented in Table 2. The estimated shadow price can be used to assess whether an input is overused in relation to its cost. It may serve as a reference in designing tax rates or subsidies on the use of certain inputs, for example, pesticide or fertiliser.

Table 2: The value of marginal product (VMP) of inputs (in EUR 1,000)

	land	labour	capital	fertiliser	pesticides	miscel.
Conventional farms:						
VMP	1.82	16.56	0.018	-1.09	1.25	0.84
Approx S.E.	0.22	4.26	0.034	0.55	0.37	0.15
Input Price (IP)	0.32 (1)	28.4 (2)	0.11 (3)	0.98	1.10	1.05
Approx p-value (h_0: vmp=0)	0.000	0.000	0.604	0.049	0.001	0.000
Approx p-value (h_0: vmp=IP)	0.000	0.006	0.007	0.000	0.693	0.157
Organic farms:						
VMP	2.66	4.17	0.18	2.22	2.79	1.36
Approx S.E.	0.97	6.13	0.12	1.85	3.06	0.26
Input Price (IP)	0.32 (1)	28.4 (2)	0.11 (3)	0.97	1.11	1.08
Approx p-value (h_0: vmp=0)	0.007	0.498	0.137	0.234	0.364	0.000
Approx p-value (h_0: vmp=IP)	0.018	0.000	0.567	0.502	0.584	0.274

The VMPs are evaluated at the sample means, at average output price index 0.953 for conventional farms and 0.979 for organic farms; prices of fertiliser, pesticides, and miscellaneous inputs are average price indices.
(1) Land price is based on average rent per ha farmland during 1990-1999 (LEI).
(2) Labour price per man-year is calculated from the sample data.
(3) Capital price is calculated as 10% of average capital price index.

For conventional farming, farmers' return from each additional euro of pesticide use was €1.25. A statistical test showed that the VMP is not significantly different from the pesticide price €1.10, which suggests that pesticides were optimally used at the farm level. However, at the level of society, it is likely that pesticides were overused if environmental externalities are taken into account. Oude Lansink and Carpentier (2001) derive a shadow price (weighted over herbicides, fungicides and other pesticides) of €2.8 per additional euro of pesticide use in Dutch arable farming sector over the period 1989-1992[14]. The large difference may result from the failure in the latter study to address the heterogeneity across farms and from the

[14] The original monetary unit was guilders.

assumption of a positive marginal product. A more recent non-parametric study (Oude Lansink and Silva, 2004) yields an even higher shadow price. Note that for organic farms, the VMP estimate of pesticides was €2.79, which is more than twice the input price. However, no concrete conclusions can be drawn in terms of statistical significance.

Unlike pesticides, the average VMP of fertiliser on conventional farms was significantly lower than the input price and negative, which suggests overuse of fertiliser (manure). As fertiliser contributes to the growth of weeds as well, this effect may become dominant under some circumstances. Also, the overuse of fertiliser may “burn” crops and thus reduce crop yield. In contrast to conventional farms, the VMP of fertiliser on organic farms was not significantly different from the input price due to a low application level. The policy implication is that excessive use of fertiliser (manure) should be restricted on conventional farms, which would benefit both farmers and society economically and environmentally. A policy with this aim (the so-called MINAS program) was introduced for arable farming in 1998 in the Netherlands.

Land proved to be productive in both farming systems. An additional hectare of land yielded €1.82 thousand of output on conventional farms and €2.66 thousand on organic farms, which was significantly higher than the average rent of land. Labour is less intensively used and therefore more productive in conventional farms. But the shadow prices in both farming systems are significantly lower than the average wage in the sample, which suggests overuse of labour in Dutch arable farms. In contrast to labour, capital in conventional farms is much less productive than that of organic farms. One additional euro of capital investment brought about only 2 cents of return. If the annual depreciation of capital is set at 7 per cent[15] and interest rate set at 3 per cent, capital investment was making a net loss. This indicates that Dutch conventional farms are over-capitalised, which is consistent with the finding in Zhengfei and Oude Lansink (2003). The productivity estimates suggest intensive use of labour, capital and fertiliser in conventional farms.

The miscellaneous inputs on organic farms had a payoff of about 70 per cent more than those on conventional farms. Seed cost as a major item included in this category may be the main reason for the difference. Seed cost relates to crop varieties, and resistant crop variety contributes tremendously to the damage-abatement process when pesticide use is restricted.

The elasticities reported in Table 3 provide further information on the output response to individual inputs and on the economies of scale in the arable farming sector.

[15] Weighted average over that of building, machinery and equipment if depreciation rate is set at 4 per cent for building and 10 per cent for machinery and building.

Table 3. Production elasticities of inputs

	land	labour	capital	fertiliser	pesticides	miscel.
Conventional farms:						
Input elasticity (IE)	0.594	0.141	0.019	-0.051	0.104	0.176
Approx p-value (h_0: IE=0)	0.000	0.000	0.604	0.049	0.001	0.000
Organic farms:						
Input elasticity (IE)	0.426	0.055	0.168	0.034	0.011	0.362
Approx p-value (h_0: IE=0)	0.007	0.498	0.137	0.234	0.364	0.000

The input elasticities are evaluated at the sample means.

The input elasticities sum to 0.98 in conventional farms and 1.06 in organic farms. The returns to scale for conventional farms are consistent with the result reported by Oude Lansink (1997). Although both farming systems operate approximately at constant returns to scale, the results may imply that conventional farms are operating beyond the optimal scale while the organic farms are producing below optimal scale. The relatively lower land elasticity in organic farms reflects the fact that organic farming uses a relatively less land-intensive technology than conventional farming. At the same time, the high elasticities of land found in both types of farms suggest land is a scarce input and constrains the arable farming sector.

5. Conclusions

Policies aimed at pesticide reduction hinge critically on the contribution of pesticides to production. However, the restricted specifications for damage-abatement functions found in the existing literature may bias productivity estimates and thus entail incorrect policy implications. This paper contributes to the literature theoretically by proposing a generalised asymmetric specification that allows for both a negative productivity of pesticides and a damage-abating role for labour and machinery. Tests show that the new specification is not rejected.

Empirically, the paper compares the production technology *and* damage-abatement process of conventional and organic farming systems. The application addresses the Dutch arable farming sector. Statistical tests reject the hypothesis of identical technologies in conventional and organic farms. Conventional farms rely considerably on pesticides and machinery for damage abatement whereas organic farms mainly rely on machinery use. In organic farming, cultural practices (e.g., longer rotation regimes) and resistant crop varieties may also contribute to damage abatement.

With the specification developed in this article, pesticide productivity is found to be lower than reported in the previous literature. The estimated shadow price of pesticides suggests that pesticides were not over-used at the farm level. At the level of society, however, over-use is likely to be the case if the environmental externalities are taken into account, which justifies the pesticide reduction programmes of the Dutch government. The evidence of over-use of fertiliser in conventional farms strongly suggests a nutrient reduction programme. Such a programme was introduced for arable farms in 1998. Land is found to be the limiting factor for Dutch arable farms. More specifically, Dutch conventional field crop production is characterised by intensive use of labour, capital and fertiliser on farms with little land. This result suggests the need for policy incentives to stimulate enlargement of land area per farm.

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Appendix:

Summary statistics of Dutch arable farming 1990-1999

Table A1: Summary statistics (in EUR 1,000, deflated to 1990 prices)

	Variable	Symbol	Number of Observations	Mean	Std Dev
Conventional	Output	y	1746	219.74	164.30
	Pesticides	z	1746	17.40	12.37
	Land (ha)	x1	1746	68.26	44.56
	Labour (man-year)	x2	1746	1.78	1.06
	Capital	x3	1746	223.26	164.62
	Fertiliser	x4	1746	9.74	6.94
	Miscel.	x5	1746	43.88	30.34
Organic	Output	y	133	253.39	136.25
	Pesticides	z	133	0.99	1.84
	Land (ha)	x1	133	39.64	16.69
	Labour (man-year)	x2	133	3.26	1.52
	Capital	x3	133	234.55	127.06
	Fertiliser	x4	133	3.84	2.81
	Miscel.	x5	133	65.75	40.17

Chapter 3

Integrating Agronomic Principles into Production Function Estimation: A Dichotomy of Growth Inputs and Facilitating Inputs

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Abstract

This article presents a general conceptual framework for integrating agronomic principles into economic production analysis. We categorize inputs in crop production into growth inputs and facilitating inputs. Based on this dichotomy we specify an asymmetric production function. The robustness of the asymmetric framework is tested using crop-level panel data on potato production in the Netherlands. The test results do not reject the proposed framework, and the asymmetric specification better represents the underlying production technology.

Keywords: asymmetric specification, endogeneity, input dichotomy, production function

1. Introduction

Agronomy and agricultural economics both study agricultural production, but with different focuses and approaches. Agronomy focuses on the natural processes of crop growth in terms of the role of climatic factors, water, nutrients and other agronomic inputs. Traditionally it has been experiment-based, and since the 1970s, systems analysis and modeling have been used increasingly. Agricultural economics studies broader socio-economic processes of empirical agricultural production, often at a more aggregated level, e.g. the farm or region. The inputs studied in agricultural economics include not only agronomic inputs, but also socio-economic inputs (e.g. labor and capital). Although both disciplines study relations between inputs and outputs, they have generally developed and evolved in parallel.

In modeling agricultural production, economists in general have a preference for "flexible" functional forms, particularly the translog and quadratic production functions. In these flexible functional forms, inputs are treated symmetrically. For example, fertilizer and labor, two of the basic inputs in agricultural production, are assumed to contribute to crop growth in the same way even though fertilizer is directly involved in the biological process of crop growth whereas labor is not. The symmetric treatment of inputs does not distinguish the unique functions of different categories of inputs in the underlying biophysical processes. This approach may lead to biased productivity estimates (Lichtenberg and Zilberman, 1986) and thus result in erroneous policy implications.

The existing agricultural economics literature that does recognize specific biophysical processes is limited to either pesticide or fertilizer use. Several studies have addressed the damage-reducing role of pesticides versus the productivity-increasing role of other inputs (see e.g., Lichtenberg and Zilberman, 1986; Chambers and Lichtenberg, 1994; Carpentier and Weaver, 1997; Saha, Shumway, and Havenner, 1997; Oude Lansink and Carpentier, 2001). In these studies, the asymmetric role of pesticide was distinguished from that of other inputs (without being tested). Yet in reality, the differences between inputs in agricultural production are much broader than damage-abating vs. productive. We argue that a more general framework is needed to accommodate various types of differences (e.g. differences between fertilizer and labor, seed and machinery, water and other inputs, etc.); this framework should be testable in empirical studies.

The literature that studies the specific role of fertilizer includes those by Paris (1992); Chambers and Lichtenberg (1996); Berck, Geoghegan, and Stohs (2000); and Holloway and Paris (2002). These authors focused on crop response and nutrient deficiency, with a particular interest in the functional form of the agronomic response function. They used experimental data on crop responses to nutrients and water; other categories of inputs (e.g., labor, capital, and pesticide) were not addressed, with an implicit assumption that the growth conditions or production environment were strictly controlled in the experiments. In empirical studies using real farm data, however, no such assumption can be made; the varying growth conditions may bias the crop response studies.

The agricultural economics literature on the economics and econometrics of pesticide and fertilizer use recognizes the relevance of agronomic insights and their implications for the theoretical framework, choice of functional form and the appropriate estimation method. However, since the classic works by Paris (1992) and by Lichtenberg and Zilberman (1986), there has been no further in-depth integration of the concepts provided by agronomy and agricultural economics. The main concern in recent studies is not with empirically relevant theory but with testing alternative specifications for the role of separate inputs and the use of different econometric techniques. For example, Chambers and Lichtenberg (1996) develop the dual implications of the von Liebig-Paris nutrient-response technology and parametric and nonparametric tests for this technology. Carpentier and Weaver (1997) pursue direct estimation of the production function with panel data, addressing heterogeneity across farms as well as the possibility of input levels affecting risk as in Just and Pope (1978). Kumbhakar (2001) proposes accommodating productive inefficiency when estimating production functions. Holloway and Paris (2002) present a Bayesian procedure to estimate von Liebig production function and frontier models. These studies have enriched the literature. However, for crop production analysis, the testing of alternative specifications and the use of estimation techniques must have a solid foundation: a conceptually plausible and empirically relevant theory that addresses the fundamental agronomic aspects of the underlying process of crop production.

This article intends to make three contributions to the literature. Firstly, drawing on agronomic literature, we present a new paradigm for production economics. From an agronomic perspective, different categories of inputs contribute to yield through distinct processes, and we show that this has important implications in empirical analysis. Agronomic literature defines different crop yield levels, corresponding to different growth conditions and factors affecting yield (Rabbinge, 1993; Van Ittersum and Rabbinge, 1997; Wossink and Rossing, 1998; De Koeijer et al., 1999; Van de Ven et al., 2003). We incorporate the insights from this literature into a generic economic model. An important concept we propose in this article is the dichotomy of inputs in agricultural production: *growth* inputs and *facilitating* inputs. To our knowledge, no economic studies to date have distinguished the fundamental differences between different categories of inputs and have integrated them into one comprehensive theoretical framework for empirical production analysis.

Secondly, this article presents a procedure for testing the robustness of the asymmetric framework we propose. We estimate the production function with the generalized method of moments (GMM) estimator. The GMM does not require distributional assumptions on error terms; it accounts for heteroscedasticity and is asymptotically more efficient than 2SLS (Hall, 2005). As endogeneity is a constantly disturbing problem in the estimation of production functions, GMM framework provides the possibility of testing the validity of the estimation by testing the moment restrictions. Despite these advantages, few agricultural economists (except Thijssen, 1996; Carpentier and Weaver, 1997; Druska and Horrace, 2004) have applied GMM for panel data analysis.

Thirdly and finally, we apply the proposed theory to real farm crop-level data and estimate the marginal productivity of inputs. The empirical study uses panel data on Dutch potato production. The paradigm proposed in this article is applied successfully in the case study.

2. Conceptual Framework

In agronomy, three production levels are distinguished: potential, attainable, and actual level (Rabbinge, 1993; Van Ittersum and Rabbinge, 1997; Van de Ven et al., 2003). These correspond to matching growth conditions defined by a hierarchy of three groups of growth factors: growth-defining, growth-limiting, and growth-reducing factors. The growth-defining factors determine potential growth and production levels; they include the genetic plant characteristics, atmospheric CO_2 concentration, and climatic factors that are beyond the farmer's control. The potential yield level is the highest production level achievable with the given physical environment and genetic plant characteristics and assuming no growth-limiting and growth-reducing factors. Growth-limiting factors include shortage of water and nutrients. When these factors occur, the resulting yield is defined as attainable yield.[1] The farmer can control the level of water and nutrients by irrigating and fertilizing to attain a certain yield level. The attainable yield level assumes no growth-reducing factors, defined as weeds, diseases, pests and pollutants in the agronomic literature. Growth-reducing factors lower the production level further to the actual yield level. Yield reduction can be controlled by yield-protecting inputs and measures (such as weeding and use of pesticide). In field crop production, nutrient supplies are rarely non-binding and thus potential yield is typically not observed in on-farm data. Besides, the economically optimal use of nutrients or water may be lower than the agronomic non-limiting use that aims at achieving potential yield. In this study we will distinguish the attainable yield and actual yield levels only.

In field production, apart from weeds, diseases, pests and pollutants, factors like imperfect land preparation, nonoptimal sowing and planting, and non-uniform input

[1] In agronomic literature, the attainable production level is often called the water- or nutrient-limited production level.

application may all affect actual yield. For example, Cassman and Plant (1992), and Ndiaye and Yost (1989) have shown that spatial variability of soil conditions and non-uniform fertilizer application decrease crop yield. These operational factors affect actual yield by affecting how efficiently the crop uses light, water and nutrients and may make crops more susceptible to disease. The impact of these factors on yield can be controlled or limited with the proper use of machinery and labor.

To integrate agronomic theory and insights into economic analysis, we propose dichotomizing agricultural inputs into:

1) *Growth inputs*, which are directly involved in the biological or agronomic process of crop growth; this category includes land, seed, nutrients, and water. These inputs are essential in the natural growth processes.
2) *Facilitating inputs*, which are used to help create favorable growth conditions in preparing land, sowing and planting, applying fertilizers or water, crop protection, and harvesting. This category of inputs includes labor, capital, and pesticides, which are not directly involved in the basic biological processes of crop growth.

Growth inputs contribute directly to crop growth, and their levels determine the crop yield attainable under the given growth-defining factors. Facilitating inputs affect yield indirectly by creating, controlling or altering growth conditions under which growth inputs take effect. In economic analysis of crop production, traditional specifications of the production function tend to disregard the differences between growth inputs and facilitating inputs and treat them identically. Such symmetric treatment of inputs basically ignores agronomists' efforts and unique perspective in modeling crop growth response, where water and nutrients are seen as central given growth conditions.

Lichtenberg and Zilberman (1986) suggested that the damage-abating role of pesticides be taken into account explicitly in the specification of the production function through an asymmetric treatment of "productive" inputs (***x***) and "damage-abating" pesticides (***z***): $y = F(x, D(z))$, where *D(z)* is the so-called damage-abatement function. Although partly addressing the problem of symmetric treatment discussed above, this model does not recognize other forms of differences in inputs, particularly the more fundamental difference between growth inputs and facilitating inputs.

Based on the dichotomy of growth and facilitating inputs, we propose a new conceptual model of crop production:

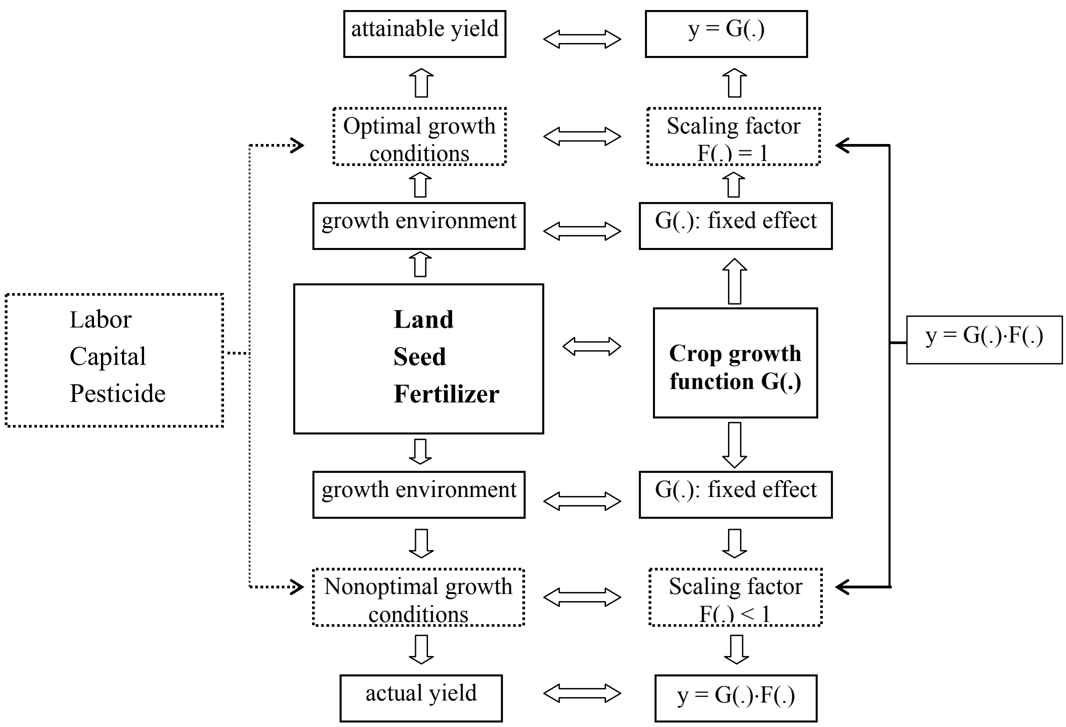
$$(1) \qquad y = Q\big(G(x_1, x_2, x_3, h; E), F(z_1, z_2, z_3)\big)$$

where x_1, x_2, x_3 and h are the growth inputs land, seed, fertilizer, and water, respectively; z_1, z_2, and z_3 are the facilitating inputs labor, capital, and pesticides, respectively. E

represents growth environment, i.e. the given growth-defining factors. In model (1), growth inputs and facilitating inputs affect crop yield in a different way, reflected by the different functional forms of *G*(.) and *F*(.). Accommodating agronomists' perspective in modeling crop growth and integrating the theory on crop production levels, the above model can be written as:

(2) $$y = G(x_1, x_2, x_3, h; E) \cdot F(z_1, z_2, z_3)$$

where *G*(.) is a crop growth model and *F*(.) is a scaling function. This modeling framework is illustrated in figure 1. In this framework, the growth inputs take the central position and define the attainable yield through crop growth model *G*(.), under a specific biophysical environment. The value of *F*(.) is defined in the interval of [0,1]. Given the level of growth inputs, when the growth conditions are optimal (i.e. under optimal crop management), the value of *F*(.) reaches 1 and the output *y* attains its maximum: the attainable yield. Under nonoptimal conditions, the actual output is downscaled by the factor *F*(.).



Note: At a given level of growth inputs, optimal growth conditions imply optimal crop management using capital, labor, and pesticides or other means of crop protection.

Figure 1. The modeling framework based on input dichotomy

Unlike in controlled experiments on which most agronomic studies of crop response are based, in real farm production, crop yield fluctuates over years or across farms because of differing growth conditions (due to growth-reducing factors, nonoptimal soil conditions, and non-uniform input application). If the growth conditions are not controlled, the fluctuating yield levels observed could bias the crop response studies. Controlling for the growth conditions with *F(.)*, model (2) makes it possible to estimate crop response functions *G(.)* using real farm data, thereby extending agronomists' experiments into real-world field production.

This modeling framework incorporates the concept of dichotomy and assumes weak separability between dichotomous groups of inputs, which implies that the marginal rate of technical substitution (MRTS) between any pair of inputs in one group is independent of the quantity of inputs in the other. Inputs $\boldsymbol{x}$ and inputs $\boldsymbol{z}$ are weakly separable in y = $q(\boldsymbol{x},\boldsymbol{z})$ if:

(3) $$\frac{\partial}{\partial z_k}\left(\frac{\partial y/\partial x_i}{\partial y/\partial x_j}\right)=0 \qquad \forall i,j,k, \qquad \text{and} \qquad i\neq j$$

and

(4) $$\frac{\partial}{\partial x_k}\left(\frac{\partial y/\partial z_i}{\partial y/\partial z_j}\right)=0 \qquad \forall i,j,k, \qquad \text{and} \qquad i\neq j$$

In empirical studies, the robustness of the conceptual framework laid out in this section and the assumption of weak separability can be tested when the explicit functional forms of the production function are specified.

3. Data

The theoretical model was applied to ware potato production in the Netherlands. The Netherlands has favorable production conditions for potatoes: suitable climate, generally fertile soils, little water stress on clay soils, and irrigation systems usually available for sandy soils. Potatoes are the most profitable crop for many farmers and hence are well fertilized and are grown in reasonably narrow (about 1:4) crop rotations with intensive crop protection. The crop-level data used in this study were from the farm accountancy data network (FADN) of the Dutch Agricultural Economics Research Institute (LEI). Panel data from 323 farms with a total of 1425 observations were available for the period 1990-1999. The panel is unbalanced and farms stay in the sample for an average of 4 to 5 years.

One output and six inputs were distinguished. The output is the revenue from ware potatoes. Compared to seed and starch potatoes, ware potato production in the Netherlands is rather homogeneous in terms of variety and production season. A priori this reduces the degree of heterogeneity of production across farms and should lead to a more robust analysis of input–output relations in crop response modeling.

The inputs included three growth inputs: land, seeds, and fertilizer, and three facilitating inputs: labor, capital, and pesticides. Land was measured in hectares; labor was measured in quality-corrected man-years and included family labor as well as hired labor. The rest of the inputs were measured in euros at 1990 prices. The prices for output, seed, fertilizer, and pesticides (obtained from LEI) were used to derive the price indices and to detrend the data. Capital was capital stock aggregated over machinery, equipment, and buildings. As the three components provide different types of services, capital was aggregated over the replacement values, instead of the services, of its components. The aggregated capital stock was deflated with the Törnqvist price index derived from the three components. As the crop rotation a priori affects yield, it was also accounted for through the percentage of farm area used for potato production.

Labor and capital were only available at the farm level. To calculate the labor share for an individual crop, the normative labor requirements of about 40 crops (covering almost all the crops grown on the sampled farms) were used. The labor share of a crop *k* on farm *i* was calculated as:

$$S_{ik} = \frac{l_k \cdot A_{ik}}{\sum_k l_k \cdot A_{ik}} \tag{5}$$

l_k is the labor required per ha of crop *k*, based on expert knowledge (Spigt and Janssen, 1997); A_{ik} is the area of crop *k* on farm *i*.[2] Thus the labor used for a specific crop was derived as:

$$L_{ik} = S_{ik} \cdot L_i \tag{6}$$

where L_{ik} is labor used for *K*-th crop on the *I*-th farm, L_i is the total labor of the *I*-th farm.

The share of labor was also used to assign capital to the same crop, as in field crop production the machinery and labor are basically two complementary inputs and so

[2] This approach assumes that there are no economies of farm size for the labor requirements per hectare of the crops grown.

decisions about machinery use are often made jointly with decisions about labor use. This assumption might be somewhat strong, but it seems plausible and is easy to implement in practice.

Summary statistics of the data used in the study are presented in table 1.

Table 1. Summary Statistics of Ware Potato Production in the Netherlands, 1990-1999 (in 1990 prices)

Variable	Unit	Mean	Std Dev.
output	1,000 euro	55.67	52.80
land	hectare	12.44	9.66
seed	1,000 euro	9.58	8.47
fertilizer	1,000 euro	2.75	2.30
labor	man-year	0.48	0.38
capital	1,000 euro	60.00	66.82
pesticides	1,000 euro	4.92	4.44
rotation	share potato area	0.29	0.12

Source: Dutch Agricultural Economics Research Institute (LEI)
Note: The statistics are per farm year, computed with 1425 observations from 323 farms.

4. Empirical Models

The empirical application requires specific functional forms of the production function. In this section we propose alternative functional forms and a test procedure for selecting the appropriate one. We will then describe the estimation techniques.

4.1 Alternative Specifications

Without assuming any prior knowledge about the production process, economists often use the translog production function. In this study, we specified the traditional translog production function as follows:

$$(7) \qquad \ln(y\ ) = c + \sum_{i=1}^{N-1} c_i + \sum_{t=91}^{99} d_t + \delta \cdot R + \sum_{k=1}^{3} \alpha_k \ln(x_k) + \frac{1}{2}\sum_{k=1}^{3}\sum_{j=1}^{3} \alpha_{kj} \ln(x_k)\ln(x_j) +$$
$$\sum_{m=1}^{3} \beta_{0m} \ln(z_m) + \frac{1}{2}\sum_{m=1}^{3}\sum_{q=1}^{3} \beta_{mq} \ln(z_m)\ln(z_q) + \sum_{k=1}^{3}\sum_{m=1}^{3} \gamma_{km} \ln(x_k)\ln(z_m) + \varepsilon$$

where c is a constant; c_i is the farm dummy; d_t is the year dummy; R is the rotation regime; $\delta, \alpha, \beta, \gamma$ are slope parameters to be estimated, and ε is the error term. The farm dummy addresses the heterogeneity across farms, which may arise from differences in biophysical environment and managerial capabilities. The year dummy reflects the yield variation between years, where weather conditions play an important role. The overall fixed effects (farm and year dummy) capture the growth-defining factors E in the theoretical model. As an essential growth input in the crop growth process, water is not explicitly accounted for in (7) due to data limitations. It is assumed to be a non-binding factor because of the favorable climate and irrigation conditions. Notice that if water does become binding for some farms, the effect is captured by farm dummy; the year-to-year variation in water would be picked up by the year dummy. The variable R addresses the impact of rotation regime on the yield of potatoes. A priori, a narrow rotation regime, i.e. a high proportion of the land under potato, may induce a high disease and pest pressure and thus lead to reduced yield. On the other hand, rotation could also affect input use, specifically pesticide. Therefore, rotation effect needs to be controlled in the model. Rotation regime can be seen as a part of the growth environment for the short and medium terms because from a farm management perspective the choice of rotation is a strategic decision.

The translog specification is routinely used in economics literature because of its "flexibility". However, the translog as such is a specific functional form regardless of how well or how poorly it can "approximate" the true function, and the flexible functional form implicitly assumes that nothing is known about the production process. We will now address how the translog specification in (7) can be modified to integrate agronomic principles and apply the conceptual framework proposed in this study. To implement the asymmetric concept, the scaling function $F(.)$ has to be effectively defined in the interval [0,1]. Here we define it as:

$$(8) \qquad F(z_1, z_2, z_3) = \exp[-(\beta_0 + \beta_1 z_1 + \beta_2 z_2 + \beta_3 z_3)^2]$$

By constraining the scaling factor within [0,1] and not imposing monotonicity in arguments, this function does not restrict the marginal productivity of inputs to be positive and therefore is more flexible.

Having defined the scaling function, an asymmetric model can now be specified. The separability implied in model (2) can be tested in the traditional translog production function (7) with the null hypothesis that the parameters γ_{km} are jointly zero. If not rejected, the asymmetric model can be specified as:

(9)
$$\ln(y) = c + \sum_{i=1}^{N-1} c_i + \sum_{t=91}^{99} d_t + \delta \cdot R + \sum_{k=1}^{3} \alpha_k \ln(x_k) + \frac{1}{2}\sum_{k=1}^{3}\sum_{j=1}^{3} \alpha_{kj} \ln(x_k)\ln(x_j) - \left(\beta_0 + \beta_1 z_1 + \beta_2 z_2 + \beta_3 z_3\right)^2 + \varepsilon$$

This specification corresponds to the log form of model (2). Ignoring the squared term, equation (9) gives the attainable yield. In field production, nonoptimal growth conditions decrease crop yield. The extent to which these nonoptimal growth conditions are controlled by the use of facilitating inputs is reflected in the squared term in equation (9).

Separability might be rejected in an empirical study, because under certain circumstances there could be interactions, particularly the one between fertilizer and pesticides. Unhealthy crops may use water and nutrients less efficiently (see e.g. Spiertz, 1980; De Wit, 1992), suggesting positive interactions; on the other hand, fertilizer may contribute to weed growth and therefore decrease the effect of pesticide (e.g. herbicide), resulting in negative interactions. Without loss of generality, an alternative specification can be formulated as:

(10)
$$\ln(y) = c + \sum_{i=1}^{N-1} c_i + \sum_{t=91}^{99} d_t + \delta \cdot R + \sum_{k=1}^{3} \alpha_k \ln(x_k) + \frac{1}{2}\sum_{k=1}^{3}\sum_{j=1}^{3} \alpha_{kj} \ln(x_k)\ln(x_j) + \sum_{m=1}^{3} \beta_{0m} \ln(z_m) + \frac{1}{2}\sum_{m=1}^{3}\sum_{q=1}^{3} \beta_{mq} \ln(z_m)\ln(z_q) + \sum_{k=1}^{3}\sum_{m=1}^{3} \gamma_{km} \ln(x_k)\ln(z_m) - \left(\beta_0 + \beta_1 z_1 + \beta_2 z_2 + \beta_3 z_3\right)^2 + \varepsilon$$

The translog part embedded in (10) can be seen as a generalized crop response model that allows for interactions between growth inputs and facilitating inputs. Accommodating input asymmetry, this general framework may provide more robust tests for separability or interactions. As Eq. (10) nests two alternative specifications proposed in (7) and (9), it also provides a framework for testing the restricted models. If the concept of dichotomy, and the asymmetry derived therefrom, do not contribute to a better understanding of the underlying production process, the parameters $\beta_0, \beta_1, \beta_2$, and β_3 will be insignificant and the model simplifies to a translog function. Significant parameters $\beta_0, \beta_1, \beta_2$, and β_3 should support the conclusion that the asymmetric specification is the true underlying production function. If the parameters β_{0m}, β_{mq}, and γ_{km} are jointly zero but parameters $\beta_0, \beta_1, \beta_2$, and β_3 are not, the asymmetric specification in (9) is justified.

4.2 Estimation

Specification (7) is a log-linear model with fixed effects, which is straightforward to estimate using the least square dummy variable (LSDV) approach. Our estimation of the nonlinear models (9) and (10) used the nonlinear least square (NLS) estimator. The computation of the NLS estimator was based on the linearized model derived from the first-order Taylor series approximation of the nonlinear models (Greene, 2003, pp.166). The pseudoregressors in the linearized model are the first derivatives of the nonlinear function with respect to the corresponding parameters. The pseudoregressors associated with dummies, share of potato area, and log-linear terms are the original regressors. The pseudoregressor for the parameter β_0 is:

$$\text{(11)} \qquad w_{\beta_0} = \frac{\partial \ln y}{\partial \beta_0^0} = 2\left(\beta_0^0 + \beta_1^0 z_1 + \beta_2^0 z_2 + \beta_3^0 z_3\right)$$

where $\beta_0^0, \beta_1^0, \beta_2^0, \beta_3^0$ are true parameter values. Similarly, the pseudoregressor associated with parameters β_1, β_2, β_3 are:

$$\text{(12)} \qquad w_{\beta_k} = \frac{\partial \ln y}{\partial \beta_k^0} = 2\left(\beta_0^0 + \beta_1^0 z_1 + \beta_2^0 z_2 + \beta_3^0 z_3\right) z_k$$

where the subscript k=1,2, and 3. The parameters are solved iteratively: the pseudoregressors are evaluated at certain starting values of $\beta_0^0, \beta_1^0, \beta_2^0, \beta_3^0$ and the linearized model is estimated with linear least squares; the parameter vector obtained then serves as new values of $\beta_0^0, \beta_1^0, \beta_2^0, \beta_3^0$ to compute pseudoregressors. The iteration continues until the parameter vector converges.

A particular point of concern in the estimation is that the crop-level data on capital and labor were not observed from actual production but calculated using expert knowledge, which might lead to a measurement error problem. In order to avoid inconsistency, we used the instrumental variable method. The instruments used for the terms (log-linear and pseudoregressors) associated with labor and capital in specifications (7), (9) and (10) were the first- and second-order (including the interactions) terms of land, seeds, fertilizer, pesticides, and the farm-level capital and labor. Obviously, labor and capital use are correlated with land preparation, seeding, fertilization, and pesticide application; and the farm-level labor and capital availability limit crop-level labor and capital use.

In addition to the measurement error problem, there may be further endogeneity problems when estimating the production function. Although the farm and year dummies in the model have addressed unobserved firm-specific and time effects, the disturbance ε might still correlate with the terms associated with variable input use. Under unfavorable weather conditions, for example, the farmer may opt to reduce or increase pesticide application; meanwhile, unfavorable weather usually affects crop yield, which is captured by the disturbance. As a result, pesticide application might correlate with the disturbance term ε. Because the error term in the pseudoregression contains approximation error as well as the disturbance ε, the potential correlation challenges the validity of the estimation procedure. In this situation, the orthogonality of the error term to the regressors has to be examined. The GMM estimation used in this study provides a Sargan test (Sargan 1958, Hansen, 1982), which tests the null hypothesis of orthogonality[3].

5. Results and discussion

The Sargan test produced p-values of 0.583 for specification (7), 0.508 for specification (9), and 0.762 for specification (10), thereby confirming the validity of the estimation procedure. Below we will test the paradigm proposed in the conceptual framework and then present the results from an input productivity analysis.

5.1 Results of Hypothesis Testing

A Wald test was performed to test the joint significance of parameters γ_{km} in specification (7). The test did not reject the hypothesis that these interaction terms are jointly zero at the 5% significance level (see table 2), implying that the inputs in one group are separable from the inputs in the other group. We further tested γ_{km} in the general framework (10), and again the test result did not reject the null hypothesis. No a priori interaction between fertilizer and pesticide was detected in specification (7) (p-value 0.632) or in specification (10) (p-value 0.667).

The asymmetry based on the dichotomous division of inputs was tested against the hypothesis that $\beta_0, \beta_1, \beta_2$, and β_3 in the scaling function are jointly zero. The test with specification (9) yielded a highly significant result, further confirmed by the same test with the general framework (10). Moreover, the parameters β_{0m} and β_{mq} in (10), which represents the symmetric treatment of facilitating inputs, were jointly zero at the 5% significance level. The empirical evidence strongly supports the hypothesis of asymmetry.

[3] The statistical inference of GMM is based on asymptotic approximations. This study uses 1425 observations, which is relatively large and less likely to lead to small sample bias.

Table 2. Results of Hypothesis Testing

Hypothesis	Testing framework	Parameter restriction	p-value
Separability	Model (7)	$\gamma_{km}=0$	0.086
	Model (10)	$\gamma_{km}=0$	0.112
Asymmetry	Model (9)	$\beta_0,\beta_1,\beta_2,\beta_3=0$	0.000
	Model (10)	$\beta_0,\beta_1,\beta_2,\beta_3=0$	0.003
		$\beta_{0m},\beta_{mq}=0$	0.200
Restricted model	Model (10)	$\gamma_{km},\beta_{0m},\beta_{mq}=0$	0.072

Note: The p-value was computed from the asymptotic Wald test

The separability renders the traditional translog production function (7) inefficient, and the asymmetry makes it conceptually unattractive. An additional test suggested that parameters γ_{km}, β_{0m}, and β_{mq} in (10) were jointly zero at the 5% significance level. Altogether, the separability and asymmetry found in the general framework (10) justify the asymmetric specification (9). The choice of specification (9) was further assessed by the goodness-of-fit standard. Comparison showed that the specification (9) gave an R-square of 0.86 and an adjusted R-square of 0.82 whereas the translog specification (7) yielded values of 0.82 and 0.76, respectively. The overall results indicate that the asymmetric specification (9) outperforms the traditional translog specification, although the translog is claimed to be the most flexible and therefore the most favored specification in the literature. In fact, this finding is not surprising. The claim to be able to approximate *any* production technology is itself an intrinsic weakness of the translog: it is least informative when it comes to the question what rationale or theory underlies the production process, which is exactly the price that the translog pays for its flexibility.

Given the evidence from agronomic studies and our empirical statistical testing, we would contend that we have established the dichotomy concept and the asymmetry of inputs. The further analysis below will be based on the asymmetric specification (9).

5.2 Estimation Results and Productivity Analysis

The estimation results of model (9) are presented in table 3. Because of space constraints, the estimates of farm dummies are not presented (they can be obtained from the authors upon request).

Table 3. Estimation Results of the Asymmetric Model (Model (9))

Parameter	description	Approximate estimates	S.E.	p-value
C	intercept	1.320	0.615	0.032
d_{91}	dummy 1991	-0.013	0.029	0.640
d_{92}	dummy 1992	-0.089	0.043	0.038
d_{93}	dummy 1993	-0.036	0.053	0.497
d_{94}	dummy 1994	-0.056	0.046	0.224
d_{95}	dummy 1995	-0.110	0.047	0.019
d_{96}	dummy 1996	-0.121	0.049	0.014
d_{97}	dummy 1997	-0.032	0.052	0.537
d_{98}	dummy 1998	-0.960	0.069	0.000
d_{99}	dummy 1999	-0.321	0.078	0.000
δ	potato percentage	-0.823	0.332	0.013
α_1	$\ln(x_1)$	0.378	0.340	0.267
α_2	$\ln(x_2)$	0.492	0.158	0.002
α_3	$\ln(x_3)$	-0.035	0.275	0.898
α_{11}	$\ln(x_1)\ln(x_1)$	0.538	0.212	0.011
α_{12}	$\ln(x_1)\ln(x_2)$	-0.298	0.114	0.009
α_{13}	$\ln(x_1)\ln(x_3)$	-0.210	0.141	0.138
α_{22}	$\ln(x_2)\ln(x_2)$	0.044	0.083	0.598
α_{23}	$\ln(x_2)\ln(x_3)$	0.292	0.077	0.000
α_{33}	$\ln(x_3)\ln(x_3)$	-0.092	0.130	0.478
β_0		-0.228	0.248	0.359
β_1	z_1	0.051	0.287	0.860
β_2	z_2	-0.0018	0.0013	0.193
β_3	z_3	0.017	0.013	0.170

Note: The dependent variable of the model is ln(y); y is output (potato).
x_1 denotes land; x_2 seeds; x_3 fertilizer; z_1 labor; z_2 capital; z_3 pesticides

The trend in potato production over time can be observed from the sign and size of the estimates of year dummies. The overall trend seems to be negative, with 1998 in particular witnessing dramatically low potato yield when abnormally heavy rainfall during harvesting resulted in over 40% of potatoes being unharvested or damaged (Silvis and Van Bruchem, 2000). Table 3 suggests that a narrow rotation regime has a significant negative effect on potato yield: a 1% increase in the share of potatoes decreases yield by 0.82%. If the potato producer changes from a 6-year rotation system (16.67% potato area) to a 3-year rotation (33.3% potato area), the yield is approximately 14% less, which is comparable to the 15% reported by Hoekstra (1981). The yield reduction is mainly due to the increase in soilborne diseases from previous potato production in the same plot (Schans, 1991).

The normative crop response model *G*(.) was estimated with data from real farm production. The attainable yields for each farm can be derived from *G*(.). The average attainable yield of the sample is 58.2 thousand euros (1990 price); the average value of the scaling function is 94.7%, implying that over 5% of attainable yield has been lost. For individual farms, the yield reduction may be interpreted as inefficiency due to nonoptimal growth conditions.[4] On the other hand, it may well be the result of rational choice of profit-maximizing producers. In the scaling function *F*(.), the parameters β_0, β_1, β_2, and β_3 are jointly significant (see table 2), but individually are insignificant at the 5% level. This is not uncommon in joint tests (particularly when the individual p-values are relatively low as β_2 and β_3 in table 3), and it may suggest multicollinearity among facilitating inputs.

Based on the estimation results of model (10), we performed a further analysis of input productivity. The value of the marginal product (VMP) of individual inputs is presented in table 4. The VMP, or shadow price, of inputs was calculated as the product of the marginal product and the average price index of potato (details of the computation of VMP are available from the authors upon request) and then compared with input prices or price indices (see Data section). The standard errors were computed using the delta method (Greene, 2003, pp.70).

[4] The interpretation of inefficiency links this study to the field of stochastic frontier analysis (see Kumbhakar and Lovell (2000) for an overview). In contrast to the error component approach in this literature, we estimated the frontier *G(.)* and the efficiency *F(.)* directly, without making any assumptions about the distribution of the error terms.

Table 4. The Value of Marginal Product (VMP) of Inputs (in 1,000 euros)

Estimates	Land	Seed	Fertilizer	Labor	Capital	Pesticides
VMP	4.13	0.86	0.05	1.38	-0.05	0.46
Approx S.E.	0.56	0.37	1.55	7.64	0.04	0.62
Approx p-value (H_0: vmp=0)	0.00	0.02	0.98	0.86	0.24	0.45
Input price (IP)	0.32[a]	0.87	0.98	29.50[b]	0.11[c]	1.10
Approx p-value (H_0: vmp=IP)	0.00	0.99	0.55	0.00	0.00	0.30

Note: The VMPs were evaluated at the sample mean, at average output price index 1.088; prices of seed, fertilizer, and pesticides are average price indices.
[a] Land price is based on average rent per ha farmland during 1990-1999 (LEI).
[b] Labor price per man-year is calculated from the sample data.
[c] Capital price is calculated as 10% of average capital price index.

The only VMP estimates significantly higher than zero were the estimate for land (at the 1% significance level) and the estimate for seed (at the 5% significance level). Compared to input prices, the VMP estimates for fertilizer and pesticides are both lower than the input price. However, the differences are statistically insignificant at the 5% significance level. Without further information on the externalities of fertilizer and pesticide use, it cannot be concluded that there was definite overuse. Among fixed inputs, the estimate of capital productivity presented a surprising negative, albeit insignificant, value. Further comparison shows that the VMP of capital is significantly lower than this opportunity cost[5] at the 1% significance level, which is a strong signal of overuse. This finding is consistent with the result reported by Zhengfei and Oude Lansink (2003). The over-capitalization may have a risk interpretation: the availability of sufficient machinery could guarantee timely harvesting and prevent yield being lost due to adverse weather. On the sample farms, the average wages paid were 29.5 thousand euros per man-year. The VMP of labor in table 4 is lower than the paid wage at 1% significance level, suggesting overuse of labor. In contrast to the overuse of capital and labor, our results indicate that land is highly productive. A return of 4130 euros per hectare is more than 10 times the average rent for crop land during the period investigated (note that "potato land" is often more expensive than e.g. corn land). A further calculation of input elasticity gives a land elasticity of 0.85 (the sum of input elasticities is 0.99). The

[5] The opportunity cost of capital may consist of two components: depreciation and interest. Assuming that depreciation and interest rates are both set at 5%, the opportunity cost was calculated as 0.11, based on the average capital price index of 1.11.

sensitive response of output to land suggests that land is a binding factor in potato production, implying that cash-crop farms should increase the area under potatoes.

As a final comparison, we also computed the VMP with the translog model. We found VMPs of 4.53, 0.67, and 3.43 for land, seed, and fertilizer, respectively. For labor, capital, and pesticide they are 37.06, -0.21, and –1.50 respectively. The VMP estimates all differ in magnitude from those in table 4, and in the case of pesticide the VMP becomes negative. The standard errors of the VMPs computed from the translog are two times larger than those from the asymmetric model, suggesting less precise VMP estimates from the translog. If assessed from these large standard errors, the productivity estimates from the translog do not differ statistically from those in table 4. When compared with the input prices, labor is not overused, whereas table 4 suggests otherwise. Notice that these results should be interpreted with caution because the translog function is not the correct representation of the underlying technology as shown in our study. Thus, the statistical inference is unreliable and the VMP estimates are biased.

6. Concluding Remarks

We have proposed a novel concept of dichotomy of growth inputs and facilitating inputs in crop production. The dichotomy of inputs recognizes distinct functions of different categories of inputs and is consistent with well-founded agronomic insights and principles. Based on the dichotomy concept, we have presented a new paradigm for agricultural production analysis which connects the studies in economics and agronomy. We have further provided a procedure to test the robustness of the proposed paradigm. The proposed theory was applied to potato production in the Netherlands during 1990-1999 and was not rejected by the empirical test. The model based on the dichotomy statistically outperformed the traditional translog model, suggesting improved understanding of the agricultural production process.

Methodologically, the article has developed a method to allocate capital and labor in empirical crop level studies for which crop-level data on capital and labor are generally not available. The instrumental variable estimation solved the problem of measurement error and makes the estimates consistent. The GMM approach, in conjunction with the fixed-effect treatment, addresses other possible endogeneity problems likely to jeopardize the estimation of the production function. The scaling function defined in this article constrains the scaling factor within the interval [0,1] without imposing monotonicity and allows for a negative marginal productivity of pesticides.

Real farm crop-level data were used for the empirical application. The productivity analysis indicated that in Dutch potato production the land is highly productive whereas labor and capital are overused. An increase in the area under potato would enable full use of labor and capital and result in more efficient use of the two inputs; this could be achieved through, for instance, collaborations between arable and livestock farms (e.g., renting and exchanging land). Such collaborations have been observed in the Netherlands.

In this study, inputs within each dichotomous group were treated symmetrically. Future research could address the specific roles of individual inputs within each of the two groups. Meanwhile, the impact of the crop rotation regime on crop yield may be further analyzed by studying the entire crop rotation system in a joint production analysis allowing for interactions between crops.

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Chapter 4

Excess Capital and Its Implications in Econometric Analysis of Production

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Abstract

In this article we propose a framework for analyzing capital requirement in agricultural production and define excess capital thereupon. To estimate the capital requirement model and measure excess capital, we develop a two-step procedure that allows endogenous regressors in stochastic frontier analysis. The Generalized Method of Moments (GMM) estimator is used to solve the endogeneity problem and is robust to potential misspecification bias from omitted variables. The empirical study addresses capital use on cash crop farms in the Netherlands. Results show the presence of excess capital. The implications of excess capital are further demonstrated with a production frontier analysis.

Keywords: Capital requirement, endogeneity, excess capital, stochastic frontier

1. Introduction

In empirical analysis of production, factor demand functions are usually derived under the assumptions of profit maximization or cost minimization. The factor demand derived under these behavioral assumptions indicate how much inputs a producer *should* use in order to maximize profit or minimize cost given prices and the state of technology. In practice, however, the actual usage of inputs can be higher or lower than the optimal amount. The amount of an input used in actual production depends on various factors and can be studied directly from a technical perspective with an input requirement function. The input requirement function shows the minimum amount of an input that is required to produce a given level of output, given other inputs and the technology. This approach of studying input requirement may be desirable for several reasons. First, reality often rejects the behavioral assumptions (Lin, Dean, and Moore, 1974; Ray and Bhadra, 1993; Driscoll et al., 1997; Tauer and Stefanides, 1998), in which case, imposing behavioral assumptions to derive factor demand functions would result in biased and inconsistent estimates (Pope and Chavas, 1994). Second, the price information required for deriving factor demand functions is often unavailable which makes the traditional approaches based on profit maximization of cost minimization inapplicable. Third, a study of input actually used or technically needed yields insights on input requirement in production. This direct perspective of factor demand is particularly relevant for producers in making decisions regarding input use given resource endowment, production level, production technology adopted, and production environment, etc. The information on input requirement is also useful for policy making on resource use.

In the existing literature, primal studies on factor requirements include Diewert (1974), Kumbhakar and Hjalmarrson (1995, 1998), Battese, Heshmati, and Hjalmarsson (2000), Heshmati (2001), Kumbhakar, Heshmati, and Hjalmarsson (2002), El-Gamal and Inanoglu (2005). This literature exclusively studies labor requirement in the production process. Until now, we are not aware of any study that uses the capital requirement function. As one of the major factors of production, capital presents not only an important but also a more complex and interesting case for research. Capital is often overused in agricultural production. In studies using both farm- and crop-level data, Zhengfei et al. (2005, 2006) found that capital is overused on cash crop farms in the Netherlands. Using a nonparametric method, Zhengfei and Oude Lansink (2003) concluded that Dutch agriculture is over-invested in capital and that capital is weakly disposable (i.e., it can not be disposed of costlessly when in excess). Because of weak disposability of capital, findings in these studies suggest that producers tend to have excess capital, which is either not used or not fully used in actual production. As capital investment is often an irreversible decision as suggested by Pindyck (1991), excess capital tends to persist.

The presence of excess capital means more than just a failure of profit maximization or cost minimization. It has serious implications for the econometric analysis of production. It leads to systematic measurement error if accounting data of capital stock are used in econometric modeling. For empirical econometric modeling of production, the "fixedness" of capital makes it "safe" to assume that capital is exogenous. Unfortunately, the exogeneity may not be as true as it seems, because the capital *actually used* in the production depends on the production levels. In agriculture, for example, a higher output level requires more capital for harvesting, processing, and storage of the output. This implies simultaneity of capital. In fact, the measurement error and simultaneity come hand in hand. Excess capital serves as a reservoir of capital supply when more capital is needed due to a higher yield; and vice versa, when less capital is used due to a low yield, excess capital appears. Measurement error and simultaneity of independent variables are fundamental sources of endogeneity that jeopardizes the econometric estimation, if not properly addressed.

To date, excess capital has not been explicitly explored in the literature. Somewhat related to excess capital, the concepts of "excess capacity" and "capacity utilization" are proposed in the literature (Klein, 1960; Fare, Grosskopf, and Kokkelenberg, 1989; Morrison Paul, 1999; Dupont et al., 2002; Kirkley, Morrison Paul, and Squires, 2002, 2004; Felthoven and Morrison Paul, 2004). In this literature, the "capacity output" is defined as the maximum or potential output that the existing capital stock or capacity can produce under normal working conditions. If the capacity output is not achieved, there exists "excess capacity". The excess capacity is an output-oriented concept, whereas the excess capital is input-oriented by definition. It is sometimes suggested that difficulties of capital measurement may be overcome by developing capacity measures (Klein, 1960). However, excess capacity is not purely a proxy for excess capital because it is derived as an index, including other inputs as well as the capital stock. In this sense the capacity utilization is not necessarily dual to the capital utilization. More importantly, the presence of excess capital per se would bias the measurement of excess capacity and capacity utilization. Using accounting data of capital stock to model excess capacity would create such a paradox that "excess capacity" is defined without recognizing "excess capital". This situation calls for a direct measurement of capital requirement to define excess capital.

This study has three objectives. First, we define a theoretical framework of capital requirement in agricultural production from a primal, technical perspective. Compared to traditional factor demand studies, this direct approach does not rely on behavioral assumptions or require an explicit specification of production function (see, e.g., Beattie and Taylor, 1993, pp.237-241). Second, we develop a concept of excess capital based on the input requirement model defined. Compared to the definition of excess capacity in the literature, this concept addresses capital utilization directly, with an input-oriented approach. In measuring excess capital, we propose a robust econometric procedure to address the endogeneity of output in the input requirement model. The endogeneity problem is not addressed in the existing labor requirement studies discussed earlier. Third, we analyze the potential impact of measurement error and simultaneity of capital (due to the presence of excess capital) on empirical analysis of production.

2. Capital requirement and excess capital

The requirement of capital in agricultural production depends on many factors such as: the type of product produced on the farm, the production level, resource endowment and technology used in the production, natural and geographical condition, farm organizational arrangement, the demographical characteristics of the farmer, and other unobserved factors.

First, type and mix of enterprises involved in farm production determines the type of buildings, machinery, and equipment and installations to be built or installed on the farm. For example, sowing machine and harvesting combines are often necessary for cereal production while other planting and harvesting machines are required for potato production. And for each type of product, a higher production level generally requires a higher capital stock. Second, the resource endowment of the farm and the technology adopted in production directly affect input-output combinations and the capital stock required. Strategically, if a farm has a low endowment of land relative to labor (e.g., family labor), the farmer may adopt a labor-intensive production technology, which requires less capital for a targeted level of output. Technically, there also exists substitutability between capital and other inputs for certain operations. For example, chemicals can be used for weed control instead of mechanical weeding. In some circumstances, complementarity may exist as well, particularly between capital and variable inputs. For instance, applying fertilizer and pesticide often requires use of machinery. As a result, capital required in production depends not only on the production level, but also on the use of other inputs. Third, natural and geographical conditions that affect capital requirement are: climate, weather, geographic and soil conditions, etc. Extreme weather conditions may require additional machinery in harvesting and drying and more storage spaces. For crop production, it is usually easier for machinery to work on loose sandy soil than on sticky clay soil. As a result, clay soil is expected to require more capital than sandy soil. Fourth, organizational arrangements that affect capital requirement include land tenure regime, contract work or outsourcing, etc. Since a leased farm or land is often equipped with some basic infrastructure, the capital stock reported in the bookkeeping may differ between leased and non-leased farms. On the other hand, the difference in land tenure may induce strategic difference in production technology and capital investment. When certain operations, such as breeding, planting and soil disinfection are outsourced, capital stock to be maintained on the farm can be substantially reduced. Fifth, the demographic and personal properties of the farm operator, such as education level and farming experience, may affect how efficiently the capital is used and therefore affect the capital required in the production.

As capital requirement may differ over time, some of the capital stock may not be used or remain idle due to, for example, yearly crop rotation and weather conditions. Also, a farmer may choose to maintain a high level of capital stock on the farm simply because he is risk averse and prefers to have more capital at his disposal to guarantee timely sowing or harvesting in case of adverse weather conditions, for example. All these cases result in excess capital on the farm. In the next section, we propose a theoretical model to study capital requirements and measure excess capital.

3. Methods

Based on the discussions in the preceding section, we propose to use the stochastic frontier approach to model capital requirements and measure excess capital therefrom. The theoretical basis of the frontier approach dates back to 1950s from Koopmans (1951), Debreu (1951), and Shephard (1953). These studies first developed the concept of frontier and defined the distance relative to the frontier as an efficiency measure. The *stochastic* frontier approach originated in the work of Meeusen and van den Broek (1977) and Aigner, Lovell, and Schmidt (1977). Kumbhakar and Lovell (2000) gave a comprehensive overview of this literature. The stochastic frontier approach has been used in several studies to model labor use efficiency since Kumbhakar and Hjalmarrson (1995) first used it to study labor use in the Swedish insurance offices (Kumbhakar and Hjalmarrson, 1998; Battese, Heshmati, and Hjalmarsson. 2000; Heshmati, 2001; Kumbhakar, Heshmati, and Hjalmarsson, 2002). In estimating the labor requirement function, a common assumption in this literature is that output produced with labor is considered as exogenous. Although this assumption may not pose problems in some cases, especially when outputs are exogenous to the producers, theoretically this is a strong assumption and should not, in general, be used without proper justification. The vast literature on production function models where output is modeled as a function of inputs (including labor and capital) makes the endogeneity of output a legitimate issue to be addressed in the input requirement model. Our study proposes a procedure that addresses this problem.

The theoretical model of capital requirement function is formulated as follows:

$$k = f(Y, X, O)e^{u} \tag{1}$$

where k is the capital stock maintained on the farm, $f(.)$ is the amount of capital required on a farm, which is a function of all the factors discussed. Y is a vector of outputs produced on the farm; X is a vector of inputs except capital used in the production; O represents all the other factors discussed in the preceding section. Finally, $u \geq 0$ represents excess capital. When u is zero, e^{u} is 1 and there is no excess capital. Thus, $u > 0$ measures the percentage of capital in excess. Random factors like weather and other nonsystematic elements that affect capital use are accommodated in the model by appending a random term v. Thus the stochastic capital requirement function is

$$k = f(Y, X, O)e^{u+v} \tag{2}$$

where v can take both positive and negative values. The minimum amount of capital required to produce Y given the technology, X, O and v is given by

$$k^{*} = \frac{k}{e^{u}} = f(Y, X, O)e^{v} \tag{3}$$

Thus, the excess capital can be measured from

$$k_{e} = k - k^{*} = k - \frac{k}{e^{u}} \tag{4}$$

By taking logarithm of both sides of the equation (2), the stochastic capital requirement function can be rewritten as:

$$\ln(k) = \ln f(Y, X, O) + u + v \tag{5}$$

We assume the distributions of u and v as follows:

i) $u \sim N^{+}(0, \sigma_{u}^{2}),\ i.i.d.$

ii) $v \sim N(0, \sigma_{v}^{2}),\ i.i.d.$

iii) u and v are distributed independently of each other.

Based on these assumptions, the probability density function of the joint distribution of $e_0 = u + v$ is:

(6) $$P(e_0) = \frac{2}{\sigma} \cdot \phi\left(\frac{e_0}{\sigma}\right) \cdot \Phi\left(\frac{e_0 \lambda}{\sigma}\right)$$

where $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$, $\lambda = \sigma_u / \sigma_v$, and $\phi(.)$ and $\Phi(.)$ are the standard normal probability density and cumulative distribution functions, respectively (see Appendix A). With an explicit functional form of *f*(.), the capital requirement function can be estimated using the maximum likelihood (ML) method. Excess capital u for each observation can then be derived from the conditional expectation, $E(u \mid e_0)$ based on the conditional probability density function, $P(u \mid e_0)$.

However, the ML estimation procedure in the standard stochastic frontier approach could yield inconsistent estimates due to the presence of endogenous variable *Y*. We avoid this problem by estimating the capital requirement function and deriving the excess capital in two steps. We take care of the endogeneity problem in the first step and employ the ML estimation to derive the excess capital in the second step. For this purpose we assume a log-linear relationship between factors (*Y, X*)*,* and *O,* and rewrite eq. (5) as,

(7) $$\ln(k) = f_1(Y, X; \alpha) + f_2(O; \beta) + u + v$$

where α and β are vectors of parameter to be estimated. We further rewrite the model as:

(8) $$\ln(k) = f_1(Y, X, \alpha) + e_1$$

where

(9) $$e_1 = f_2(O, \beta) + u + v$$

The first step is to estimate the model in (8). Two problems must be addressed here. First, as *Y* is endogenous, the instrumental variable method must be used to derive consistent estimates. Second, a robust estimation procedure must be used to avoid the potential parameter inconsistency due to the omission of factors, *O*.

The effects of the omitted factors are captured by the residuals e_1. Using e_1 as dependent variable, we estimate the effect of the *O* variables on capital use as well as the extent of excess capital for each observation, in the second step. The model in the second step is estimated with ML estimator based on the distribution of the composed error $e_0 = u + v$ given in (6). As the dependent variable e_1 is not observable, it is replaced by

$$(10) \qquad \hat{e}_1 = \ln(k) - f_1(Y, X; \hat{\alpha})$$

After the estimation, the excess capital component *u* is obtained from $E(u \mid e_0)$.

4. Models

The capital requirement function in the presence of panel data is specified as:

$$(11) \qquad \ln(k_{it}) = c_0 + c_1 t + c_2 t^2 + \alpha_0 \ln(y_{it}) + \alpha_{00} \ln(y_{it}) \ln(y_{it}) + \sum_j \alpha_{0j} \ln(y_{it}) \ln(x_{jit}) + \sum_j \alpha_j \ln(x_{jit}) + \frac{1}{2} \sum_j \sum_l \alpha_{jl} \ln(x_{jit}) \ln(x_{lit}) + e_{1it}$$

where *k* denotes capital stock; the subscript *i* indexes individuals, and *t* indexes time periods; *j* and *l* index inputs. The variable *y* denotes the output level produced on the farm; the variable *t* and t^2 specify a quadratic time trend. The error term is defined as $e_{1it} = e_i + e_{it}$; e_i is the individual effect, and model (11) is a fixed effect model. This translog model is similar to production function models except that the capital stock and the output variables are switched.

The model in the second step that regresses the residuals from the first step on the other factors *O* that affect capital requirements but are not included in the first step is:

$$(12) \qquad e_{1it} = \beta_0 + \sum_{i=1}^{I-1} \beta_{0i} D_i + \sum_{m=1}^{M-1} \beta_{1m} DType_{mit} + \beta_2 DSoil_{it} + \beta_3 DTenu_{it} + \beta_4 DEdu_{it} + \beta_5 Size_{it} + \beta_6 Share_{it} + \beta_7 Contr_{it} + \beta_8 Age_{it} + e_{0it}$$

where $e_{0it} = u_{it} + v_{it}$, u_{it} and v_{it} are assumed to follow half-normal and normal distribution, respectively, as mentioned before;

DType, dummy variable for product types (0 for not being a particular product, 1 for yes),

DSoil, dummy soil type (0 for sandy soil, 1 for clay),

DTenu, dummy land tenure (0 for own land, 1 for lease),

DEdu, discrete education level (1 for primary school, 2 for non-agri education, 3 for vocational education in agriculture, 4 for higher education in agriculture), *Size,* size of farm operation, in NGE (standardized Dutch Farm Unit),

Share is the share of non-arable farming operations on the farm in terms of size

Contr, the amount of contract work

Age, the age of farmer,

D_i is the farm dummy.

In this model, the dummy variables *DType* represent the type of major product on the farm, and its number *M* depends on the number of enterprises or products in the sample. *DSoil* is a dummy variable for soil; *DTenu* is a dummy for land tenure; *DEdu* represents the level of education. *Size* is measured in standardized Dutch Farm Unit (NGE), which is defined based on the scale, intensity and income generating ability of the farm operations (Van den Tempel and Giesen, 1992, pp. 285-288). *Share* is the share of non-arable farming operations in terms of NGE for the case study of cash crop productions in the Netherlands. *Contr* denotes the amount of contract work. The variable *Age* of the farm operator is a proxy for experience and perhaps some other demographic characteristics as well.

The product dummy and the share of non-arable operation distinguish the capital requirements of different enterprises or product mixes. The farm and soil dummies capture the impacts of natural and geographical factors. Land tenure, amount of contract work, and the size of the farm represent the organizational arrangements. The education level and the age reflect the demographic differences of farm operators. The factors used in the second step cover both factors that affect the "standard" technical requirement of capital (e.g., from product or soil type) and the factors that cause additional "non-standard" or inefficient use of capital (e.g., education or experience). The unexplained part of the capital stock is due to white noise *v* and a one-sided error term *u* which captures excess capital.

5. Data and Estimation

5.1 Data Description

The empirical study of capital requirement and excess capital is applied to the data from the farm accountancy data network (FADN) of the Agricultural Economics Research Institute (LEI)) in the Netherlands. Panel data are available over the period 1990-1999 from 486 cash crop farms with a total of 2511 observations. The panel is unbalanced and farms stay in the sample for 5 years, on average.

The capital requirement function in the first-step is estimated with a single output and 5 inputs. The capital stock consists of buildings, machinery, equipment and installations. The output measured revenues from all products. The inputs included are land (x_1), labor (x_2), fertilizer (x_3), pesticide (x_4), and miscellaneous inputs (x_5). Land was measured in hectares, and labor was measured in quality-corrected man-years. Miscellaneous inputs included seed, feed, energy, and services. The capital stock, output, fertilizer, pesticide, and miscellaneous inputs were deflated to 1990 prices (prices were obtained from the LEI/CBS[1]). Tornqvist price indices were calculated for capital and miscellaneous inputs. For the second step model, 7 product types were distinguished, viz., cereals, root crops, mix of cereals and root crops, mix of root and other crops, open-field vegetables, and mix of arable, horticultural and fruit production. The soil dummy takes the value 0 for sandy soil and 1 for clay soil. Land tenure distinguished own land and leased land[2] for the farm production. The education of farm operators was measured in 4 levels from low to high. The dummy soil type is time invariant for individual farms; The dummy product type, land tenure and education have no or little variation over time. Other variables include the amount of contract work, the size of the farm, and the age of the farm operator. The summary statistics of non-dummy variables are presented in table 1.

[1] CBS denotes Central Bureau of Statistics in the Netherlands.

2 when i) more than 2/3 of the land is owned by the farm operator, or ii) more than 1/3 is own land and the value of affiliated buildings on the land exceeds 9075 euro (20,000 guilders), the tenure is recorded as own land in the accounting system, otherwise recorded as leased land.

Table 1. Summary Statistics of Cash Crop Farms in the Netherlands, 1990-1999

Variable	Unit	Mean	Std Dev.
Capital	thousand euro	229.33	180.57
Output	thousand euro	224.82	175.34
Land	hectare	64.92	43.63
Labor	man-year	1.92	1.18
Fertilizer	thousand euro	9.24	6.72
Pesticide	thousand euro	16.58	12.09
Misc.	thousand euro	47.46	39.01
Contract work	thousand euro	10.27	7.40
Size	Dutch farm unit (NGE)	114.93	79.55
Age	years	49.08	10.94
Share non-arable	ratio	0.09	0.12

Source: Dutch Agricultural Economics Research Institute (LEI)
Note: The statistics are per farm year, computed with 2511 observations from 486 farms; the monetary unit is in 1990 prices.

5.2 Estimation

Step 1: The model in (11) is a panel data model. There are three issues to be addressed in the estimation: i) The heterogeneity across farms, ii) the endogeneity of output, and iii) impact due to the omissions of other variables (i.e., those used in the second-step). The first issue points us to the fixed-effect estimation. Notice that time-invariant factors (e.g., soil type), if included in this step, would be dropped out in the estimation of the fixed effect model, which also justifies the two-step method in this study. Solving the endogeneity problem requires an instrumental variable method. The consequence of omitting other factors is that these factors are captured by the residuals e_1, which may cause the residuals to correlate with the regressors in the first-step model and result in biased and inconsistent estimates (see, e.g., Pindyck and Rubinfeld, 1998, p.185). This problem must be explicitly addressed, for which a robust estimation procedure must be used in the estimation. Moreover, the robustness to bias and inconsistency should be testable. We propose using the generalized method of moment (GMM) in the estimation since it uses instruments and provides the possibility of testing.

We use first-differencing to remove the individual effects. In the differenced equation, the error term is $\Delta e_{1it} = e_{1it} - e_{1i,t-1}$. Thus it has a first-order autocorrelation structure. Moreover, it is correlated with the transformed variable $\Delta \ln(y_{it}) = \ln(y_{it}) - \ln(y_{i,t-1})$ since y is endogenous. To solve this problem we use a further lag $\ln(y_{i,t-2})$ as instrument, which implies the following moment condition:

$$E[\ln(y_{i,t-2})\Delta e_{1it}] = 0 \tag{13}$$

In principle all historical observations of $\ln(y_{it})$ prior to t-2 period may be used as instruments as well. As later periods in the panel have more historical values, more instruments are available thereby. For individual i, the matrix of the instruments is:

$$Z_i = \begin{pmatrix} [ln(y_{i0})] & 0 & \cdots & 0 \\ 0 & [ln(y_{i0}), ln(y_{i1})] & & 0 \\ \vdots & & \ddots & 0 \\ 0 & 0 & \cdots & [ln(y_{i0}), \ldots, ln(y_{i,T-2})] \end{pmatrix} \tag{14}$$

In the same way, instruments for other regressors associated with y in the model can be constructed. The setup of instruments is similar to Arellano and Bond (1991).

In the first-step model, another variable that needs to be instrumented is miscellaneous inputs (x_5) as its components, energy consumption and services (of, e.g., storage and delivery), may depend on the capital stock of machinery and buildings. The instruments for the regressors associated with x_5 were set up the same way as in (14). We used a two-step GMM estimator for the estimation. First, consistent estimates of the first-differenced residuals $\hat{\Delta e_1}$ are obtained from a preliminary consistent estimator. Next, the GMM weighting matrix is constructed as $W_N = \left[\frac{1}{N}(Z' \hat{\Delta e_1} \hat{\Delta e_1}' Z)\right]^{-1}$ and then used in the estimation (N is the sample size). As the weighting matrix in the two-step estimator depends on estimated parameters, the usual asymptotic approximations are less reliable, particularly in the case of heteroskedasticity, compared to the one-step estimator. Simulation studies suggest that standard errors for the two-step estimators tend to be too small (Arellano and Bond, 1991; Blundell and Bond, 1998). This study uses a finite-sample correction proposed by Windmeijer (2005). In the unbalanced panel, farms stay in the sample for an average of 5 years. The number of farms that stay longer than 5 years decreases with the length of the panel, which means fewer observations are available for the moment conditions in later years. This may cause problems for the asymptotic approximations in GMM. Therefore, we restricted the instruments up to the 5th lag of endogenous regressors.

The Hansen *J* test (Hansen, 1982) available in the GMM framework can be used to test the null hypothesis that instruments used are indeed valid. Not rejecting the null means a consistent estimate of e_1 for the second-step model has been obtained, implying that the three problems discussed at the beginning of this section have been solved.

Step 2: After correcting the endogeneity problem in model (11) with GMM, we proceed to estimate the second-step model in (12) with ML estimation based on the joint distribution of *u* and *v* given in Eq. (6). The log likelihood function to be maximized for a sample of *N* observations is:

$$\ln L = constant - N \cdot \ln \sigma + \sum_i \sum_t \ln \Phi\left(\frac{e_{0it}\lambda}{\sigma}\right) - \frac{1}{2\sigma^2} \sum_i \sum_t e_{0it}^2 \tag{15}$$

where *i* and *t* indexes individual farms and time periods, and *N* is 2511 for this study.

6. Results

6.1 Estimation Results

The Hansen *J* test of the overidentified moment restrictions in the GMM estimation of model (11) produces a p-value of 0.175 which is larger than the 5% significance level. Therefore, the null hypothesis is not rejected, implying that the estimation procedure is robust. The estimation results of the model are presented in table 2.

Table 2 suggests a significant technical change over time in the capital requirement function. Both the first- and second-order term of time trend are highly significant; the parameter estimates of c_1 and c_2 show that the capital requirement decreases over time but at a diminishing rate, suggesting technological progress in agriculture. The negative sign of the first-order terms of land, labor, fertilizer, and pesticide may suggest substitutability between capital and these inputs. However, the substitution effects are insignificant except for fertilizer.

Table 2. Estimation Results of Model (11)

Parameter	Description	Estimates	Corrected S.E.	p-value
c_0	constant	3.997**	0.862	0.000
c_1	t	-0.031**	0.007	0.000
c_2	t^2	0.002**	0.0008	0.002
α_0	ln(y)	0.846*	0.332	0.011
α_{00}	ln(y)ln(y)	-0.052	0.053	0.325
α_{01}	ln(y)ln(x_1)	-0.122	0.097	0.211
α_{02}	ln(y)ln(x_2)	0.036	0.058	0.530
α_{03}	ln(y) ln(x_3)	0.085	0.083	0.302
α_{04}	ln(y) ln(x_4)	0.057	0.098	0.561
α_{05}	ln(y) ln(x_5)	-0.030	0.073	0.679
α_1	ln(x_1)	-0.380	0.383	0.320
α_2	ln(x_2)	-0.255	0.254	0.315
α_3	ln(x_3)	-0.543**	0.202	0.007
α_4	ln(x_4)	-0.072	0.301	0.812
α_5	ln(x_5)	0.002	0.327	0.994
α_{11}	ln(x_1)ln(x_1)	0.084	0.083	0.309
α_{12}	ln(x_1)ln(x_2)	0.030	0.071	0.682
α_{13}	ln(x_1)ln(x_3)	0.018	0.065	0.782
α_{14}	ln(x_1)ln(x_4)	-0.005	0.078	0.947
α_{15}	ln(x_1)ln(x_5)	0.093	0.106	0.381
α_{22}	ln(x_2)ln(x_2)	0.006	0.014	0.670
α_{23}	ln(x_2)ln(x_3)	-0.045	0.036	0.213
α_{24}	ln(x_2)ln(x_4)	-0.041	0.049	0.409
α_{25}	ln(x_2)ln(x_5)	0.059	0.062	0.337
α_{33}	ln(x_3)ln(x_3)	0.003	0.012	0.779
α_{34}	ln(x_3)ln(x_4)	-0.042	0.053	0.428
α_{35}	ln(x_3)ln(x_5)	0.035	0.069	0.611
α_{44}	ln(x_4)ln(x_4)	0.041	0.042	0.330
α_{45}	ln(x_4)ln(x_5)	-0.080	0.081	0.319
α_{55}	ln(x_5)ln(x_5)	0.0004	0.049	0.993

Note: The dependent variable of the model is ln(k); k is capital stock. y denotes output; x_1 land; x_2 labor; x_3 fertilizer; x_4 pesticide; x_5 miscellaneous inputs. (*) and (**) indicate that the estimate is significant at the 5% and 1% significance level, respectively.

A result that has important implications is that the output level has a significant impact on capital requirement, which is consistent with the *a priori* expectation. The significant effect of output on the capital requirement implies endogeneity of capital in the production process. The endogeneity of capital found in our study requires a consistent estimation procedure be used in the econometric analysis of production, such as production function or production frontier models, to which we will come back shortly.

From table 2 it is clear that most of the parameters are insignificant, suggesting that capital requirement does not respond significantly to most inputs in terms of production possibilities. Table 3 presents the estimation results of the second-stage model (12)[3].

Table 3. Estimation Results of Model (12) [a]

Parameter	Description	Estimates	Corrected S.E.	p-value
β_0	constant	-1.676	0.069	0.000
β_{11}	general arable	0.026	0.017	0.118
β_{12}	cereals	0.033	0.097	0.735
β_{13}	cereals & root crops [b]	0.044	0.034	0.194
β_{14}	root & other crops	0.025	0.005	0.000
β_{15}	open-field vegetables	0.354	0.023	0.000
β_{16}	mixed type [c]	0.004	0.030	0.900
β_2	DSoil	1.954	0.124	0.000
β_3	DTenu	-0.092	0.006	0.000
β_4	DEdu	-0.039	0.042	0.349
β_5	Size	0.001	0.0002	0.000
β_6	Share	0.085	0.087	0.330
β_7	Contr	-0.004	0.0009	0.000
β_8	Age	-0.002	0.0008	0.024

[a] Seven product types are distinguished by 6 product dummies and one default product type which is root crops.
[b] root crops include potato, sugar beet, fodder beet, and chicory.
[c] mixed type is a combination of arable, horticultural, and fruit production

In table 3, β_1's are dummies that distinguish product types. The coefficients on "root and other crops" and "open-field vegetables" are positive and highly significant.

[3] For space considerations, the individual effects (i.e., parameter estimates of farm dummies) are not presented.

Particularly, the size of the estimate of "open-field vegetables" is substantially larger than estimates of other product types, indicating that vegetable production are capital intensive and requires 35% more capital than the specialized root crop production (the default product type). Production on clay soils requires more capital than on sandy soils, as *a priori* expected. It is also expected that larger farms use more capital. Farms with leased land (*DTenu*) and outsourcing (*Contr*) require less capital, which is consistent with our *a priori* expectations. Furthermore, farm operators with more experience (*Age*) and higher education level (*DEdu*) use capital more efficiently and require less capital, but the education effect is insignificant.

After controlling for various factors that affect capital requirement, the unexplained capital stock is picked up in the residuals of (12), which are composed of the excess capital component u and a noise component v. A close look at the estimates of u for each observation shows that over 80 percent of observations in the sample have excess capital on the farm. The accounting data over-reported capital by 21%, on average. After removing the excess capital, we find that the average capital is 195.39 thousand euros[4]. The presence of excess capital implies misallocation of resources on the farm and it contributes to direct economic loss.

6.2 Implications of excess capital to econometric analysis of production

We used a standard translog production frontier model to demonstrate the impact of endogeneity of capital on empirical analysis of production (refer to Appendix B for details). The composed error structure in the frontier is $e_{it} = \varepsilon_{it} - \eta_i$. ε_{it} is the noise component, and the nonnegative η_i is a farm-specific inefficiency component. We estimated the frontier model under the assumption of endogeneity and exogeneity of capital, respectively, to show the difference of the resulting efficiency measures. In both cases, the inefficiency component is allowed to be correlated with regressors, and the frontier was estimated in two-steps. First, we estimated the frontier model with the within estimator without imposing distribution assumptions, and derived consistent parameter estimates (except intercept). Under the assumption of endogeneity, instruments were used for the regressors associated with capital,[5] and no instruments were used under the assumption of exogeneity. Second, we used the residuals from the first step as dependent variable and regressed on an intercept as $\hat{e}_{it} = \text{constant} + \varepsilon_{it} - \eta_i$. In this step, the

[4] Using the average for comparison, the capital is over-reported by 17.4%.
[5] The first- and second-order terms of inputs x_1 to x_5 (including cross terms), and all the factors included in model (12) were used as instruments for regressors associated with capital. For the estimation procedure for fixed-effect model with endogenous variables, refer to Baltagi (2005, p.114).

distribution assumptions were imposed on the composed error term and the ML estimator was used.

Results showed that farms' production efficiencies differ significantly under different assumptions and scenarios. When endogeneity is assumed, the technical efficiency (TE_{en}) of farms has a mean of 0.43. When exogeneity is assumed, however, the efficiency (TE_{ex}) has an average of 0.46.[6] The Wilcoxon signed rank test strongly rejects the null hypothesis of no difference between TE_{en} and TE_{ex} (p-value 0.000). The efficiency measures differ greatly for individual farms, as indicated by the low correlation coefficient, 0.63, between TE_{en} and TE_{ex}. The evidence from our study suggests that not recognizing the measurement error and simultaneity of capital could lead to systematically biased estimates of efficiency measures in the empirical study.

7. Concluding Remarks

Drawing on the literature that reported over-investment and weak disposability of capital, this study hypothesized that over-investment and "fixedness" of capital would result in excess capital. Excess capital causes two problems in the econometric analysis of production. First, it is a source of measurement error; and second, it allows variability of capital use in actual production, which implies simultaneity. In both cases, not recognizing excess capital would lead to endogeneity problem and result in inconsistent estimates.

This study proposed a theoretical framework for analyzing capital requirement in agricultural production and defined excess capital thereupon. The input-based framework provides a primal approach compared to the output-oriented capacity utilization measurement in the literature. Methodologically, this study developed a two-step procedure that allows endogenous variables in stochastic frontier analysis, where the maximum likelihood estimator does not allow endogenous variables. The GMM estimator used in this study addressed the endogeneity problem and is robust to potential misspecification bias from omitted variables.

The empirical study addressed capital use on the cash crop farms in the Netherlands. Results suggested that excess capital commonly exists on the farm, and that the accounting data over-reported capital by 21%, suggesting mismeasurement of capital. Furthermore, estimation results indicated that output level has a significant impact on capital, which supports endogeneity of capital in the production process. The implications

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[6] The average efficiency is 0.70 if random effects are assumed for η_i and ML estimator is used directly in a single step.

of these conclusions were further demonstrated with a production frontier analysis, which produced significantly different efficiency estimates under different treatment of capital.

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Appendix A:

The Density Function of Normal – Half Normal Joint Distribution

The composed error term is $e_0 = u + v$. The nonnegative term u follows a positive half normal distribution and its density function is

(A1) $$P(u) = \frac{2}{\sqrt{2\pi}\sigma_u} \cdot \exp\left(-\frac{u^2}{2\sigma_u^2} \right)$$

The noise component v follows a normal distribution and its density function is:

(A2) $$P(v) = \frac{1}{\sqrt{2\pi}\sigma_v} \cdot \exp\left(-\frac{v^2}{2\sigma_v^2} \right)$$

The joint density function of u and v is:

(A3) $$P(u,v) = \frac{2}{2\pi\sigma_u\sigma_v} \cdot \exp\left(-\frac{u^2}{2\sigma_u^2} - \frac{v^2}{2\sigma_v^2} \right)$$

Replacing v with $v = e_0 - u$, the joint density function of u and e_0 is:

(A4) $$P(u,e_0) = \frac{2}{2\pi\sigma_u\sigma_v} \cdot \exp\left(-\frac{u^2}{2\sigma_u^2} - \frac{(e_0 - u)^2}{2\sigma_v^2} \right)$$

Then the marginal density function of $e_0 = u + v$ is:

(A5) $$\begin{aligned} P(e_0) &= \int_0^\infty P(u,e_0)du \\ &= \int_0^\infty \frac{2}{2\pi\sigma_u\sigma_v} \cdot \exp\left(-\frac{u^2}{2\sigma_u^2} - \frac{(e_0 - u)^2}{2\sigma_v^2} \right) du \\ &= \frac{2}{\sqrt{2\pi}\sigma} \left[1 - \Phi\left(-\frac{e_0\lambda}{\sigma} \right) \right] \cdot \exp\left(-\frac{e_0{}^2}{2\sigma^2} \right) \end{aligned}$$

$$= \frac{2}{\sigma} \cdot \phi\left(\frac{e_0}{\sigma}\right) \cdot \Phi\left(\frac{e_0 \lambda}{\sigma}\right)$$

where $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$, $\lambda = \sigma_u / \sigma_v$, and $\phi(.)$and $\Phi(.)$ are the standard normal probability density and cumulative distribution functions, respectively.

Appendix B:

The Specification of the Translog Production Frontier

The production frontier model is specified as:

$$\text{(B1)} \quad \ln(y_{it}) = c + \sum_{t=91}^{99} c_t D_t + \delta R_{it} + \gamma_0 \ln(k_{it}) + \gamma_{00} \ln(k_{it})\ln(k_{it}) + \sum_{j=1}^{5} \gamma_{0j} \ln(k_{it})\ln(x_{jit}) + \sum_{j=1}^{5} \gamma_j \ln(x_{jit}) + \frac{1}{2}\sum_{j=1}^{5}\sum_{l=1}^{5} \gamma_{jl} \ln(x_{jit})\ln(x_{lit}) + e_{it}$$

where D_t is year dummy, capturing year effect which is important in agricultural production; R is the share of root crops in terms of growing area, addressing the difference in the rotation regime. All other variables in (A1) are defined as in model (11). c, δ and γ are parameters to be estimated. The error term is defined as

$$\text{(B2)} \qquad e_{it} = \varepsilon_{it} - \eta_i$$

The distributions of the composed errors are assumed as:

1) $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2),\ i.i.d.$

2) $\eta_i \sim N^+(\mu, \sigma_\eta^2),\ i.i.d.$

3) ε_{it} and η_i are distributed independently of each other.

where ε_{it} is the noise component and follows a normal distribution. The nonnegative η_i is an inefficiency component and follows a normal distribution truncated below at zero.

Chapter 5

The Source of Productivity Growth in Dutch Agriculture: A Perspective from Finance

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Abstract

In corporate finance, the impact of capital structure on firm performance has been widely studied. This article extends the capital structure study to the situation in agriculture, explicitly addressing the difference between family farms and corporate firms. We use the Malmquist productivity growth index as a proxy for performance to study the impact of capital structure (debt) on farm performance. We compare the results with those from the traditional performance model that uses profitability (e.g. return on equity (ROE)) as performance measure. Using data from Dutch arable farms, results show debt has no effect on ROE, whereas it has a positive effect on productivity growth.

Keywords: Capital structure, dynamics, endogeneity, farm performance, productivity growth, serial correlation

1. Introduction

The impact of capital structure on firm performance has been widely studied in the corporate finance literature. Modigliani and Miller (MM) (1958) conclude in their seminal paper that capital structure is irrelevant to firm value, under a set of strong assumptions. They assume, among others, that managers maximize shareholders' welfare; perfect financial markets, and symmetric information. After MM's study, the irrelevance theorem was challenged from different aspects under more realistic settings. A well-established result in the literature is that capital structure does affect firm value and performance. The main reasons include tax effects (see, e.g., DeAngelo and Masulis, 1980; Myers, 1984; Graham, 2000), bankruptcy costs (see, e.g., Kim, 1978; Myers, 1984), information asymmetry and agency problems (see, e.g., Jensen and Meckling, 1976; Douglas, 2002), and product-market interactions (see, e.g., Brander and Lewis, 1986; Bolton and Scharfstein, 1990). The studies in the literature are mostly applied to corporate firms in industrial and service sectors and have paid relatively little attention to agriculture where the family farm is the dominant organizational form. There are similarities between corporate firms and farms as discussed by Ahrendsen, Collender, and Dixon (1994). However, farm businesses differ from corporate firms in many important aspects, for example, in participation of family members, business life cycle, legal form and liability status, taxation, and governmental subsidization, etc. These differences may cause the relationship between capital structure and performance for farm businesses to be different than that for firms in other sectors. The distinctive setting in farm business may result in a different pattern of decision making, and the impact of capital structure on farm performance is unclear.

Studies addressing the impact of capital structure on farm performance are rare. Whittaker and Morehart (1991) compared cost efficiencies measured with and without financial constraints and showed that the efficiency of one out of five grain farms in midwestern U.S. is limited by financial constraints; Nasr, Barry, and Ellinger (1998) concluded that short-term debt increases the technical efficiency of Illinois grain farms; Weersink, Turvey, and Godah (1990) found debt to asset ratio has a negative effect on the overall technical efficiency of Ontario dairy farms. However, none of these studies explicitly investigated the difference between farms and corporate firms and its potential impact. A second problem not addressed in this literature relates to econometric estimation: farm performance can have an impact on capital structure, potentially giving rise to an endogeneity problem in estimation. The fact that there is a large literature on capital structure decisions (see, e.g., Barry, Bierlen, and Sotomayor, 1994; Ahrendsen, Collender, and Dixon, 1994) and credit evaluation and scoring (see, e.g., Katchova and Barry, 2005; Splett et al., 1994; Novak and LaDue, 1997; Barry et al., 2000, pp. 203-213) renders the concern of endogeneity a legitimate issue to be addressed.

In corporate finance literature, performance is often measured through Tobin's *q* (e.g., Lang, Stulz, and Walkling, 1991), return on equity (e.g., Krishnan and Moyer, 1997; Waddock and Graves, 1997) or other financial indicators. Financial indicators, however, depend critically on the market environment which is beyond the control of management. Market prices have a direct impact on firms' revenues and costs and can dramatically alter the firms' profitability and firm value, even if the firm is efficiently managed. Meanwhile, the internal financial policy, such as fixed asset depreciation regime, can also influence profit. Therefore, financial indicators may not fully signal real firm performance and management effort. This article proposes an alternative measure, i.e., *productivity growth*, to study performance and compares it with traditional models of financial indicators.

In recent economics literature, the Malmquist productivity growth index (Fare et al., 1994) is often used as a measure of total factor productivity. In finding the factors affecting productivity growth, a two-step approach is often used where the Malmquist index is computed in the first step and regressed on a set of explanatory variables in the second step (see e.g. Umetsu, Lekprichakul, and Chakravorty, 2003; Zhang, Zhang, and Zhao, 2002). Simar and Wilson (2003) criticized two-step approaches, arguing bootstrapping should be used to solve the serial correlation problem which otherwise jeopardizes the econometric estimation. Unfortunately, the bootstrapping method is computationally demanding. Of more concern with the two-step approach is the model specification in the second step. We find that static models are routinely used in the literature (see e.g. Umetsu, Lekprichakul, and Chakravorty, 2003; Zhang, Zhang, and Zhao, 2002). However, we notice that firm performance has its specific dynamics when panel data are used. Models not addressing these dynamics are potentially subject to misspecification problem and likely provide biased estimates. We find the misspecification problem also exists in models using financial indicators such as ROE.

The objective of this article is threefold. First, this article extends corporate finance theory into agriculture, investigating and explicitly controlling for differences between corporate firms and family farms. The impact of capital structure on firm performance is then tested in the extended theoretical framework with a sample of Dutch arable farms. In doing so, the article investigates the impact of capital structure and other factors (e.g., investment decisions) on the performance of farm businesses. Second, this article specifies a dynamic model and develops a robust estimator for modeling performance. The dynamic model solves the misspecification problem in static models. The Generalized Method of Moments (GMM) estimator used in this study addresses the endogeneity and the serial correlation problem and produces consistent parameter estimates and estimates of standard errors. Third, the article proposes using productivity growth indices to study debt effect and investigates the differences of the proposed model and a traditional model that measures performance through return on equity. The results in this study show that the traditional model does not detect the debt effect, whereas the productivity model does.

2. Capital Structure and Firm performance

2.1 Theoretical Background

The pros and cons of debt and their impact on firm performance have been widely studied in financial literature. An important advantage of debt financing is the tax benefit from the tax-deductible interest incurred from debt. The tax benefit increases the firm value and therefore induces firms to increase debt. An increase of debt, however, results in an increased probability of bankruptcy, which is costly to firms. Bankruptcy cost involves expenses for administration and legal procedures; assets are often under-valued if the firm is liquidated, and costs can be substantial if the firm is reorganized (Kim, 1978). The risk of bankruptcy or financial distress works as a countervailing power and keeps the debt ratio within a reasonable region.

The symmetric information assumed in Modigliani and Miller's (1958) irrelevance theory is unrealistic. The borrower usually has more information than the lender at the time of establishing a borrowing contract which may create adverse selection, and after the establishment of a contract which may allow moral hazard. These agency problems induce the lender to charge the borrower an extra premium and thus decrease firm value. Apart from this, agency problems often result in reporting and other costs for the borrower (Jensen and Meckling, 1976) and therefore lower financial performance. On the other hand, debt financing may reduce the need for external equity and therefore the equity-related agency costs (e.g. from less management effort and increased work-related perquisites) are effectively avoided.

Previous literature has also studied the relation between performance and financial slack, i.e. low debt level. There are two opposite hypotheses about the impact of financial slack. One hypothesis proposes that financial slack invites inefficiency. Jensen's (1986) free-cash-flow theory says that if a firm is left with too much free cash flow and little debt, management tends to behave with laxness and may invest in capital projects and acquisitions that are less profitable or provide insufficient expected returns (Lang, Stulz, and Walkling, 1989). A higher debt level holds management's feet close to fire and pushes management to be efficient to meet the debt obligation. Yet another hypothesis argues that slack is a valuable resource to counter external threats (Greenley and Okemgil, 1998) and facilitate proactive strategic initiatives (Cyert and March, 1963). Financial slack implies higher borrowing capacity that may serve as a cushion to stabilize business operation in a risky environment. In agriculture, for example, a higher borrowing capacity may be important to address seasonal needs or counteract market fluctuation (due to, e.g., disease outbreaks or extreme weather conditions).

2.2 Distinctive Setting in Agriculture

In agriculture, borrowing is common (see, e.g. Barry, Bierlen, and Sotomayor, 1994). The seasonal nature of agricultural production results in a lag between input decisions and yields. The mismatched timing of cash in-flow and out-flow creates the need for external financing. On the other hand, the risky business environment and low profit margin make borrowing an important buffer to counteract the instability of income and seasonality of production. Moreover, as farms in general lack access to equity markets compared to publicly traded companies (Ahrendsen, Collender, and Dixon, 1994), credit constraints are also important to farms with weak internal finance positions (Bierlen et al., 1998). Limited access to credit or debt may have negative impact on farm performance. However, the traditional financial theory on capital structure discussed in the previous section may not apply to agriculture straightforwardly because of fundamental differences between farms and corporate firms.

In agriculture, the dominant organizational form of business is family farms for many commodities where family members run the business and provide labor for farm production. Compared to firms hiring labor from competitive labor markets, firing employees is not an option in financial hardship. And the rigidity in disposing of excess labor can make the situation worse. As farming provides employment and livelihood to the whole family, this presumably influences the risk perception and the decision making of farms. Furthermore, farming provides not only a business but also a life style in many circumstances. Farmers going bankrupt may have to change their life style, which imposes an additional psychological cost apart from the traditional bankruptcy cost.

The organizational form of farm business gives rise to another issue: the life cycle of farms has a significant impact on capital structure decision and farm performance. The life cycle theory (Boehlje and Eidman, 1984, pp. 9-14; Boehlje, 1992; Kay and Edwards, 1994, pp. 218-219) states that the life cycle of the farm operator parallels the life cycle of the family farm, which consists of three stages: entry, expansion and consolidation, and exit or divestment. According to this theory, debt level is high in the first years when the farmer invests to expand and then gradually decreases in the consolidation phase, whereas farm performance improves over time after the adjustment period and accumulation of experience. The life cycle of farms complicates the study of capital structure and performance as investment decisions, debt level, and the performance of the farm are influenced by and coincide with its life cycle, which, if not accounted for, could bias estimates of the effect of debt on farm performance.

In contrast to corporate firms, farms mostly take the legal form of sole proprietorships or partnerships. Farms of sole proprietorship assume full liability up to the total assets of the proprietor for obligations of the farm. Partnerships are mostly established between family members (e.g., parent-child), in which case at least one of the partners assumes full liability. Banks providing loans to farms often take the farms' land and houses as collateral. To borrowers, not meeting debt obligations means they might lose their private belongings in addition to the farm's assets. Compared to other industries, the agency cost associated with capital structure is less a problem in agriculture because the interests of equity holders and debt holders are to some extent aligned due to the full liability of the proprietor. In this context, the negative effects of agency costs are of second-order importance. Jensen's free-cash-flow theory seems to be a more plausible hypothesis. The internal incentive to run the farm more efficiently driven by debt obligations is presumably strong. Thus, debt should have a larger disciplinary power in farm business than in other industries.

Associated with the legal form, the technical aspect of taxation in farm businesses also differs from corporate firms. Farm operators in sole proprietorship and partnership pay personal (rather than corporate) income taxes. Consequently, the tax effect of debt presents a more complex picture. In the Netherlands, for example, farms organized as sole proprietorships and partnerships pay a personal income tax based on the total family income from both farm business and off-farm income, net of interest. Although the interest is tax deductible, the off-farm income and expenditure diminish the tax benefit of debt. Moreover, the "crowding-out" effect from non-debt tax deductions, such as depreciation deductions and deductibility of some particular types of insurance cost of the family (e.g., "national insurance" in the Netherlands), further diminishes the importance of tax benefit of debt. Nonetheless, the positive aspect associated with debt is that farms get additional subsidy from government for specific investments (e.g., in environment-friendly technology), which enhances the benefit of debt in addition to the tax deductibility of interest.

A further aspect that makes farm business different from other types of corporate firms is that agriculture is heavily subsidized. On the one hand, subsidy increases the free cash flow of farms, which may create disincentive and mitigate the disciplinary power of debt (although it relaxes the credit constraint to some extent). On the other hand, the potential subsidy-seeking behavior may affect capital investment and farming technologies when the farmer optimizes the product mix to attain high income at a low risk, which presumably has an impact on the farm's long-run performance.

As an important fixed input, land has a unique characteristic which is not observed in other industries: it has no life expectancy and depreciation, of which the impact is unclear with respect to land investment and financing. An important implication is that land provides as an ideal collateral for lenders and therefore enables land owners to have better access to credit markets.

The distinctive characteristics create a more complex setting in agriculture beyond standard corporate institutions. The next sections test the corporate finance theory in this atypical context.

3. Methods

This study uses a two-step approach to modeling the impact of capital structure on performance. In the first step, two performance measures, Malmquist productivity growth index (Fare et al., 1994) and ROE, are constructed; in the second step the impact of capital structure on the performance measures are estimated with regression models.

3.1 Proxy of Firm Performance

The Malmquist productivity growth index has become a widely adopted way of measuring productivity. The index is constructed with input-output data, which may provide more accurate information about actual managerial performance, because, unlike financial indicators, it is not affected by market prices of inputs and outputs. The output-oriented Malmquist index of productivity growth is defined as:

$$(1) \qquad M_o^{t+1}(x^{t+1}, y^{t+1}; x^t, y^t) = \left(\frac{D^t(x^{t+1}, y^{t+1} \mid C, S)}{D^t(x^t, y^t \mid C, S)} \cdot \frac{D^{t+1}(x^{t+1}, y^{t+1} \mid C, S)}{D^{t+1}(x^t, y^t \mid C, S)} \right)^{1/2}$$

where $\boldsymbol{x}$ is a vector of inputs used to produce a vector of outputs $\boldsymbol{y}$. $D^t(x^t, y^t \mid C, S)$ is a firm's distance function in period t measured against the technology of the same period, assuming constant returns to scale (denoted by C) and strong disposability of outputs (denoted by S).[1] The same applies to $D^{t+1}(x^{t+1}, y^{t+1} \mid C, S)$. $D^t(x^{t+1}, y^{t+1} \mid C, S)$ and

[1] Strong disposability of output means that the output, when it is undesirable, can be disposed of without cost.

$D^{t+1}(x^t, y^t \mid C, S)$ are t-period distance function measured relative to the technology of the t+1 period, and vice versa (refer to Fare and Grosskopf (2000) for the computation). The Malmquist index measures input-output relations non-parametrically. An index of 1 indicates no change in productivity. A value less than 1 indicates a productivity decrease, and a value larger than 1 represents a productivity increase.

In addition to Malmquist index, we use the return on equity (ROE), a traditional financial indicator, as a second performance measure. ROE is calculated as the ratio of net income to average equity.

$$ROE = \frac{NI}{(E_0 + E_1)/2} \tag{2}$$

where NI is net income, defined as total revenue (excluding subsidies) minus total cost; E_0 and E_1 are the equity at the beginning and the end of the year, respectively.

3.2 Model specification

As the Malmquist productivity index has a lower bound of zero, the logarithm of the index is used as the dependent variable.[2] The model in the second step is specified as:

$$\begin{aligned} y_{it} = {} & c + \sum_{91}^{99} c_t + \alpha_1 y_{i,t-1} + \alpha_2 y_{i,t-2} + \beta_1 LD_{it} + \beta_2 SD_{it} + \beta_3 I_{it} + \beta_4 I_{i,t-1} + \beta_5 I_{i,t-2} \\ & + \gamma_1 Age + \gamma_2 Sub_{it} + \gamma_3 Size_{it} + \gamma_4 DFami + \gamma_5 DForm_{it} + \gamma_6 DTenu_{it} \\ & + \gamma_7 DEdu_{it} + \gamma_8 DSoil_{it} + \gamma_9 DType_{it} + \varepsilon_{it} \end{aligned} \tag{3}$$

where: $\varepsilon_{it} = \eta_i + v_{it}$

y denotes the logarithm of Malmquist productivity index, or the ROE measure

LD denotes the ratio of long-term debt to asset,

SD, the ratio of short-term debt to asset,

I, the ratio of fixed asset investment to fixed asset,

Age, the age of farmer

Sub, subsidy rate (subsidy divided by revenue),

Size, size of farm operation, in NGE (Dutch farm unit),

DFami, dummy labor from family members (0 without family member, 1 with family member),

---

[2] The transformation of Malmquist productivity index into logarithms yields a different interpretation to the estimates. The marginal change in independent variables gives the percentage change of Malmquist productivity index, e.g., $\partial M/M$.

DForm, dummy legal status of farm (0 for family farm, 1 for partnership),

DTenu, dummy land tenure (0 for own land, 1 for lease)[3],

DEdu, discrete variable of education level (1 for primary school, 2 for non-agri education, 3 for vocational education in agriculture, 4 for higher education in agriculture),

DSoil, dummy soil type (0 for sandy soil, 1 for clay) ,

Dtype, dummy farming type (0 for conventional, 1 for organic),

c_t is year dummy; ε is disturbance, which consists of individual effect η_i, and disturbance v_{it}, assumed to be iid. c, c_t, α and β and γ are parameters to be estimated

The productivity growth rate is a cross-period index. Consequently, the previous period growth rate has a direct impact on the current period growth rate, resulting in a negative intertemporal serial correlation in individuals' productivity growth indices[4]. The interpretation is rather straightforward: a high growth in the previous year leaves less potential for farms to further improve their productivity. The intertemporal serial correlation problem exists with ROE measures, but it is positive *a priori*: if a firm has a high earning capacity this year, the earning capacity tends to be high as well next year. To address the dynamics of performance, we include two lags of the dependent variable, specifying a dynamic panel data model in (3).

Three financial variables, i.e., capital structure, investment rate, and subsidy rate, are included. Long-term and short-term debt ratios (*LD* and *SD*) are included separately to investigate their differential impact on productivity growth. Debt level is a measure of the credit constraints faced by the farm. Long-term debt is often associated with long-term project or changes in strategic aspects that affect growth prospects. It may also reflect differences in farmers' demographic properties across farms and within farms over different stages of the farm life cycle. According to the pecking order theory, firms would first exhaust internal finance sources, and then turn to debt (see, e.g., Myers, 1984;

[3] When i) more than 2/3 of the land is owned by the farm operator, or ii) more than 1/3 is own land *and* the value of affiliated buildings on the land exceeds 9075 euro (20,000 guilders), the tenure is recorded as own land in the accounting system, otherwise recorded as leased land.

[4] The negative correlation can be seen from the rotating numerators and denominators of indices of consecutive years:

$$\left(\frac{D^t(x^{t+1}, y^{t+1} \mid C,S)}{D^t(x^t, y^t \mid C,S)} \cdot \frac{D^{t+1}(x^{t+1}, y^{t+1} \mid C,S)}{D^{t+1}(x^t, y^t \mid C,S)}\right)^{1/2},$$

$$\left(\frac{D^{t+1}(x^{t+2}, y^{t+2} \mid C,S)}{D^{t+1}(x^{t+1}, y^{t+1} \mid C,S)} \cdot \frac{D^{t+2}(x^{t+2}, y^{t+2} \mid C,S)}{D^{t+2}(x^{t+1}, y^{t+1} \mid C,S)}\right)^{1/2}$$

where $D^{t+1}(x^{t+1}, y^{t+1} \mid C,S)$ in the previous year's index rotates into next year's denominator.

Brealey and Myers, 2000, pp. 526) in case of an imbalance of internal cash flow and real investment opportunities. A higher long-term debt ratio may suggest better investment opportunities while a low ratio reflects limited investment opportunities. Considering these aspects, long-term debt a priori should have a positive effect on farm performance. Short-term debt usually relates to the seasonality of farm production and the liquidity need in the case of market and production risk. The effect on performance seems less evident.

Decisions on fixed asset investment (I) per se can have a direct impact on the firm's productivity. Meanwhile, a spike in investment may coincide with the adoption of a new production technology driving the productivity growth. Two lags of the investment rate are included because capital investment involves adjustment costs and an adjustment period may be needed for an investment to take its full effect.

To address the organizational form of family farm, the participation of family members (*DFami*) in farm operation is included in the model as a dummy. Farming for a whole family's livelihood could motivate farmers to be more productive. The farmer's age (*Age*), in conjunction with debt level and investment rates, intends to capture the effect of farms' life cycle on performance. Age also controls the effect of experience on farm performance. Meanwhile, older farmers should be less financially constrained than younger farmers owing to longer relationships with their lenders, greater equity accumulations, and generally stronger financial measures (Bierlen et al., 1998). The legal form of farms (*DForm*) takes either sole proprietorship or partnership, which implies full liability for farm operators, distinguishing farm business from corporate firms in other industries. As a partnership is an external source of equity, it may have two consequences for farms: i) a reduced need for borrowing and, ii) a reduced managerial effort and other agency problems. Therefore, a priori, it is expected that a partnership reduces farm performance. As all farms in the sample assume full liability of debt obligation, the impact of full vs. limited liability cannot be estimated directly. But the liability status is controlled in the sample, the potential bias is thus avoided. Governmental subsidy (*Sub*) is included to address the potential impact of subsidization of farm business.

In agriculture, land leasing (*DTenu*) is a substitute of debt because a lease payment, a fixed obligation like a loan, displaces debt and reduces debt capacity (Ang and Peterson 1984; Bierlen et al., 2000). *DTenu* also accounts for the agency problems between land owners and tenant, or other unobservable incentives. Education (*DEdu*) is categorized into four levels from low to high; a higher level a priori contributes to higher farm performance. Soil type (*DSoil*) addresses the difference in productivity of sandy soil and clay soil. Farming type (*DType*) distinguishes conventional farming and organic farms.[5] The

[5] There are no farms with mixed farming type in the sample.

variable *Size* is measured in standardized Dutch Farm Units which is a measure of the income generating capacity of all farm activities (Van den Tempel and Giesen, 1992, pp. 285-288).

4. Data and Estimation

4.1 Data

The data used in this study are farm accountancy data (from the Dutch Agricultural Economics Research Institute (LEI)) of cash crop farms in the Netherlands. Panel data are available over the period 1990-1999 from 557 farms with 2036 observations. The panel is unbalanced. On average, farms stay in the sample for about 4 years.

One aggregated output and six inputs are used in the computation of the Malmquist index. The output is measured in revenue and aggregated over potatoes, sugar beets, onions, and cereals. Inputs include land, labor, capital, fertilizer, pesticide, and miscellaneous inputs. Land is measured in hectares. Labor is measured in quality-corrected man-years. Capital is the replacement value of machinery, equipment, and buildings. Miscellaneous inputs consist of seed, feed, contract work, energy, and storage and delivery. Capital and miscellaneous inputs are deflated with Törnqvist price indices derived from their components and price information obtained from the LEI. Output, capital, fertilizer, pesticide, and miscellaneous inputs are measured in 1990 prices. After computing the Malmquist indices and taking lags of the indices, there are 1204 observations from 271 farms available for the estimation of model (3). For ROE model estimation, 1497 observations from 271 farms are available.

Summary statistics of data used in the computation of Malmquist indices and in the estimation of model (3) are presented in table 1. The average Malmquist index is 1.05, indicating a productivity progress during 1990-1999. However, the negative ROE (–0.079) suggests poor financial performance. The discrepancy between the two indicators suggests that technical performance reflected by the input-output relations can be dampened by price factors when translated into financial indicators. The overall debt ratio amounts to roughly 25%. Almost all farms borrow, and 70% of the farms have a debt level over 10%. The average annual investment amounts to 11% of the capital stock. Data examinations show that young farmers have a higher education level, borrow and invest more, and lease more land.[6]

[6] The Pearson correlation coefficients of age to education, debt ratio, investment rate and land leasing are -0.15, -0.34, -0.08, -0.15, respectively. All are different from zero at a 1% significance level.

Table 1. Summary Statistics of Dutch Arable Farms 1990-1999 (in 1990 price)

Variable	Unit	Number of Observations	Mean	Std Dev.
Output	1,000 euro	2036	194.25	147.76
Land	hectare	2036	54.25	35.37
Labor	man-year	2036	1.77	1.06
Capital	1,000 euro	2036	200.33	157.84
Fertilizer	1,000 euro	2036	7.68	5.44
Pesticides	1,000 euro	2036	13.53	10.81
Miscel.	1,000 euro	2036	42.76	33.42
Malmquist index (MI)		1204	1.05	0.534
Growth rate	log of MI	1204	-0.007	0.302
Return on Equity	ratio	1497	-0.079	0.433
Long-term debt ratio		1497	0.225	0.196
Short-term debt ratio		1497	0.019	0.035
Investment rate	ratio	1497	0.113	0.377
Age	years	1497	47.2	10.1
Subsidy rate	ratio	1497	0.025	0.036
Size	Dutch farm unit	1497	96.75	62.14
Participation family	dummy	1497	0.465	0.499
Legal form	dummy	1497	0.290	0.454
Land tenure	dummy	1497	0.544	0.498
Education level	dummy	1497	3.595	0.706
Soil type	dummy	1497	0.738	0.440
Farming type	dummy	1497	0.057	0.233

4.2 Estimation

The distance functions used for computing Malmquist indices are measured against a frontier constructed with sample data. By construction, these measures are inter-dependent across individuals in the sample, which may result in a cross-individual serial correlation problem in the second-step regression. Simar and Wilson (2003) recommend using bootstrapping to solve this problem. Following the works of Simar (1992), and Simar and Wilson (1998, 2003), bootstrapping is widely used in the literature of efficiency and productivity (see, e.g. Casu and Molyneux, 2003; Xue and Harker, 1999). However, bootstrapping methods are computationally demanding and therefore may not be an appealing option for empirical research. In our case, the problem becomes more complex because of: 1) the use of panel data and the intertemporal serial correlation, 2) the dynamic specification, and 3) potential endogeneity of capital structure.

In panel data models, treatment of heterogeneity across firms is one of the major concerns. Heterogeneity may result from differences in geographical locations, management capabilities and motivations. The individual effect η_i in Eq. (3) renders the OLS estimator inconsistent if it correlates with regressors. In this study, first-differencing is used to remove the individual effect. In the differenced equation, the error term is $\Delta v_{it} = v_{it} - v_{i,t-1}$, and it has a first-order autocorrelation. Moreover, it is correlated with the transformed first lag of the dependent variable $\Delta y_{i,t-1} = y_{i,t-1} - y_{i,t-2}$ since $v_{i,t-1}$ and $y_{i,t-1}$ are correlated. Therefore, the estimation must use an instrumental variable method. Since $y_{i,t-2}$ is correlated with $\Delta y_{i,t-1}$ but not with Δv_{it}, it is a valid instrument:

(4) $$E[y_{i,t-2}\Delta v_{it}] = 0$$

In fact, all historical observations of the dependent variable prior to *t-2* are valid instruments as well. Based on this concept, Arellano and Bond (1991) proposed a *difference GMM* estimator that exploits all the valid historical values of the lagged dependent variables as instruments for individual *i*:

(5) $$Z_i = \begin{pmatrix} [y_{i0}] & 0 & \cdots & 0 \\ 0 & [y_{i0}, y_{i1}] & & 0 \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & [y_{i0}, \ldots, y_{i,T-2}] \end{pmatrix}$$

where $i = 1,\dots n$, T is the number of time periods. Following the same reasoning, $\Delta y_{i,t-2}$ is instrumented by $y_{i,t-p}, \forall p \geq 3$. The difference GMM solves the following minimum loss function:

(6) $$\min_{\hat{\theta}} \left(\frac{1}{N}\left[Z' \hat{\Delta v} \right]' \cdot W_N \cdot \frac{1}{N}\left[Z' \hat{\Delta v} \right] \right)$$

where $\hat{\theta}$ is the parameter vector; N is the sample size; Z is the matrix of instruments; $\hat{\Delta v}$ are consistent estimates of the first-differenced residuals obtained from a preliminary consistent estimator; W_N is a weighting matrix, which is $\left[\frac{1}{N}(Z' \hat{\Delta v} \hat{\Delta v}' Z) \right]^{-1}$. The matrix of instruments Z corresponds to $(Z_1', Z_2', ..., Z_n')'$. When the panel is unbalanced, for individuals with incomplete data the rows of Z_i corresponding to the missing observations are deleted, the missing values in the remaining rows are replaced with zeros. The minimand in (6) is also a test statistic for the validity of the overidentifying moment restrictions under the null hypothesis that these restrictions are valid (Sargan, 1958; Hansen, 1982).

In model (3), the explanatory variable long-term and short-term debt are potentially endogenous, in which case farm performance affects its credit worthiness evaluated by lenders in risk rating and credit scoring (see, e.g., Katchova and Barry, 2005; Splett et al., 1994; Barry et al., 2000, pp. 203-213) and therefore has an impact on the capital structure. Similarly, the variable investment rate and its lags are likely to be affected by farm performance as well. Thus, in the differenced equations, the first differences of these potentially endogenous variables are instrumented by the lagged levels, which implies the following moment conditions:

(7) $$E[x_{i,t-1} \Delta v_{it}] = 0$$

Thus, the number of columns in the block diagonal of matrix Z_i increases with the number of endogenous variables. The other variables in (3) are treated as exogenous variables.

Additional moment conditions in level equations can be exploited if there are instruments available that are uncorrelated with individual effect η_i. For example, if the series in the model (3) is mean-stationary, first differences Δy_{it} is uncorrelated with η_i, which implies a valid moment condition in the level equation:

(8) $$E[\Delta y_{i,t-1}(\eta_i + v_{it})] = 0$$

Similarly, the lagged first differences of endogenous explanatory variables can be used as instruments for the level equation, and the moment condition is:

(9) $$E[\Delta x_{i,t-1}(\eta_i + v_{it})] = 0$$

This is a weaker assumption than $E[x_{i,t-1}(\eta_i + v_{it})] = 0$. Arellano and Bover (1995), Blundell and Bond (1998) combine the set of moment conditions in differenced equations and the set of moment conditions in the level equation. This approach is called "*system GMM*" in the literature. The system GMM is particularly useful for this study because the model includes some variables that only vary across individuals (e.g., soil type), for which the identification of parameters would be impossible or inefficient with the differenced equations. More importantly, when individual series have near unit root properties, the lagged levels of the series provide a weak instrument for the differenced equations because the correlation between $y_{i,t-2}$ and $\Delta y_{i,t-1}$ (or between $x_{i,t-1}$ and Δx_{it}) becomes weak. Blundell and Bond (1998) show that the difference GMM estimator is subject to serious finite sample biases when the instruments are weak.

In this study, the estimation uses the DPD program for Ox package described in Doornik, Arellano, and Bond (2002), which produces the finite sample corrected standard errors (Windmeijer, 2005). For a given cross-sectional sample size, using too many instruments in later cross sections may result in biased estimates, particularly when the model includes endogenous regressors (Doornik, Arellano, and Bond, 2002). In order to make the number of instruments comparable across years, this study restricts the maximum lag on any variable used as instrument to two periods.

A key identifying assumption for the GMM approach is that there is no serial correlation in the level disturbances v_{it}, which can be tested by testing for no second-order serial correlation in the first differenced residuals Δv_{it} (Arellano and Bond, 1991; Bond, 2002). As the serial correlation is also a concern in efficiency and productivity literature, a statistical test with the GMM approach can show whether the estimation procedure in this study solves the problem and provides a valid alternative to bootstrapping.

5. Results

Using lags as instruments further reduced the actual number of observations used in estimation. The number of observations used is 567 for the productivity model and 913 for the ROE model. The estimation results of model (3) from system GMM are presented in table 2. Sargan test of over-identifying restrictions yields a p-value of 0.25 for ROE model and 0.21 for productivity model, which means that instruments used in the system GMM estimation are valid. The hypothesis of no second-order autocorrelation of Δv_{it} was not rejected at 5% significance level for both ROE model (p-value 0.31) and productivity model (p-value 0.16), implying that there is no serial correlation in the level disturbances v_{it}. This result indicates that the identifying assumption required for the GMM approach is satisfied. Notice that the differenced disturbance $\Delta v_{it} = v_{it} - v_{i,t-1}$ has a first-order autocorrelation by construction. But this does not affect the statistical inference as the GMM approach produces consistent estimates of standard errors in the presence of serial correlation.

In the ROE model, the lagged dependent variables were positive and highly significant, which is consistent with a priori expectation. The negative relations between productivity growth and its lags were also confirmed by the results from the productivity growth model, suggesting that the inherent dynamics should be accounted for to avoid misspecification when modeling performance.

Debt ratios were found to have no effect on farms' return on equity at the 5% significance level, which might suggest that the negative and positive effects of debt are balanced. An alternative interpretation is that the debt effect is diluted by price changes and factors which are beyond farmers' control. All other variables were insignificant in the ROE model, except year dummies which partly capture the potential impact of market prices of inputs and outputs. The ROE model suggests land leasing, with a negative estimate at nearly 5% significance level, tends to decrease farm performance. The productivity model, however, suggests that land leasing has no significant effect on productivity. The difference may arise from the fact the farms with leased land pay an extra cost of rent, which decreases the profit but not productivity. The results from the two models provide support for the argument that financial indicators may be imprecise indicators of managerial effort.

Compared to the ROE model, the productivity growth model presents more informative results regarding debt, subsidies, and age. The variable farm size and farming type, although insignificant, have considerably lower p-values in the productivity model. The analysis hereafter mainly focuses on the results from the productivity growth model.

Table 2. Results from Return on Equity Model and Productivity Growth Model

	ROE Model [a]			Productivity Growth Model [b]		
Variable	Coefficient	t	p-value	Coefficient	t	p-value
y(-1)	0.274 **	14.80	0.000	-0.439 **	-7.62	0.000
y(-2)	0.186 **	2.95	0.003	-0.338 **	-6.03	0.000
LD	-0.576	-0.82	0.415	0.331 *	2.30	0.022
SD	14.86	1.72	0.086	0.126	0.21	0.835
I(0)	-0.012	-0.12	0.909	0.046	0.60	0.549
I(-1)	-0.027	-0.97	0.332	-0.061	-1.51	0.133
I(-2)	-0.035	-1.00	0.318	-0.025	-0.96	0.339
Age	0.0013	0.43	0.664	0.0034 **	2.61	0.009
Sub	-1.329	-1.02	0.309	-1.483 *	-2.26	0.024
Size	-0.0001	-0.29	0.776	-0.0004	-1.66	0.097
DFami	-0.044	-1.06	0.288	0.037	1.67	0.096
DForm	-0.019	-0.38	0.704	-0.0004	-0.01	0.990
DTenu	-0.256	-1.95	0.052	0.005	0.20	0.840
DEdu	-0.031	-0.54	0.588	-0.015	-0.72	0.473
DSoil	-0.028	-0.63	0.528	0.025	1.02	0.307
DType	-0.002	-0.02	0.983	-0.178	-1.83	0.069
Constant	0.009	0.02	0.981	0.088	0.71	0.478
C_{93}	-0.007	-0.12	0.901			
C_{94}	0.189 **	2.66	0.008	-0.188 **	-6.25	0.000
C_{95}	0.188 *	2.19	0.028	-0.343 **	-8.65	0.000
C_{96}	0.114	1.54	0.121	-0.316 **	-8.34	0.000
C_{97}	0.142	1.62	0.105	-0.120 **	-3.39	0.001
C_{98}	0.228 *	2.46	0.014	-0.292 **	-5.65	0.000
C_{99}	0.142	1.74	0.083	-0.395 **	-8.59	0.000

[a] For ROE model, Sargan test yields a $\chi^2(81)$ statistic 89.36 (p-value 0.246); AR(2) test produces an N(0,1) statistic 1.017 (p-value 0.309).
[b] For productivity growth model, Sargan test yields a $\chi^2(72)$ statistic 81.48 (p-value 0.208); AR(2) test produces an N(0,1) statistic –1.418 (p-value 0.156).
* significant at 5% level ; ** significant at 1% level.

Table 2 shows that long-term debt has a positive effect on productivity growth (at the 5% significance level) while short-term debt has no significant effect. The insignificant effect of short-term debt is consistent with a priori expectation as it is a routine decision associated with seasonal needs and liquidity of the farm. Since the fixed asset investment is controlled in the model, the positive effect from long-term debt suggests forces beyond investment. On the one hand, it suggests the psychological effect of debt becomes stronger in the context of farm business as a result of its full liability, consistent with the previous discussion. On the other hand, the positive effect may be due to such factors as better investment opportunities and entrepreneurship proxied by the long-term debt. Furthermore, the longer term over which the obligations persist increase the risk of long-term borrowing, particularly because the market situation and government policies may dramatically alter over time, affecting farms' income and debt-service ability. For lenders, the risk of long-term borrowing requires more involvement in farm business. Their monitoring and consultation provide professional assistance in business operation. Farmers with long-term debt are thus more exposed to information or new ideas of running business.

Investment rate and its two lags were insignificant at the 5% significance level. The overall insignificant effect from capital investment may be explained by over-investment of Dutch arable farms (see Zhengfei and Oude Lansink, 2003). Examination of the data shows that the correlation between investment rate and debt (long-term debt) is 0.03 (0.02) and the correlation between investment rate and the dummy legal form is 0.01, which are all low and statistically insignificant. This suggests that investment is mostly financed from internal cash flow. The internal financing may signal poor investment opportunities as suggested by pecking order theory. The poor investment opportunities and lack of discipline from debt could result in low-return investment and thus justify the insignificant effect of investment.

The subsidy from Dutch government and from European Union under the framework of European Common Agricultural Policy is granted according to the type of crops and cultural practices. These subsidies have a significant negative impact on productivity growth. The negative relationship is consistent with the *a priori* expectation that subsidy creates disincentives to farmers and harms competitiveness. Moreover, it may suggest that crops and cultural practices resulting from subsidy-seeking slow down productivity growth. In both cases, the policy implication is clear: removal of subsidies will make Dutch arable farming more productive, ceteris paribus.

The coefficient of age was positive and significant, suggesting that productivity increases with experience and when the farmer adjusts his goal in the later stage of the life cycle, focusing on improving efficiency (after investing and expansion). The participation of family members increased productivity, but the effect is statistically insignificant at the 5% significance level. All other farm characteristics variables are insignificant in the model. The agency problem a priori expected from partnership was not detected, which may be justified by the special partnership between family members (e.g., parent-child) in agriculture. The agency problem expected from land leasing was not confirmed by the results. A higher education level failed to enhance productivity growth.

6. Concluding remarks

Agriculture presents an atypical setting for the study of capital structure due to its distinctive characteristics. This study tested and extrapolated corporate finance theory into farm business, accounting for these differences. Dynamic models were specified using both return on equity and Malmquist productivity index as performance measures. Using data from Dutch cash crop farms over 1990-1999, empirical results showed that traditional static models of farm performance are misspecified. The robust estimation procedure addressed both endogeneity and serial correlation problems and provides an alternative to often-recommended bootstrapping.

The traditional model of return on equity failed to provide evidence that debt level affects farm performance, whereas the productivity model proposed in this study detected a positive effect of debt. This result suggests that financial indicators may not fully signal management effort when studying the effect of debt. Empirical results showed that long-term debt increases productivity growth. The fact that family farms provide a livelihood for the whole family and the full liability associated with the legal form of proprietorship and partnership presumably changes the risk perceptions of the farmer and increases the disciplinary effect of debt. Besides the debt level, the investment rate and the farmer's age accounted for the farm life cycle. Capital investment, often characterizing the earlier stage of the life cycle, has no effect on productivity growth, suggesting that Dutch arable farms are over-invested. The farms' productivity improves in the later stage of the life cycle as the farmer's goal changes and experience increases. As a priori expected, subsidization slows down productivity growth in agriculture.

The use of debt may reflect the differences in the farmer's goals, perceptions and motivations. Thus debt level may be an important indicator of these personal characteristics. Future research should address the relation between debt level and personal characteristics, such as innovation, risk attitudes, perceptions and motivations.

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Chapter 6

General Discussion and Conclusions

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1 Introduction

The main objective of this thesis was to reconceptualize and extend the primal approach in production analysis. This research approached the objective from both product supply and factor demand side. The study on the supply side was motivated by the thinking that traditional production models that rely on “universal” flexible functional forms do not exploit available knowledge about the agricultural production process. In the case of the translog, for example, it denies any prior knowledge, assuming nothing is known about agricultural production, which is obviously incorrect. The product supply study in this thesis was aimed at rebuilding the primal approach, integrating agronomic knowledge and theory into the economic model of production. The factor demand study in this research was motivated from the observation that the traditional primal approach requires behavioral assumptions and an explicit specification of the production function (see, e.g., Beattie and Taylor, 1993, pp. 237-241). This part of the research proposed a direct approach to analyzing capital demand that relies neither on behavioral assumptions nor on the precondition that a production function be explicitly specified.

While pursuing the main objective from a theoretical perspective, this research also addressed issues of empirical importance, namely, the environmental and economic sustainability of Dutch agriculture. The environmental aspect was analyzed from a farming system perspective, comparing conventional and organic farming systems; the economic aspect was approached from the perspective of productivities of individual inputs, total factor productivity growth, and capital use.

In addition to the theoretical and empirical issues, this research paid special attention to the development of methodologies that are necessary for implementing the theory in empirical studies. The methodological issues mainly relate to the specification and estimation of econometric models and were presented in detail in each specific case.

This chapter reviews the research covered in the thesis and opens a general discussion on the theory, methodology and empirical results, followed by suggestions for future research and some general conclusions.

2. Discussion of theoretical, methodological and empirical issues

2.1 Theoretical issues

2.1.1 Product Supply Side

Agricultural production activities involve many aspects and dimensions, both qualitative and quantitative, such as the types and quantity of product to produce, the type and quantity of inputs to use, and the biophysical environment and growth conditions, which are studied in many disciplines (e.g., biology, agronomy, and economics), from different perspectives and with different approaches. In economics, production is mostly studied with a closed-form mathematical model. Once mathematics come into play, production basically loses its non-quantitative dimensions, which implies much of the information on production is purposely neglected. On the other hand, some information, which does not come from production, is often imposed on the production for pure mathematical purposes, an example is that the production function is assumed to be continuous and twice differentiable. Although it is sometimes convenient to do so, the abstraction in economics is not always justifiable in reality.

In recent years, flexibility has become an important criterion to judge whether a functional specification of a production function is a good or poor one. The quadratic function and translog have become the dominant functional forms for empirical production analysis. The once popular Leontief production function, for example, has declined in popularity nowadays. One reason is that it is mathematically not flexible. However, the pursuit for flexibility sacrifices a basic principle in agricultural production: inputs used in the production process differ in functionality and affect the yield differently. In flexible production models, all inputs are treated in the same way, which means the type or the functionality of inputs does not matter in the theoretical model. This may sound absurd to specialists in agricultural production, say, agronomists. But surprisingly, it has been well received and widely practiced in economics, and practitioners would feel uneasy without using flexible functions. As an anonymous reviewer of Chapter 3 of this thesis put it, "using a standard economic model [like quadratic or translog model] to make important implications and inroads into empirical intricacies in most agricultural complexes does seem absurd, but many do use that model without apology, in fact, many have manufactured careers on the practice…"

Lichtenberg and Zilberman (1986) suggested that in agricultural production, pesticide has a unique functionality, namely, damage-abating instead of productive as compared to other inputs. They proposed an asymmetric to account for difference explicitly in the specification of the production function. Paris (1992) proposed a "von Liebig" model which recognizes the peculiar functionalities and yield-limiting mechanisms of different nutrients. The model seeks to mimic the crop response, taking into account agronomic principles. Although these studies still have limitations from an economic (Chapters 2 and 3) and agronomic (De Wit, 1992) point of view, what is important in these works is the attempt to acknowledge the relevance of the underlying biophysical processes of agricultural production.

Following this practical way of thinking, this research looked at the agricultural production more closely from an agronomic perspective and from the operational aspects of production. The practical attitude was first taken to the empirical research problem of comparing conventional and organic farming systems in Chapter 2. Clearly, organic farming is very restrictive in the use of chemical inputs, in particular pesticides. If pesticides can not be used for damage control, there must be a substitute for that purpose. Mechanical and manual weeding may be the first options available to producers, in which case machinery and labor are performing the "damage-abating" role as well. From this it follows that defining machinery and labor as purely "productive" as in Lichtenberg and Zilberman (1986) is no longer plausible. A second issue was that traditional functions found in the literature restrict the marginal product of pesticide to be non-negative, which contradicts the evidence that over-dosage of chemicals may well damage the crops (Oskam et al., 1992; Wossink and Rossing, 1998). Based on these observations, Chapter 2 redefined the functionality of labor and capital as both damage-abating and productive and further designed a model that also allows a negative marginal product of pesticide. The new model specification based on the theory was tested against the traditional translog function. The empirical study of conventional and organic farming systems provided a good case to test the theory under different circumstances. Results indicated that the new model accommodating the proposed theory was not rejected, whereas the traditional translog model was strongly rejected.

Following Chapter 2, this research continued on developing a more general conceptual framework from a different perspective, motivated by some casual thoughts surfaced during the writing of Chapter 2. The leading thought here was that some inputs are not necessary *if* the biophysical conditions for crop growth are satisfied. That is, the natural process can do without labor once the seed is in place, nutrients are available, the temperature is suitable, and sunlight is sufficient, for example. A second thought was why economists are interested in inputs like labor and capital whereas agronomists often do not consider them when studying crop yield. Agronomists' unique perspective should have a point, particularly as their perception seems to be more practically relevant with respect to crop yield than that of social scientists. However, agricultural production takes place in a social environment and necessarily involves labor, capital and other inputs, whereas agronomists study crop production mainly in controlled experiments. In empirical production analysis, the agronomists' approach is obviously not feasible as, in reality, growth conditions vary across farms and over time, and thus must be accounted for in the model. All this reasoning converged to one research aim: to develop a model that connects agronomy and economics, specializing the economics approach and generalizing the agronomic approach. For this purpose, the research then focused on the definition of the functionality of inputs involved in agricultural production and on the construction of a model that reflects this logic. In agronomic studies, nutrients and water are the most commonly studied inputs in crop response models. In crop production, crop growth cannot take place without these two inputs, and this applies to seed as well. Therefore it would be reasonable to group these inputs into one category, namely, *growth inputs*. In theory, crop growth may do without land, as in a laboratory or nutrient solution. In practice, however, land cannot be replaced by other inputs, as land provides much of the nutrients in crop growth and it carries the basic growth environment in farm production. Therefore, it was defined as a growth input as well. Intuitively, labor and capital were defined as facilitating inputs as they are used to help create growth conditions. It may seem less intuitive that pesticide was also considered as a facilitating input, as it appears to be involved in the biophysical process of crop growth. In fact, the purpose and functionality of pesticide is to create an (agronomically or economically) optimal growth condition and it would be redundant if there were no pests or diseases. The essence of the categorization of growth inputs and facilitating inputs can be best conveyed by an allegorical anecdote about a farmer in a feudal state of ancient China some 2500 years ago. The farmer was not happy with the slow growth of his crops. One day he came up with a novel idea and spent a whole day pulling up all the crops in the field. After that the crops did look taller, but all died the next day. This story tells a simple truth that the natural law can not be violated; and amazingly, it shows, literally, that labor does not work the way manure (or fertilizer) works with respect to crop growth.

The dichotomy of growth inputs and facilitating inputs in this research forged a foundation for building a model that offers economists agronomic perspective and insights, and meanwhile, generalizes the agronomists' crop response experiments into a broader socio-economic context. The robustness of the theoretical model based on this concept was tested in an empirical study using crop-level data on potato production in the Netherlands. The test results showed that the new model better represents the underlying production technology, and the traditional translog model was rejected, as in Chapter 2 where farm-level data were used. The rejection of the translog at both farm- and crop-level model suggests that there is no free lunch for flexibility and a model that does not respect agronomic processes will have to pay a price for it.

2.1.2 Factor Demand Side

In production economics, factor demand has been mainly studied under the duality framework, founded on the behavioral assumption of profit maximization and cost minimization (Shephard, 1953, 1970; McFadden 1978; Diewert, 1982). Factor demand functions may also be derived with the primal approach, but in the literature the primal approach is not as widely practiced as is the dual approach, because it requires an explicit specification of a production function, in addition to the assumption of profit maximization or cost minimization (see, e.g., Beattie and Taylor, 1993, pp. 237-241). The precondition of an explicit production function suggests that the primal factor demand study is dependent on the study of product supply.

Factor demand, however, is of equal relevance and interest as product supply. Hence, this research conducted a capital requirement study from a primal, technical perspective, without tying up to some explicit form of production function or imposing behavioral assumptions. The research sought to establish a conceptual framework that explains the capital requirement and then apply it in empirical study. The direct approach provides an open and general framework for capital demand study that may be subject to further restricting or testing, if desirable. For example, the proposed framework accounted for the natural and geographical factors that affect the capital requirement while the common practice in the traditional factor demand study concerns mostly the prices and quantities of inputs and outputs in a profit maximizing or cost minimizing context. Not accounting for natural and geographical factors in such a context assumes that the producers are homogenous in these factors, or these factors do not affect the capital requirement. The capital requirement model proposed in this study provides a general framework to test these assumptions. Neoclassical economic theory commonly assumes non-increasing marginal product of inputs, which requires concavity of the production function with respect to input, say, capital. In a capital requirement model, it would mean the function is convex with respect to output, which can also be tested with the model.

It is worth noting that in relation to the technical aspect of input use, there is a literature on the input distance function which studies input-output relations from a performance measurement perspective. The input distance function basically focuses on establishing a frontier which locates the set of minimum possible inputs required to produce a certain amount of output. For a specific producer, its distance relative to the frontier is an indicator of its performance in input use. The input distance function is mainly aimed at deriving a multi-input index which indicates to what extent the amount of inputs could be reduced and it is still possible to produce the same amount of output. The function is essentially a dual to the cost function (Cornes, 1992, pp.125-130). The capital requirement study in this research differs from the distance function literature in its motivation and approach. The differences and their implications can be further explored in future research.

2.2 Methodological issues

The methodological issues relate to the implementation or application of the concepts and theory discussed above into empirical studies. The issues mainly relate to model specifications and econometric estimations.

The first methodological issue, addressed in Chapter 2, was how to devise a damage abatement function that could produce a value between zero and one and meanwhile allow both positive and negative marginal product of damage-abating inputs. The traditional specifications (e.g. Pareto or exponential distribution) all produce values between zero and one, but to allow both positive and negative marginal product, the function must be allowed to decrease at a certain stage, and there were no examples in the literature. The first-increasing-and-then-decreasing property can be satisfied with a quadratic function in general. However, there is no easy way to restrict the value between zero and one in a quadratic function. This research proposed an exponential function to the power of a quadratic function with the quadratic function restricted to be non-positive. The new damage abatement function devised in this research successfully implemented the theoretical concept in Chapter 2, and was further redefined as a "scaling function" in Chapter 3 to reflect the facilitating functionality of pesticide, labor and capital.

From a very different perspective, the scaling function in Chapter 3 (or the damage abatement function in Chapter 2) can be seen as an efficiency measure, which can be immediately justified by its value range between zero and one. This appeared to be an interesting and useful, alternative interpretation of the scaling function aimed at a different goal in this research. In the translog model, the squared term of the scaling function (refer to Equation 9 in Chapter 3) may be considered as a part of a composed error term. The structure of the composed error term plus the non-negative property of the squared term is exactly the specification the efficiency and productivity literature has been pursuing. In that literature, to regulate the efficiency component to be non-negative in the production or profit frontier, the efficiency component has to be assumed to follow a non-negative distribution, for example, positive half normal or normal distribution truncated below at zero (Kumbhakar and Lovell, 2000). The estimation of the frontier models involves a painstaking derivation of joint distribution of the composed error term and then using the maximum likelihood estimator. And after the estimation, the efficiency component has to be separated from the noise component based on a conditional distribution. Compared to the complicated and tedious procedure in the frontier literature, the specification and estimation procedure in this research are rather straightforward, and the method has several advantages:

1) no explicit distributional assumptions have to be imposed on the efficiency;
2) the efficiency can be directly computed from the parameter estimates after estimation;
3) the standard error and therefore the confidence interval of the efficiency can be derived from the parameter estimates and their covariance matrix using the delta method (Greene, 2003, pp.70);
4) the factors that affect the efficiencies may be identified directly;
5) in the panel data model, the time-varying pattern of efficiency need not be imposed.

In addition to these advantages, the specification of the scaling function can be slightly modified for a broader use. For example, replacing the minus sign in front of the squared term by a plus sign will form a new structure of the composed error term, which precisely corresponds to the error structure of a cost frontier. In the case of panel data, the scaling function could be reduced to a single squared parameter for each individual firm without including efficiency-affecting factors. In some sense this modified approach looks similar to the fixed-effect approach in the frontier literature, but it produces direct estimates of the efficiency component, and more importantly, the estimates are of a stochastic nature. All these interesting properties suggest that the alternative interpretation of the scaling function is of no lesser methodological and empirical value in its own right, and the contribution to efficiency analysis could be further exploited.

Another methodological issue is Chapter 3 is the method developed for allocating labor and capital from aggregated farm level data to individual crops. As individual farms differ greatly in labor and capital use, the standard level of labor requirement per hectare for a certain crop as suggested by experts was not very helpful. Deriving crop-level labor by multiplying standard labor requirement per hectare and the hectares grown would almost surely lead to inconsistency between the total actual labor and the calculated labor summed across crops. Furthermore, the simplistic calculation does not add more information than just the area grown, because the labor data derived would be perfectly collinear with land area data. The approach developed in this research avoided these problems. Farms may differ considerably in total labor use, but the percentage of total labor devoted to a specific crop might not differ much across farms. The instrumental variable method used in the estimation further addressed the potential misallocation problem. The whole procedure developed in this research is useful for future crop-level studies.

The methodological issue raised in Chapter 4 is whether capital is an exogenous input or endogenous input. In fact this is more than just an econometric methodological issue. In the literature of production analysis, it is never questioned that capital is an exogenous input, simply because it is “fixed”. This research contended that this is clearly a misconception. The large body of literature on capital (dis)investment suggests that there are underlying factors that drive the (dis)investment and the adjustment process, a clear indication of an endogenous process over time, at least in “the long run”. In the short run, say, one year or one production season, it is not difficult to imagine that if a producer is planning a higher production level for the current year, he will probably make an investment plan at the beginning of the year to meet the need of the new production level. The simultaneous decision implies that endogeneity is now becoming a legitimate concern. When it comes to the actual production, the concern is then turned into a reality. In agricultural production, a large amount of capital stock is devoted to harvesting and storage, and it follows that a higher yield level will require more machinery and storage space, in which case simultaneity is obvious. The other way around, if it turns out to be a bad year, less capital will be needed for harvesting and storing. In addition to simultaneity, this would also imply the presence of excess capital and therefore mismeasurement of capital if the data on the balance sheet are used, which is another source of endogeneity. The presence of excess capital serves as a reservoir when more capital is needed, and thus warrants the variability of capital in actual use, which eventually challenges the concept of “fixedness” of capital. In line with these arguments, Chapter 4 defined a concept of excess capital based on the capital requirement model, and further this chapter showed that treating capital as endogenous in the production frontier model yielded significantly different efficiency estimates.

Chapter 5 proposed a robust estimation procedure for modeling farm performance that addresses dynamics, serial correlation and endogeneity. Dynamics is simply inherent in the definition of many performance indicators. The Malmquist productivity growth index studied in this chapter is a measure of growth rate. By definition, it is a cross-period index, comparing the relative performance of two consecutive periods.. Chapter 5 specifically addresses the financial aspect of farm businesses and for this purpose uses return on equity (ROE) as an alternative performance indicator. ROE is defined as the net income divided by the average equity of the year. The average is the sum of the beginning balance and the ending balance of the year, divided by two. As the ending balance of this year will be the beginning balance of the next year, it affects both years’ ROE measure. The same dynamics also applies to return on asset (ROA). The dynamics inherent in the definition of the performance indicators are obvious, but this issue has not been recognized in the literature, to the knowledge of the author. The dynamics lead to misspecified (static) models and serial correlation as the dynamics are captured by the error term in these models. In addition, Chapter 5 argues that endogeneity poses a problem when modeling performance. All three problems are non-trivial in econometrics, and Chapter 5 addressed them by means of a dynamic model specification and a generalized method of moments (GMM) estimator.

For econometric estimations, this research used nonlinear least squares (NLS), generalized method of moments (GMM), and maximum likelihood (ML) for different chapters. Chapter 3 further employed GMM to address the measurement error problem of capital and labor. In terms of methodology, Chapter 2 and 3 are quite consistent as both chapters use NLS and nonnested tests; model specifications in the two chapters are also consistently linked with each other. Nonetheless, Chapter 3 fundamentally differs from Chapter 2 in the underlying concepts and motivations, and theoretically Chapter 3 is a large step forward. In some sense these two chapters are complementary as well, as one focused on the farm level while the other made a more specific analysis at crop level. Chapter 4 and Chapter 5 used similar GMM estimation techniques, but the latter followed a more sophisticated system GMM due to its special focus on econometrics. It is worth noting that the argument for an endogenous treatment of capital in Chapter 4 would have an implication to the analysis in Chapter 2, but for the crop-level study in Chapter 3, this issue, as one of the interests, was explicitly addressed with GMM estimation.

2.3 Empirical issues and main results

The empirical focus of this thesis was on environmental and economic sustainability of the Dutch arable farming sector. Environmental aspects were mainly covered by Chapters 2 and 3, while economic aspects appeared in Chapters 2-5.

The comparison of conventional and organic farming systems in Chapter 2 provides policy makers with insights in the differences of the production processes and input productivities. This information could be used for identifying environment-friendly farming practices. For this purpose, Chapter 3 also provides relevant information on the shadow price of pesticide and fertilizer. As expected a priori, conventional and organic farms indeed use different production technologies, particularly in the damage control process. In conventional farming, pesticide and machinery were the major means of damage control while in organic farming, machinery and cultural practices played a major role. Interestingly, results suggested that labor use (e.g., manual weeding) does not play a significant role in the damage control on organic farms.

Chapter 2 reported lower pesticide productivity than previous studies in the literature, and Chapter 3 resulted in a rather low pesticide productivity estimate as well. Organic farms were found to have rather high pesticide productivity. A concern, however, is that pesticide use on organic farms (subject to restrictions on the type and toxicity of pesticides) is usually low and sometimes negligible. Insufficient data variation, in addition to the small sample size of organic farms, led to an imprecise estimate of pesticide productivity in terms of its standard error. A further issue on pesticide productivity is that this research did not consider the externalities of pesticide use in agriculture, which certainly is an important element to be addressed for policy implications. On the issue of fertilizer use, Chapter 2 concluded that fertilizer was overused on the conventional farms in the Netherlands. A special issue associated with fertilizer use was the negative shadow price in conventional farming. Although not significantly different from zero, it suggests that further investigation of the effect of fertilizer, preferably in a dynamic setting, may be desirable. In general, Dutch arable farms were found to be using too much labor and capital. The arable farming sector is over-invested in capital as suggested throughout Chapters 2-5 of this thesis, in addition to a nonparametric study of Zhengfei and Oude Lansink (2003). As concluded in Chapter 2, the arable farming sector is characterized by intensive use of labor and capital on farms with little land. From an economic viability point of view, the government could consider introducing policy incentives to stimulate merging, restructuring, and spinning-off in the sector. In fact, Dutch agriculture has been witnessing a dramatic drop in the number of farms and an increase in acreage per farm during the past decades.

An interesting, but not surprising, result in Chapter 5 is that subsidy significantly slows down the productivity growth in the sector, suggesting that removing subsidies might not compromise the future viability of the sector. Chapter 5 further concluded that access to credit market increases farms' productivity growth.

Finally, it is worth mentioning that agricultural production is a complex process and involves many dimensions, for example, inputs and outputs, the natural and biophysical environment and dynamics. An economic study that intends to perfectly address all these dimensions is impossible. A simple example is that inputs used for empirical economic studies are usually aggregated to some extent (the same applies to outputs). Even fertilizer, a relatively narrow category, includes different types of plant nutrients (e.g., N, P, K); consideration of total fertilizer use captures little of the complexity of crop growth. Using more detailed information would yield more, accurate insights. In this respect, there is still a great deal of work that can be done in future research. In the meantime, a more sophisticated theoretical model could be developed to integrate more prior knowledge, for example, introducing asymmetries within the category of growth inputs and facilitating inputs. On the output side, the farm-level study could allow multiple outputs and the interactions among different crops.

3. Relevance for non-arable farming

The present study focused entirely on arable farm production; a final issue to be discussed is the relevance of this study to non-arable farming sectors, such as livestock production or mixed farming. As Chapter 4 and 5 have less operation-specific characteristics, this question is particularly relevant to the crop production studies in Chapters 2 and 3. In principle, the way of thinking and the modeling principle seem to be applicable; for example, in livestock farming growth inputs may be defined as breed, feed, and water, and facilitating inputs may include capital, labor, and veterinary inputs (cf. Van de Ven et al., 2003). This definition is consistent with the dichotomy defined in Chapter 3. There might be some other elements to be addressed when studying livestock production, but the bottom line remains the same: inputs have distinctive functionalities that must be accounted for in empirical modeling, or more generally, a model must be conceptually plausible and empirically relevant.

4. Main conclusions

i) Evidence in the literature suggests that the dual approach of production analysis, albeit elegant in concept, is either incorrect or inefficient in practice, calling for a reviving of the primal. However, the generic production models of the primal approach do not respect agronomic reality and lack a solid theoretical foundation (Chapters 1, 2 and 3).
ii) This research acknowledges the relevance of agronomic knowledge in economic analysis of production, recognizing distinct functionalities of inputs. The research proposes a dichotomy of growth inputs and facilitating inputs. A theoretical model based on this dichotomy provides a new paradigm for empirical production analysis (Chapter 3).
iii) In the empirical application, the test results reject the traditional translog model, in favor of the model proposed in this research that integrates agronomic knowledge regarding the functionalities of inputs, suggesting that the new model better represents the underlying production technology (Chapters 2 and 3).
iv) The factor demand study provides a direct approach from a technical perspective, without imposing behavioral assumptions or assuming production functions. Using this direct approach, an empirical study of capital requirement suggested that excess

capital widely exists in Dutch arable farming; not accounting for excess capital in empirical production analysis would result in biased studies (Chapters 4).

v) Dutch arable farms are over-invested in capital: the shadow price of capital is lower than the cost of capital; most farms have excess capital; capital investment does not contribute to productivity growth (Chapters 2, 3, 4 and 5).

vi) From an economic point of view, fertilizer is overused on conventional arable farms in the Netherlands, whereas pesticides are not, without accounting for their environmental externalities (Chapters 2 and 3).

vii) Empirical results confirmed that subsidies slow down productivity growth as was expected from theory (Chapter 4).

viii) Access to credit market helps producers increase productivity growth (Chapter 4).

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Summary

Introduction

This thesis seeks to rebuild and extend the primal approach in production analysis by: a) developing a new paradigm for agricultural production analysis that acknowledges the relevance of the agronomic aspects of the production processes; b) defining factor demand in agricultural production from a primal, technical perspective. The theory and approach developed are used to address aspects of environmental and economic sustainability of agriculture in the Netherlands.

Damage-abating and productive inputs

Inputs used in agricultural production have different functionalities and affect yield differently. Chapter 2 proposes a theoretical model that distinguishes between the damage-abating and productive role of inputs. Pesticide is considered a damage-abating input. Land, fertilizer, and other miscellaneous variable inputs (e.g., seed) are productive inputs. Capital and labor are used for both productive (e.g. sowing and harvesting) and damage-abating activities (e.g. machinery or manual weeding). The theoretical model proposed in this study explicitly addresses these differences and treats inputs asymmetrically. The model further allows negative marginal products of damage-abating inputs, particularly relevant for pesticide in the case of overdosage. The asymmetric model is tested against the traditional model. The test results reject the translog model in favor of the asymmetric model. The asymmetric model is then used for the comparison of the production technologies used in conventional and organic farming systems. Empirical study addresses Dutch arable farming. Results suggest that the two farming systems have different damage control processes; fertilizer is overused whereas pesticides are used optimally on conventional arable farms, in contrast with previous results in the literature.

Growth and facilitating inputs

Chapter 3 further develops the concept of asymmetric functionality of inputs. This chapter recognizes that differences in inputs are broader than damage-abating vs. productive. Examples are the differences between labor and fertilizer, seed and machinery, water and other inputs. This chapter proposes a more general concept, distinguishing growth inputs and facilitating inputs. Growth inputs are directly involved in the biological process of crop growth and include land, seed, fertilizer, and water; facilitating inputs help create or alter growth conditions, under which growth inputs take effect, and include labor, machinery, and pesticide. Based on this dichotomy, a general conceptual framework is proposed. The conceptual framework connects agronomy and economics, presenting a new paradigm for agricultural production analysis. The robustness of the new paradigm is tested using crop-level data on potato production in the Netherlands. The results from a nonnested test do not reject the new model, indicating the model that acknowledges the relevance of agronomic aspects better represents the underlying production technology.

Capital demand from a primal, technical perspective

Chapter 4 proposes a direct approach to modeling factor demand in agricultural production, focusing on the capital requirements from a primal, technical perspective. Factors that affect the technical requirement of capital are investigated. Based on the capital requirement model, this study defines a concept of excess capital and then separates the excess capital from the residuals, i.e., the unexplained capital in the capital requirement model. Results show that excess capital widely exists. The presence of excess capital implies mismeasurement of capital in production analysis that uses accounting data. This chapter further argues that the output level affects the level of capital stock in actual use, implying simultaneity of capital in production models. The implication of mismeasurement and simultaneity of capital is analyzed with a production frontier model. Results show that models not addressing these problems yield biased and inconsistent efficiency estimates.

Source of productivity growth

Malmquist productivity growth indices are derived for Dutch arable farms in Chapter 5. The average productivity growth index suggests a productivity progress over 1990-1999. In finding factors that affect productivity growth, this study shows that traditional performance models are subject to misspecification, endogeneity, and serial correlation problems. To solve these problems, this study proposes a dynamic model and a system generalized method of moments (GMM) estimator. Empirical results show that access to credit market boosts the productivity growth of arable farming. Investment has no effect on productivity growth, suggesting over-investment in the sector. As expected from theory, subsidization slows down productivity growth.

Main conclusions

i) Evidence in the literature suggests that the dual approach of production analysis, albeit elegant in concept, is either incorrect or inefficient in practice, calling for a reviving of the primal. However, the generic production models of the primal approach do not respect agronomic reality and lack a solid theoretical foundation (Chapters 1, 2 and 3).

ii) This research acknowledges the relevance of agronomic knowledge in economic analysis of production, recognizing distinct functionalities of inputs. The research proposes a dichotomy of growth inputs and facilitating inputs. A theoretical model based on this dichotomy provides a new paradigm for empirical production analysis (Chapter 3).

iii) In the empirical application, the test results reject the traditional translog model, in favor of the model proposed in this research that integrates agronomic knowledge regarding the functionalities of inputs, suggesting that the new model better represents the underlying production technology (Chapters 2 and 3).

iv) The factor demand study provides a direct approach from a technical perspective, without imposing behavioral assumptions or assuming production functions. Using this direct approach, an empirical study of capital requirement suggested that excess capital widely exists in Dutch arable farming; not accounting for excess capital in empirical production analysis would result in biased studies (Chapters 4).

v) Dutch arable farms are over-invested in capital: the shadow price of capital is lower than the cost of capital; most farms have excess capital; capital investment does not contribute to productivity growth (Chapters 2, 3, 4 and 5).

vi) From an economic point of view, fertilizer is overused on conventional arable farms in the Netherlands, whereas pesticides are not, without accounting for their environmental externalities (Chapters 2 and 3).

vii) Empirical results confirmed that subsidies slow down productivity growth as was expected from theory (Chapter 4).

viii) Access to credit market helps producers increase productivity growth (Chapter 4).

Samenvatting (Summary in Dutch)

In dit proefschrift staat de primale benadering in de econometrische modellering van de landbouwproductie centraal: a) er wordt een nieuw paradigma ontwikkeld voor de econometrische modelering dat rekening houdt met de agronomische aspecten van het productieproces; b) de vraag naar arbeid in de landbouw wordt benaderd vanuit een primair, technisch perspectief. De ontwikkelde theorie en econometrische benadering worden vervolgens gebruikt voor een analyse van economische en miliekundige aspekten van de duurzaamheid van de Nederlandse landbouw.

Gewasbeschermende en opbrengstverhogende productiemiddelen

Productiemiddelen in de landbouw hebben verscheidene functies en beïnvloeden de opbrengst op verschillende manieren. In Hoofdstuk 2 wordt een model geïntroduceerd dat onderscheid maakt in de gewasbeschermende en opbrengstverhogende rol van productiemiddelen. Bestrijdingsmiddelen worden uitsluitend beschouwd als een gewasbeschermende input. Landbouwgrond, meststoffen en andere overige inputs (bijv. zaaizaad) zijn opbrengstverhogende productiemiddelen. Kapitaal en arbeid worden ingezet bij zowel opbrengstverhogende (bijv. zaaien en oogsten) als gewasbeschermende bewerkingen (bijv. machinale of handmatige onkruidbestrijding). Het theoretische model in Hoofdstuk 2 van dit proefschrift maakt expliciet onderscheid in deze twee verschillende functies en behandelt productiemiddelen asymmetrisch. Bovendien kunnen in dit model de marginale opbrengsten van gewasbeschermende productiemiddelen negatief zijn, vooral van belang voor bestrijdingsmiddelen in geval van overdosering. Het nieuwe, asymmetrische model wordt empirisch getest ten opzichte van het traditionele Translog model. De test resultaten verwerpen het traditionele model ten gunste van het asymmetrische model. Het asymmetrische model wordt vervolgens gebruikt voor een vergelijking van de productietechnologie in de gangbare en de biologische landbouw. De empirische toepassing betreft de Nederlandse akkerbouw. De resultaten wijzen erop dat de twee bedrijfstypen met name gekenmerkt worden door een verschil in de wijze van gewasbescherming. Daarnaast duiden de resultaten op een overgebruik van kunstmeststoffen en een optimaal gebruik van bestrijdingsmiddelen in de gangbare akkerbouw; dit is in tegenspraak met eerder gepubliceerde bevindingen.

Gewasgroei productiemiddelen en ondersteunende productiemiddelen

Het idee dat functies van productiemiddelen als asymmetrisch dienen te worden beschouwd is verder uitgewerkt in Hoofdstuk 3. In dit hoofdstuk wordt onderkend dat het verschil tussen productiemiddelen verder gaat dan gewasbeschermend en opbrengstverhogend. Bijvoorbeeld het verschil tussen arbeid en kunstmest, zaaizaad en machinepark, water en andere productiemiddelen. In Hoofdstuk 3 wordt een meer algemeen concept ontwikkeld, namelijk dat van gewasgroei inputs en ondersteunende inputs. Gewasgroei productiemiddelen zijn rechtstreeks betrokken bij het biologische proces van gewasgroei en betreffen land, zaaizaad, meststoffen en water. Ondersteunende inputs zoals arbeid, mechanisatie en bestrijdingsmiddelen zorgen voor de juiste groeiomstandigheden zodat de gewasgroei inputs hun werk kunnen doen. Het conceptuele raamwerk in Hoofdstuk 4 verbindt de agronomie met de economie en dit resulteert in een nieuw paradigma voor de econometrische analyse van de landbouwproductie. Het nieuwe paradigma wordt getest met gegevens van de Nederlandse consumptie-aardappelproductie. De non-nested test resultaten verwerpen het nieuwe model niet, wat aangeeft dat het op de agronomie geïnspireerde model het onderliggende productieproces beter beschrijft.

Vraag naar Kapitaal vanuit het primale perspectief

Hoofdstuk 4 presenteert een directe benadering voor het modelleren van de vraag naar productiefactoren in de landbouw. De focus ligt daarbij op de vraag naar kapitaal vanuit een primaal, technisch perspectief. Factoren die de vraag bepalen worden onderzocht. Deze studie ontwikkelt een concept van overbodig kapitaal en onderscheidt overbodig kapitaal van residuen in het 'capital requirement' model. De resultaten laten zien dat overbodig kapitaal veelal aanwezig is op de onderzochte akkerbouwbedrijven. De aanwezigheid van overbodig kapitaal impliceert fouten bij het meten van kapitaal in de boekhouddata. Dit hoofdstuk argumenteert voorts dat het productieniveau invloed heeft op de hoogte van de kapitaalvoorraad, wat duidt op simultaniteit van kapitaal in het productiemodel. De implicaties van meetfouten en simultaniteit van kapitaal worden geanalyseerd met een productie frontier model. De resultaten laten zien dat het niet corrigeren voor deze problemen leidt tot bias en inconsistentie in de schatting van de efficiëntie.

De herkomst van productiviteitsgroei

In hoofdstuk 5 worden Malmquist productiviteits groei indices bepaald voor Nederlandse akkerbouw bedrijven. De gemiddelde groei van de productiviteit is positief in de periode 1990-1999. Dit hoofdstuk laat zien dat traditionele modellen van de performance van bedrijven te kampen hebben met misspecificatie, endogeniteit en seriële correlatie. De oplossing die wordt voorgesteld in dit hoofdstuk is een dynamisch model dat wordt geschat door een system Generalized Method of Moments (GMM) schatter. De empirische resultaten laten zien dat toegang tot krediet leidt tot een hogere productiviteitsgroei op akkerbouwbedrijven. Investeringen hebben geen effect op productiviteitsgroei, wat impliceert dat de sector overgekapitaliseerd is. Subsidies hebben een negatief effect, zoals werd verwacht op basis van de theorie.

Belangrijkste conclusies

i) De literatuur suggereert dat de duale benadering in productie analyse, alhoewel conceptueel elegant, incorrect is en inefficiënt. Toch ontbeert de generieke primale benadering een solide theoretische basis en doet het geen recht aan agronomische wetmatigheden. (Hoofdstukken 1, 2 and 3).

ii) Dit onderzoek onderkent de relevantie van agronomische kennis in de economische analyse van productie door recht te doen aan de verschillende functies van inputs. Dit onderzoek onderscheidt gewasgroei inputs en ondersteunende inputs. Een theoretisch model gebaseerd op dit onderscheid resulteert in een nieuw paradigma voor empirische productie analyse. (Hoofdstuk 3).

iii) De resultaten van de statistische testen verwerpen het traditionele Translog model. Het model dat agronomische kennis ten aanzien van de functies van inputs integreert in de productiefunctie wordt niet verworpen. De resultaten suggereren dat het nieuwe model de onderliggende productietechnologie beter weergeeft. (Hoofdstukken 2 and 3).

iv) De modellering van de vraag naar productiefactoren is een directe benadering, vanuit een technisch perspectief en legt geen veronderstellingen op ten aanzien van het gedrag. De empirische resultaten van deze benadering suggereren dat er overbodig kapitaal is op veel akkerbouwbedrijven. Niet corrigeren voor overbodig kapitaal resulteert in biases in de schattingen. (Hoofdstuk 4).

v) Nederlandse akkerbouw bedrijven zijn overgekapitaliseerd: de schaduwprijs van kapitaal is lager dan de prijs van kapitaal; de meeste bedrijven hebben overbodig kapitaal; kapitaal investeringen dragen niet bij aan de groei van de productiviteit. (Hoofdstukken 2, 3, 4 and 5).

vi) Vanuit een economisch gezichtspunt gebruiken gangbare akkerbouwbedrijven teveel kunstmest, maar niet teveel pesticiden; zonder rekening te houden met hun milieukundige externaliteiten (Hoofdstukken 2 and 3).

vii) De empirische resultaten laten zien dat subsidies de productiviteitsgroei vertragen, zoals werd verwacht op basis van de theorie (Hoofdstuk 4).

viii) Toegang tot kredieten verhoogt de productiviteitsgroei (Hoofdstuk 4).

List of Publications

Journal articles

Zhengfei, G., and A. Oude Lansink. 2003. "Input disposability and efficiency in Dutch arable farming", *Journal of Agricultural Economics* 54: 467-478

Zhengfei, G., A. Oude Lansink, A. Wossink and R. Huirne. 2005. "Damage abating inputs: a comparison of conventional and organic farming systems." *European Review of Agricultural Economics* 32: 167-189.

Zhengfei, G., A. Oude Lansink, M.K. van Ittersum, A. Wossink. 2006. "Integrating agronomic principles into production function estimation: A dichotomy of growth inputs and facilitating inputs." *American Journal of Agricultural Economics* 88*,* in press.

Zhengfei, G., and A. Oude Lansink: Forthcoming. "The source of productivity growth in Dutch agriculture: a perspective from finance" *American Journal of Agricultural Economics*, in press.

Zhengfei, G., S.C. Kumbhakar, and A. Oude Lansink. "Excess Capital and its Implications in Econometric Analysis of Production." Submitted to *American Journal of Agricultural Economics.*

Conference papers

Zhengfei, G., and A. Oude Lansink: "Analysis of Input disposability and efficiency in Dutch horticulture." North American Productivity Workshop II (June 20-22, 2002, Union College, Schenectady, U.S.A.)

Zhengfei, G., and A. Oude Lansink: "The source of productivity growth in Dutch arable farming: a perspective from finance." The 8th European Workshop on Efficiency and Productivity (September 25-27, 2003, University of Oviedo, Oviedo, Spain)

Zhengfei, G., A. Oude Lansink, M.K. van Ittersum, A. Wossink: "A new specification of production frontier: integrating production ecological principles in stochastic frontier analysis." North American Productivity Workshop 2004 (June 22-25, 2004, University of Toronto, Toronto, Canada)

Zhengfei, G., and A. Oude Lansink: "A robust estimator for performance modelling." The 9th European Workshop on Efficiency and Productivity Analysis (June 29-July 2, 2005, Brussels, Belgium).

About the Author

Guan Zhengfei was born on November 21, 1968 in Xuyi, Jiangsu Province, China. He finished his secondary education at Xuyi High School in 1988. In the same year he began his study at Nanjing University, majoring in International Economics and Trade. He obtained his degree of Bachelor in 1992. From 1992 till 1999, he was working at Jiangsu Agribusiness Group (reorganized from former Jiangsu State Farms Bureau), where he worked in the Department of Planning and Finance and in the World Bank Program. He started his MSc study in the Agricultural Economics and Management program at Wageningen University in September 1999, and he obtained his MSc degree (*cum laude*) in March 2001. The title of his MSc thesis was "Non-parametric Efficiency Measures of Dutch Horticultural Firms." From February 2001 till August 2005 he was working in the Business Economics Group at Wageningen University on his PhD research project, entitled "Econometric Analysis of Agricultural Production: New Primal Perspectives." He followed his PhD education program in the Mansholt Graduate School of Wageningen University and in the Netherlands Network of Economics (known as NAKE in Dutch acronyms, http://www.nake.nl). He completed the full NAKE program and received his NAKE diploma in 2004.

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