TUM School of Life Sciences

Innovation and Productivity in the European Dairy and Food Sectors

Fabian Frick

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Vorsitzender: Prof. Dr. Heinz Bernhardt

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1. Prof. Dr. Johannes Sauer
2. Prof. Dr. Stefan Hirsch
3. Prof. Dr. Uwe Latacz-Lohmann

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Summary

The European dairy sector has undergone substantial changes in recent years. After decades of production under the milk quota regime, the European Union took steps to lead the sector towards greater world market orientation. Before the final quota abolition in 2015, a soft-landing was intended by gradually increasing milk quota volumes, decreasing intervention price levels, and liberalizing milk quota transfers. This phase of deregulation was accompanied by increased raw milk price volatility especially after 2007, which brought numerous dairy farms into financial distress. These events were embedded in the context of the long-term trend of steadily decreasing numbers of European dairy farms and increasing average herd sizes. The new policy objectives also have implications for the closely linked stage of dairy processing. Without production being capped by the milk quota, it is uncertain how raw milk production volumes will develop, leaving dairies the challenge of finding viable ways of marketing the changing raw milk supply.

This thesis presents four empirical studies on the European dairy and food processing sector. Their aim is to shed light on the links between firm-level and aggregate productivity, innovation, and recent changes in the political framework and market conditions.

The first two essays focus on dairy farming and trends in aggregate productivity and technical change against the background of the quota phase-out and turbulent raw milk prices. The first study employs farm-level panel data on dairy farms in southeast Germany and estimates farm-level productivity by a proxy variable approach which is robust with respect to endogenous input choice. The results uncover that the reallocation of resources towards more productive farms increased sector productivity in southeast Germany during the phase-out of the milk quota.

The second study examines technical change in dairy farming during the phase of deregulation and volatile milk prices. To this end, it estimates distance functions

to accommodate multi-output, multi-input production technologies of specialized and mixed dairy farms. The results indicate stagnation in technical change in recent years for both specialized and mixed dairy farms in Germany.

The third and fourth studies focus on the food and dairy processing stage and the effect of innovation activity on productivity. The third study estimates the effect in the European manufacturing sector by employing an estimation routine that tackles endogeneity of innovation output and selection issues caused by the survey design. The results highlight the importance of accounting for heterogeneity in innovation behavior in subsectors of the manufacturing industries. By a comparison of the food sector with two high-tech sectors, the results suggest positive labor productivity effects for the food sector but not the high-tech sectors.

The fourth study focusses specifically on the dairy processing sector. It uses a unique dataset combining financial data and data on innovation activity. As innovation indicators, patent data is used as a proxy for process innovation activity, and literature-based new product count data is used as an indicator of product innovation activity. The findings indicate positive effects of new product introductions on dairy processors' efficiency, but only when new product quality is taken into account. In contrast, no positive effects of process innovation measured as patenting activity became apparent.

Zusammenfassung

Der europäische Milchsektor war in den vergangenen Jahren einem stetigen Wandel unterworfen. Eine Zäsur in den politischen Rahmenbedingungen ergab sich mit der Abschaffung der Milchquote, welche über Jahrzehnte hinweg die Milcherzeugung in der Europäischen Union regulierte. Vor dem endgültigen Auslaufen des Quotensystems im Jahr 2015 verfolgte die Europäische Union einen „soft-landing“ Ansatz, indem die Quotenvolumina schrittweise erhöht wurden. Des Weiteren wurden schon zuvor weitere Schritte unternommen, um den europäischen Milchsektor hin zu einer größeren Weltmarktorientierung zu lenken. Hierfür wurden Quotentransfers zwischen Betrieben liberalisiert und Interventionspreise für Milchprodukte gesenkt. Diese Deregulierungsschritte wurden besonders ab 2007 von einer erhöhten Volatilität des Milchpreises begleitet, welche viele Milcherzeuger in finanzielle Schwierigkeiten brachte. Diese Ereignisse waren eingebettet in den langfristigen Trend einer schrumpfenden Zahl von Milchviehbetrieben und stetig steigenden durchschnittlichen Herdengrößen. Die neuen Politikziele hatten nicht nur auf den landwirtschaftlichen Sektor, sondern auch auf den nachgelagerten Bereich der Milchverarbeitung Auswirkungen. Ohne die limitierende Wirkung der Milchquote ist die zukünftige Entwicklung der Milchproduktion mit einer höheren Unsicherheit behaftet, was Molkereiunternehmen vor die Herausforderung stellt, geeignete Vermarktungsmöglichkeiten für das sich verändernde Milchangebot zu finden.

Diese Dissertation präsentiert vier empirische Studien im europäischen Milch- und Lebensmittelsektor. Hierbei werden Zusammenhänge zwischen Produktivität, Innovation und dem veränderten politischen Rahmen sowie den neuen Marktbedingungen beleuchtet.

Die ersten zwei Studien legen den Fokus auf die Stufe der Milcherzeugung und die Entwicklungen von aggregierter Produktivität und technischem Wandel vor dem Hintergrund des Auslaufens der Milchquote und turbulenten Rohmilchpreisen. Die erste Studie nutzt einen Paneldatensatz bayerischer Milchviehbetriebe

und schätzt die Betriebsproduktivität mithilfe eines Verfahrens, welches robust gegenüber der Endogenität der Inputs im Hinblick auf die Produktionsfunktion ist. Die Ergebnisse zeigen, dass die Reallokation von Ressourcen hin zu produktiveren Betrieben während der stufenweisen Abschaffung der Milchquote positiv zur Sektorproduktivität in Bayern beigetragen hat.

Die zweite Studie untersucht den Verlauf des technischen Fortschritts während der Phase der Deregulierung und volatiler Milchpreise. Hierzu werden Distanzfunktionen geschätzt, welche die Produktionstechnologie mit mehreren Inputs und Outputs sowohl für spezialisierte als auch für gemischt wirtschaftende Milchviehbetriebe abbildet. Die Ergebnisse zeigen eine Stagnation des technischen Fortschritts, sowohl für spezialisierte als auch diversifizierte Milchviehbetriebe in Deutschland.

Die dritte und vierte Studie beschäftigen sich mit dem Effekt von Innovationsaktivitäten auf die Produktivität von Firmen der Lebensmittel- und Milchverarbeitung. Die dritte Studie schätzt diesen Effekt für europäische Firmen in der verarbeitenden Industrie mithilfe einer Methode, welche robust bezüglich der Endogenität des Innovationsoutputs sowie bezüglich Selektionsverzerrungen durch das Umfragedesign ist. Die Ergebnisse betonen die Wichtigkeit der Berücksichtigung von sektorspezifischer Heterogenität bezüglich dem Innovationsverhalten von Firmen der verarbeitenden Industrie. In einem Vergleich unterschiedlicher Subsektoren zeigen sich positive Produktivitätseffekte der Innovationsaktivität bei Firmen des Lebensmittelsektors, aber nicht bei Firmen zweier High-Tech-Sektoren.

Die vierte Studie konzentriert sich im Speziellen auf den Sektor der Milchverarbeitung. Hierzu verwendet sie einen Datensatz, welcher Jahresabschlussdaten mit Daten zu Innovationsaktivitäten der Molkereien kombiniert. Als Indikator für Prozessinnovationsaktivitäten dienen Angaben zu Patentanmeldungen, während Informationen über Produktneueinführungen in Fachzeitschriften als Produktinnovationsindikatoren verwendet werden. Die Ergebnisse deuten auf positive Effekte von Produktneueinführungen auf die Effizienz von Molkereien hin, jedoch nur bei Berücksichtigung der Qualität der neuen Produkte. Keine positiven Effekte zeigen sich demgegenüber durch Prozessinnovationsaktivität gemessen als Patentaktivität.

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CIS	Community Innovation Survey
EU	European Union
FE	Fixed effects model
GMM	Generalized Method of Moments
OLS	Ordinary Least Squares
R&D	Research and development
SEC	Scale efficiency change
SFA	Stochastic frontier analysis
TC	Technical change
TE	Technical efficiency
TEC	Technical efficiency change
TFP	Total factor productivity
WLP	Wooldrige-Levinsohn-Petrin estimation routine

Part I. Introduction and Methods

1. Introduction

This thesis is concerned with dynamics in productivity, technical change, and the effects of innovation in the European food and dairy sectors. The European dairy sector faced significant changes to its political and market environment, and these are reviewed in this section, together with the general characteristics of both the dairy farming and processing sector. Subsequently, the relevance of productivity in this context is discussed, and the aims of this thesis are presented in more detail.

1.1. Overview of the European dairy sector

1.1.1. Dairy farming

The dairy sector is a major contributor to aggregate output and employment in European agribusiness. At the same time, the aggregate milk production of the member states of the European Union accounts for a significant share of world milk production.[1] In the last decades, European market participants on both the stages of raw milk production and milk processing have faced significant changes with respect to the market environment and the political framework. Similar to other farm sectors, dairy farming across Europe is characterized by the long-standing and continuing trend of decreasing farm numbers and increasing average farm size. With the closure of a substantial share of farm businesses and the implementation of labor-saving technologies, herd sizes have grown continuously, resulting in considerable structural change. In Germany, the number of farms with dairy cows declined by 71% and the average herd size more than doubled from

[1] Following vegetables and horticultural plants, milk was the second largest agricultural output based on the output value of the EU-28 in 2016 (Eurostat 2017a, 44). As an aggregate, the member states are the largest milk producer in the world with 163 million tonnes in 2017, followed by the USA (98 million tonnes), India (84 million tonnes), and Brazil (33 million tonnes, FAOSTAT 2019). Within the EU, the largest producers are Germany (20% of production); France (15%); the United Kingdom and the Netherlands (each 9%); and Poland (8%, FAOSTAT 2019).

1990 to 2013. Similar trends are observed in France and the United Kingdom, two other major cow milk producers in the European Union (see figure 1-1). This profound change in producer structure continued although the production of cow milk has been one of the most regulated farming activities in the European Union. In the past, a variety of instruments to support and regulate the dairy market have been introduced, including export refunds, intervention measures, and the milk quota system.

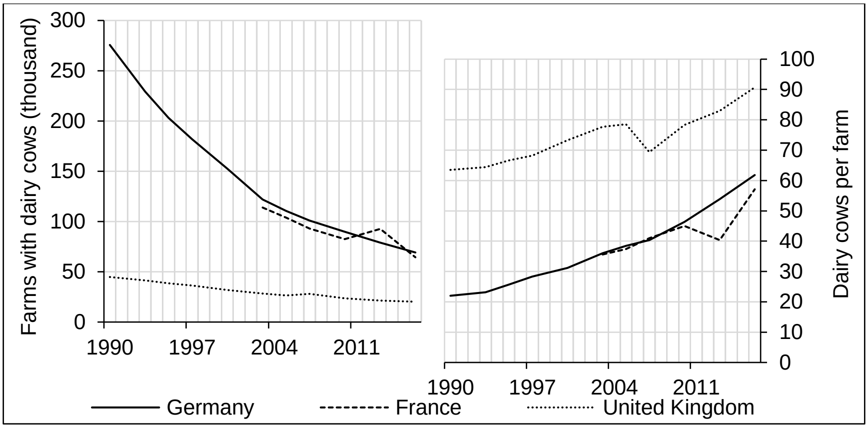

Figure 1-1. Number of farms with dairy cows (left) and average number of dairy cows per farm (right) in Germany, France, and the United Kingdom

Source of data: Eurostat (2020)

The production quotas were introduced in 1984 to counter the phenomenon of "butter mountains and milk lakes," referring to high production surpluses that were caused by intervention prices guaranteed by the European Union that were well above world market levels. With the milk quota, each dairy farm in the European Union was allocated a production allowance based on its past production volume and production above this level was sanctioned by a "superlevy". Quota transfers between farms have been administered individually in each member state but typically transfers were restricted, for example, by being tied to the land a farmer cultivates. The milk quota was originally introduced only as a temporary instrument but was extended several times (Council of the European Union 2003). To allow dairy farmers to respond to growing demand in world markets, it was decided in the 2003 “Mid Term Review” that quotas were to be abolished in 2015; and this final date was confirmed by the 2008 “Health Check” (European Commission 2015b).Since then, the European Commission took steps to prepare the dairy farming sector for a market free of production quotas. For a smooth phase-out of the quota system, a “soft landing” approach was intended by gradually increasing the quota volumes over several years. Also, during the whole period of the quota regime, quota transfers between farmers became increasingly liberalized after permanent transfers without land were permitted in 1987 (Baldock et al. 2008). This was implemented individually in each member state but, in general, transfer regimes moved from the quotas being tied to land to market-based mechanisms without the coupling to land (Baldock et al. 2008). For example, in Germany, quota exchanges were installed in 2000 that allowed permanent transfers without land. Other measures undertaken by the European Union to decrease government influence were the lowering of intervention price levels and the reduction in export refunds.

With these reforms, the European Union took steps to lead its dairy sector towards greater world market orientation. This has been mirrored in producer prices for raw milk being increasingly influenced by world market price movements. Figure 1-2 illustrates the development of raw milk prices and policy measures in recent years. For a long time, farm-gate milk prices in the European Union were characterized by only seasonal variation. Starting in 2007, dairy farmers have been facing increased price volatility. This was initially caused by strong domestic and worldwide demand leading to a price high that was followed by a price drop from 2008 to 2009 due to lower demand and a rebound in supply. These price lows brought many dairy farmers into financial distress. Calls for financial aid for farmers were answered by the European Commission (European Commission 2009b).

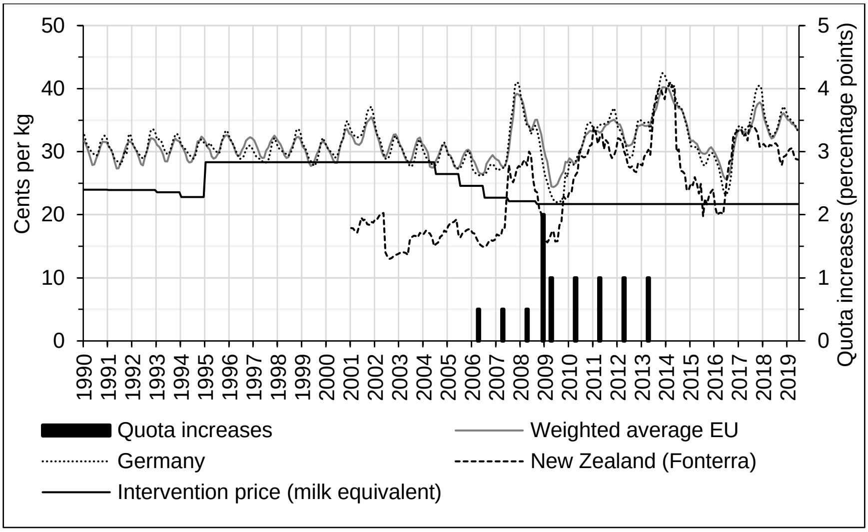

Figure 1-2. Producer milk prices, intervention price levels, and quota increases in the EU and Germany

Source of data: EU Milk Market Observatory (2019), European Commission (2020), AHDB (2019)

1.1.2. Dairy processing

The second stage in the dairy supply chain consists of dairy processing, which transforms raw milk into a wide range of milk products. This stage contributes significantly to the aggregate production of the European Union. While the food processing sector as a whole accounts for a major share of value added and employment in the manufacturing sector (Eurostat 2017b), the production value of dairy processing amounted to approximately 17% of the EU-28 food sector in 2017 (Eurostat 2019). In dairy processing, a structural change similar to that in the farming sector has been observed in recent years. To exploit economies of scale and to create strategic advantages, a plethora of mergers and acquisitions have been conducted, increasing market concentration in the industry. Data for Germany shows that the number of raw milk-collecting enterprises decreased by

64%, from 284 in 1994 to 102 in 2015. In France, this number halved during the same period (815 to 404) and in the United Kingdom decreased by 66%, from 1063 in 1997 to 367 in 2015 (figure 1-3).

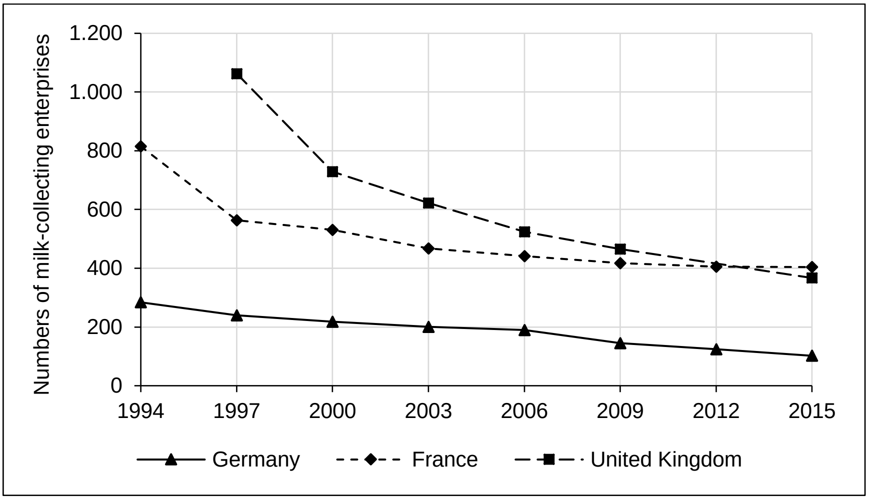

Figure 1-3. Number of milk-collecting enterprises in Germany, France, and the United Kingdom

Source of data: Eurostat (2018a)

The relevance of this development for the farming sector becomes apparent when considering the close link between the two stages. Via the milk payout price, the economic well-being of dairy farms is largely determined by the financial situation of the dairy processor. Additionally, due to the perishable nature of raw milk, farmers are often bound to a local dairy processor and confronted with an oligopsonistic market structure (Grau and Hockmann 2018). Another characteristic of the dairy sector is the significant share of farmer-owned dairy cooperatives. For example, in 2006, 57 out of 198 dairy processors were cooperatively organized in Germany (BMELV 2008). Due to their financial structure, necessary investments in new markets and products are a pertinent challenge especially for cooperatively-owned dairies (Grau, Hockmann, and Levkovych 2015).

However, not only dairy cooperatives but also investor-owned dairies face the challenge of finding viable ways to market the changing raw milk supply, which is no longer limited by a quota system. Overall, the necessary flexibility to react to political and market events increased in recent years for dairy processors (Hirsch et al. 2019). Additionally, on the demand side, European food firms are confronted with, in general, saturated markets and small growth rates in aggregate demand due to low population growth (Menrad 2004; European Commission 2016). They must cope with changing consumer preferences (Busse and Siebert 2018; Bigliardi and Galati 2013; Gormley 2018; Aguilera 2006); for example, trends toward organic and socially responsible products (European Commission 2016). Furthermore, they have to manage product quality and safety requirements (Trienekens and Zuurbier 2008), as well as legal requirements (Wijnands et al. 2008). Dairy processors also face growing vertical and horizontal competition due to increasing retail concentration (Weiss and Wittkopp 2005). For example, the German food retail sector is dominated by the five largest grocers who account for 70 percent of the retail market (USDA 2017). Consequently, the bargaining power of food retailers has increased in recent years, with possible implications for price transmission along the food chain (European Commission 2009a). Additionally, food retailers have started to compete directly with food processors by vertical integration with the help of private labels (Dobson, Waterson, and Davies 2003; Venturini 2006).

As a response to these challenges and also due to milk supply surpluses in domestic markets, one strategy followed by many dairies in recent years is the internationalization of business activities. Correspondingly, this entailed an internationalization of competition and the appearance of new competitors on foreign and domestic markets (Guillouzo and Ruffio 2005; Meyer, Feil, and Schaper 2019).

Considering this challenging market environment, it is not surprising that profit persistency among European dairy processors was found to be low compared to other sectors (Hirsch and Hartmann 2014). Therefore, dairy processors must find the right strategies and tools to succeed in the market over a sustained period.

1.2. The significance of productivity growth and innovation

Productivity growth—producing more output with the same amount of inputs or producing the same amount of output with fewer inputs—has been recognized as the main driver for output growth in agricultural production in developed countries over the past century (Ball et al. 2016). Although much has been achieved, improvements in agricultural productivity remain crucial for the sustainable provision of food, feed, fuel, and fiber. This becomes even more important with the current challenges of global warming and the growing world population. Dairy products are usually accredited with high nutritional values (FAO 2015). For the next decade, strong growth in dairy production is projected especially due to increasing demand in developing countries (OECD and FAO 2018). Regarding the environmental impacts, this can be seen as problematic since cattle farming is considered a particularly environmentally damaging activity mostly due to enteric methane emissions (Smith et al. 2014). In this respect, productivity increases can be a pathway to mitigate climate emissions per unit of output (Gerber et al. 2011).

Productivity growth is fueled by innovation activity, since innovations—by definition—aim to improve production technology, enable input savings per unit of output or allow higher quality outputs. Examples of innovations in dairy farming that promoted productivity in the last century include improvements with respect to genetics, milking systems, feeding, and herd management (Atsbeha, Kristofersson, and Rickertsen 2012; Gallardo and Sauer 2018).

The challenges for food processors, as outlined in the previous subsection, emphasize the importance of steady improvements in the production technology at the dairy processing stage. The ongoing concentration in the dairy processing sector and the consequent growth in the scale of operations can be one important driver for dairy processors' productivity growth. For US American dairy processors, this is shown by Geylani and Stefanou (2011). The authors find that during the period from 1972 to 1995, productivity was largely driven by the exploitation of scale effects. However, increasing the scale of production might not always be a viable strategy. In this case, dairy processors are bound to find ways of improving the production technology at the current scale of production. Therefore, innovations are pivotal for the competitiveness and the environmental impact of the food and dairy processors by allowing for a more resource and cost-efficient production. In this vein, innovation activity is generally regarded as a key factor for the competitiveness of food firms (Grunert et al. 1997). Innovative products allow producers to satisfy consumer needs and trends (Bigliardi and Galati 2013) and thereby strengthen the bargaining power of producers in negotiations with food retailers. They can also be a way to counter competition between manufacturers' and private labels (Venturini 2006). On the other hand, innovations in production processes are aimed at decreasing product costs, improving the quality of products, or enabling product innovations (OECD and Eurostat 2005). A high level of innovativeness can also prove advantageous in the context of the continuing trend of internationalization in the food sector. If food manufacturers aim at developing new, foreign markets then innovation activity can help by its expected positive effect on export performance (Lachenmaier and Wößmann 2006; Cassiman, Golovko, and Martínez-Ros 2010).

Moving beyond the firm level, from a consumer perspective, product innovation activity of food processors is a precondition for providing a wide product variety (Menrad 2004), and thereby influences consumer welfare (Stoneman, Bartoloni, and Baussola 2018).

All these considerations illustrate the significance of productivity improvements via innovation for the resource-efficient production and competitiveness for both the dairy farming and processing sector, as well as for consumer welfare.

1.3. Aim and structure of this thesis

Due to their significance for the well-being of firms and consumers, the links between innovation and productivity, as well as their external determinants have been extensively studied by researchers of various fields. Yet, the profound changes in the dairy sector in recent years have raised the need for further research on this topic. Both deregulation efforts and significantly increased milk price volatility have considerable potential to influence dairy farmers' investment decisions and innovation behavior. Thus, their implications on productivity dynamics and technological advancements in European dairy farming need to be evaluated.

Food and dairy processors are confronted with new challenges, and innovation activity can be expected to be one of the key factors that allows them to successfully compete in this dynamic market. In testing this assumption by studying the effects of innovation on firm performance, it must be considered that heterogeneity in innovation behavior across different manufacturing subsectors likely affects the links between firm performance and innovation. For example, the food sector is characterized by low research and development intensity and high new product failure rates. These specific conditions call for differentiated analyses that take into account this heterogeneity. Also, studying the effects of innovation activity on firm performance in individual subsectors such as the dairy sector allows more detailed results at the lowest level of sector disaggregation.

This thesis addresses these questions and presents four empirical studies for the European food and dairy sector, which shed light on the links between productivity, innovation, and recent changes to the political framework and the market environment.

The first two studies in chapters 3 and 4 focus on the dairy farming stage. Chapter 3 examines the aggregate productivity of the sector during the phase-out of the European milk quota regime. It tests the assumption that liberalizing the system has increased the resource reallocation toward more productive farms. Chapter 4 studies the course of technical change and investigates whether increased output price risk has had a detrimental effect on technical progress in German dairy farming.

The studies in chapters 5 and 6 focus on the stage of food processing and the firm-level productivity effect of innovation activity. Chapter 5 estimates the effects in the European manufacturing sector and explores sector heterogeneity by a comparison of the food sector with two high-tech sectors. Chapter 6 particularly focusses on the dairy processing sector and considers several innovation indicators.

Before all empirical studies are presented in full detail, the following chapter 0 discusses the general methodological framework employed by this thesis in an overview of concepts in production analysis and econometric estimation strategies. Abstracts of the studies can be found at the beginning of each chapter. Additionally, chapter 7 offers more detailed summaries of the studies. Chapter 8 finally discusses the findings and gives conclusions.

Table 1-1 summarizes the context, methods, and main findings of the empirical studies.

Table 1-1. Overview of the empirical studies (Part II)

Study/ Chapter	Research problem	Empirical case and data	Method	Core finding
Empirical study 1/ Chapter 3	Productivity dynamics in light of milk quota abolition and milk price volatility	Bavarian specialized dairy farms, financial accounts data	Endogeneity-robust production function estimation following Wooldridge (2009), calculation of sector productivity and reallocation effects following Olley and Pakes (1996)	Increase in resource allocation efficiency coinciding with the period of deregulation and high milk price volatility
Empirical study 2/ Chapter 4	Technological change with milk price volatility and milk quota phase-out	West German specialized and mixed dairy farms, financial accounts data	Output distance functions and estimation of output-biased technical change	Stagnation of technical change during the period of high milk price volatility despite the considerable willingness of farmers to invest
Empirical study 3/ Chapter 5	Differences in productivity effects by innovation in high-tech sectors vs. the food sector	Manufacturing firms, EU's Community Innovation Survey	Endogeneity-robust multi-step model following Crépon, Duguet, and Mairesse (1998)	Considerable differences in the effects of innovation: Positive effects in food firms and insignificant effects in high-tech firms
Empirical study 4/ Chapter 6	Efficiency effects of product and process innovation in dairy processing	Dairy processors operating in the German market, financial and patent data along with literature-based product innovation indicators	Endogeneity-robust estimation applying a system GMM approach	Significant positive effects by new products, but limited to products of high quality; insignificant effects for level of patenting activity

2. An Overview of Applied Concepts and Methods

This chapter reviews the concepts and methods employed in this thesis. Since the production function framework is used to measure firm performance in all empirical studies, basic concepts in this respect are laid out as follows.

2.1. Production analysis and productivity measurement

2.1.1. The production function

Production means the transformation of inputs into outputs by independent productive units, usually called firms. While the first two studies consider dairy farms as the productive units, companies in the food sector are considered in the last two empirical studies. A core assumption is that the technology of the production process can be described in mathematical form, for example, in the form of a transformation function:

$$T(q, x) = 0. \tag{2-1}$$

The vector q contains the quantities of outputs in the production process. The input vector x typically contains inputs under control of the production manager (Chambers 1988, 7). For the case of only one output, q reduces to a scalar and the transformation function can be reformulated to the production function:

$$q = f(x). \tag{2-2}$$

The production function describes the pure technical relationship between inputs and outputs. Further, it is assumed that a production manager chooses the greatest output that can be produced from a given amount of inputs. Therefore, the production function is single-valued and represents the maximum output attainable from a given set of inputs (Chambers 1988, 8).

The production function is usually ascribed a number of properties to ensure its viability from a theoretic standpoint. The list of these properties can include (Chambers 1988, 9; Coelli et al. 2005, 12):

- nonnegativity: $f(x)$ is a finite, non-negative, real number;
- weak essentiality: $f(0_n) = 0$, with 0_n as the null vector;
- monotonicity: if $x' \geq x$, then $f(x') \geq f(x)$;
- concavity: $f(\Theta x^0 + (1-\Theta)x^1 \geq \Theta f(x^0) + (1-\Theta)f(x^1)$ for all $0 \leq \Theta \leq 1$, that is, the output from any linear combination of input vectors x^0 and x^1 will be no less than the same linear combination of the outputs $f(x^0)$ and $f(x^1)$.

This list is not definitive and the degree to which these properties are maintained or imposed upon the production function depends on the individual research setting. Nonnegativity implies that output is never negative, and weak essentiality ensures that positive output cannot be produced from zero input. Monotonicity relates to how output reacts to changes in inputs and implies that an input increase is followed by a non-negative change in output. Therefore, marginal products are assumed to be non-negative, which is, however, not always self-evident. For instance, fertilizers as an input in agriculture can be assumed to have a detrimental effect on output if used excessively. Concavity implies non-increasing marginal productivities, meaning that an input increase is followed by an output decrease of the same proportion at most.

From the production function, useful measures can be derived for the analysis of the production technology. The marginal product of input n is calculated by the partial derivative of output with respect to input n:

$$MP_n = \frac{\partial f(x)}{\partial x_n}. \tag{2-3}$$

This measures the change in output quantity due to an infinitesimally small change in the quantity of input n, while all other factors are held constant. Since both output and inputs are measured in physical units, MP_n is in physical units. By multiplying MP_n with the output price, one arrives at the marginal value product (used in chapter 3 for deducting hypotheses).

A related, unitless measure is calculated by multiplying MP_n with the quotient of input n and output:

$$E_n = \frac{\partial f(x)}{\partial x_n} \frac{x_n}{f(x)}, \tag{2-4}$$

which is the output elasticity with respect to input n. It measures the percentage change in output from a given percentage change in input n while all other inputs are held constant. Under the assumptions of constant returns to scale (defined below) and cost minimization, output elasticities equal the cost shares of the respective inputs (Chambers 1988, 243) and can, therefore, indicate the importance of individual inputs in the production process.

While E_n measures the change in output due to a change in only one input, it is also of interest by how much output changes if all inputs are changed simultaneously. This can be evaluated by the elasticity of scale, computed by summing up all individual output elasticities, that is,

$$\varepsilon = \sum_{n=1}^{N} E_n. \tag{2-5}$$

A value for ε less than one signifies that a proportionate increase in all inputs will result in a less than proportionate increase in output (decreasing returns to scale). Firms operate at constant returns to scale, if ε is equal to one and a proportionate increase in all inputs will increase output by the same proportion. Increasing returns to scale are given when the result is a more than proportionate increase in output. Increasing returns to scale in general pose an incentive for profit-maximizing production managers to expand the scale of production, because, for example, a one-percent increase in inputs will increase output by more than one percent. Likewise, decreasing returns to scale are an incentive to decrease the scale of production, while constant returns to scale have neutral implications in this respect.

2.1.2. Efficiency, technical change, and productivity

The production function, in general, represents the maximum output for a given level of inputs, and firms are assumed to reach this output level. However, this assumption might be relaxed since due to certain circumstances, a firm might not be able to achieve this production maximum. This situation is illustrated for the one output, one input case in figure 2-1 (a). A firm operating at point A could move to point B and produce a greater amount of output using the same amount of input. Alternatively, it could move to point C and reduce input without reducing its output. Moving to point B or C would increase productivity, in this example equal to the average product ($AP = q/x$), which is represented by the slopes of the dashed lines through the origin.

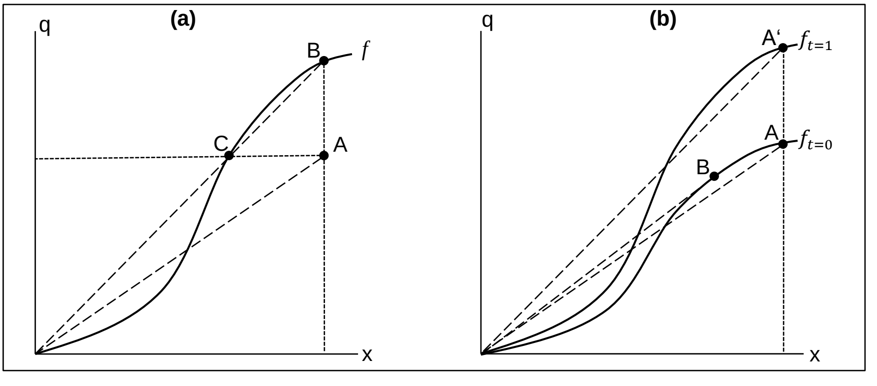

Figure 2-1. Illustration of technical inefficiency (a), scale efficiency and technical change (b)

Source: Own depiction following Coelli et al. (2005).

Since more input is needed per unit of output, a technically inefficient production plan by itself is wasteful. When firms are allowed to behave inefficiently, the production function is commonly referred to as the production frontier to emphasize that it represents the amount of output with technical efficiency. To measure the technical efficiency of a firm relative to another firm within the same industry, the production function can be modified to

$$y = A(\Theta) f(x), \tag{2-6}$$

which assumes that the firms employ production technologies that differ only by an efficiency function A, whose value depends on a parameter Θ (Chambers 1988, 246). Alternatively, technical efficiency (TE) can be described (in an output orientation) by the output distance function, which is defined as

$$TE = d_o(x, q) = \min\{\delta : (q/\delta) \in P(x)\}. \tag{2-7}$$

Here, $P(x)$ is the output set (or production possibility set), which is an alternative representation of the production technology by comprising all output vectors feasible with a given input vector x (Coelli et al. 2005, 42). Hence, by minimizing δ, the output distance function expands the output vector while remaining in the production possibility set. Accordingly, a value of one for δ would indicate technical efficiency and $\delta = 0.9$ would indicate 90% efficiency. A measure of technical efficiency change (TEC) of a firm between two periods can be constructed by comparing efficiency scores of the two periods s and t:

$$TEC = \frac{d_{ov}^{t}(q_t, x_t)}{d_{ov}^{s}(q_s, x_s)} \tag{2-8}$$

(Färe et al. 1994), which takes values above one if technical efficiency improves. A subscript v is added to emphasize that this measure is evaluated with variable returns to scale technology.

If the production technology exhibits variable returns to scale (increasing or decreasing returns to scale), then also the exact location on the efficient frontier has implications for productivity. This is illustrated in figure 2-1 (b): Firm A operates technically efficiently but can improve its productivity by moving to point B. Point B is the point of optimal scale since it maximizes productivity. Because the point of optimal scale exhibits locally constant returns to scale, a measure of scale efficiency can be computed by comparing output distance scores constructed with the assumption of constant returns to scale (d_{oc}) and variable returns to scale (d_{ov}). The scale efficiency measure

$$SE = \frac{d_{ov}(q,x)}{d_{oc}(q,x)} \tag{2-9}$$

will approach a value of one the closer the firm operates to the point of optimal scale, since in the point of optimal scale, the frontiers constructed under variables and constant returns to scale coincide. A measure of scale efficiency change can then be formulated as

$$SEC = \left[\frac{d_{ov}^t(q_t,x_t)/d_{oc}^t(q_t,x_t)}{d_{ov}^t(q_s,x_s)/d_{oc}^t(q_s,x_s)} \times \frac{d_{ov}^s(q_t,x_t)/d_{oc}^s(q_t,x_t)}{d_{ov}^s(q_s,x_s)/d_{oc}^s(q_s,x_s)}\right]^{1/2} \tag{2-10}$$

(Färe et al. 1994). The measure avoids preferring the technology of one period over the other by forming a geometric mean of two scale efficiency change measures. The first one computes scale efficiency change using period t technology (d^t), and the second one using period s technology (d^s).

When production is examined over time, it must be considered that the production technology changes over time. Technical change is illustrated in figure 2-1 (b) again for the one input, one output case. Technical progress manifests itself in an upward shift of the production frontier, allowing the production of a greater amount of output with the same amount of input. With this, a third factor that influences productivity of firms is identified: Firm A can improve its productivity by using the improved technology in $t = 1$ and moving to point A'. In terms of distances, a measure of technical change can be constructed as

$$TC = \left[\frac{d_{oc}^{s}(q_t, x_t)}{d_{oc}^{t}(q_t, x_t)} \times \frac{d_{oc}^{s}(q_s, x_s)}{d_{oc}^{t}(q_s, x_s)}\right]^{1/2} \tag{2-11}$$

(Färe et al. 1994). This measure is again a geometric mean of two technical change measures, using the information from both time periods. Each factor measures the frontier shift by comparing distances relative to period s and period t (constant returns to scale) technology, while holding outputs and input fixed.

Finally, technical efficiency change, scale efficiency change, and technical change can be combined into one productivity change measure. This measure takes the form of a Malmquist productivity index defined as

$$m_{oc}(q_s, x_s, q_t, x_t) = \left[\frac{d_{oc}^{s}(q_t, x_t)}{d_{oc}^{s}(q_s, x_s)} \times \frac{d_{oc}^{t}(q_t, x_t)}{d_{oc}^{t}(q_s, x_s)}\right]^{1/2} \tag{2-12}$$

(Färe et al. 1994), which is again a geometric mean of two indices. Each factor measures the productivity change using distances of two data points from different periods to a common technology as the reference. This index can be decomposed into the three components defined above:

$$\begin{aligned} m_{oc}(q_s, x_s, q_t, x_t) & \\ &= \left[\frac{d_{oc}^{s}(q_t, x_t)}{d_{oc}^{t}(q_t, x_t)} \times \frac{d_{oc}^{s}(q_s, x_s)}{d_{oc}^{t}(q_s, x_s)}\right]^{\frac{1}{2}} \times \frac{d_{ov}^{t}(q_t, x_t)}{d_{ov}^{s}(q_s, x_s)} \\ &\times \left[\frac{d_{ov}^{t}(q_t, x_t)/d_{oc}^{t}(q_t, x_t)}{d_{ov}^{t}(q_s, x_s)/d_{oc}^{t}(q_s, x_s)}\right. \\ &\times \left.\frac{d_{ov}^{s}(q_t, x_t)/d_{oc}^{s}(q_t, x_t)}{d_{ov}^{s}(q_s, x_s)/d_{oc}^{s}(q_s, x_s)}\right]^{1/2} = TC \times TEC \times SEC. \end{aligned} \tag{2-13}$$

By this, productivity change can be broken down into its sources of technical change, technical efficiency change, and scale efficiency change.

2.1.3. Estimation of productivity and its components

For estimation of the distances discussed above with observed production data, researchers can choose from a variety of parametric and non-parametric approaches. One prominent parametric approach is stochastic frontier analysis. Examples for applications of this model in the context of dairy farms include, among others, Hadley (2006), Alvarez and del Corral (2010), Abdulai and Tietje (2007), as well as Karagiannis, Midmore, and Tzouvelekas (2002). In this thesis, the approach is applied as a robustness check in chapter 3. Based on seminal articles by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977) the basic frontier model can be represented in logarithmic form by

$$\ln y = f(x) - u + v, \tag{2-14}$$

which is analogous to equation (2-6). Additionally, the equation contains an error term v, which accounts for idiosyncratic errors in the estimation of the equation. u is a positive, one-sided error term accounting for technical inefficiency and forms along with v a composite error term ($e = v - u$). Identification of the equation hinges on differing assumptions on the distribution of the two error terms v and u. While v is assumed to be normally distributed with zero mean and variance σ_v^2, u is assumed to be asymmetrically distributed, for example, following a half-normal distribution: $u \sim N^+(0, \sigma_u^2)$. After choosing a functional form for f, the model can then be estimated by maximum likelihood estimation.

With the help of estimated parameters, measures of efficiency change and technical change can be calculated. Technical efficiency can be estimated by $TE = E(\exp(-u)\,|e)$ (Battese and Coelli 1988), and a measure of technical efficiency change is given by

$$TEC = TE_t / TE_s, \tag{2-15}$$

which is analogous to equation (2-8). By incorporating a time index into the functional form of f, the technology is allowed to change over time. Technical change can then be evaluated using the estimated parameters. For example, by computing an index as

$$TC = \exp\left[\frac{1}{2}\left(\frac{\partial \ln y_s}{\partial s} + \frac{\partial \ln y_t}{\partial t}\right)\right] \tag{2-16}$$

(Coelli et al. 2005, 301). This index measures the change in the technology over time using the data of the two adjacent time periods and is analogous to equation (2-11). Lastly, a measure of scale efficiency change can be formulated as

$$SEC = \exp\left\{\frac{1}{2}\sum_{n=1}^{N}[E_{ns}SF_s + E_{nt}SF_t]\ln(x_{nt}/x_{ns})\right\} \tag{2-17}$$

with $SF_s = (\varepsilon_s - 1)/\varepsilon_s$ and ε_s and E_{ns} as defined by equations (2-4) and (2-5) (Orea 2002). Multiplying these components then yields the Malmquist index of productivity change. This approach is employed as a robustness check in the first empirical study in chapter 3 as well as in the second empirical study in chapter 4.

The stochastic frontier model as outlined in equation (2-14) lends itself specially to estimate a production technology with one output. With multiple production outputs, an alternative is the estimation of a distance function, for example, an output distance function as given by equation (2-7). By defining $\ln d_o \equiv -u$ and rearranging the distance function, an estimation equation similar to equation (2-14) is obtained, and the same measures of efficiency change, technical change, and productivity change can be calculated. This approach is applied in the second empirical study and further details can be found in the methodology section of chapter 4.

Another approach applied in this thesis is the direct estimation of the production function as

$$\ln y = f(x) + v, \tag{2-18}$$

with only one composite error term v, which contains both idiosyncratic errors and technical inefficiency. This approach avoids making specific assumption on the distributional shape of inefficiency. With estimates on the parameters of the production function, an estimate of firm-level efficiency can then be calculated as the residual composite error by rearranging the estimation equation (van Beveren 2012). This technical efficiency measure is equal to the time-specific productivity level if constant returns to scale apply. The approach is employed in the first study in chapter 3 and in the fourth study in chapter 6.

2.2. Measurement of innovation activity and links between productivity and innovation

A precondition for examining the relationship between innovation and productivity is a valid strategy to measure both variables. While productivity can be measured with the tools described in the preceding section, the question of correctly measuring innovation activity remains. In the past, a wide variety of innovation indicators has been developed (Dziallas and Blind 2019). Early seminal studies focused on expenditures for research and development activities (for example refer to studies in Griliches 1984). However, it can be argued that the innovation process is to be seen as a self-contained activity within the firm, which transforms innovation inputs into innovation outputs. Research and development expenditures then represent the input for the knowledge production process that builds up a firm's knowledge stock, which then, in a subsequent step, affects firm productivity (Pakes and Griliches 1980). Hence, it is not the innovation inputs but innovation outputs that are relevant for studying the influence of innovation on firm performance. While Pakes and Griliches (1980) propose patents as a measure of the relevant knowledge stock that affects firm productivity, other measures of innovation output include the number of new products and processes a firm implements (Becheikh, Landry, and Amara 2006; OECD and Eurostat 2005).

As discussed in section 1.2, innovation can be expected to be an important determinant of firm-level productivity. At the same time, a firm's productivity can be a determinant of the firm's decision on the level of innovation activities. For example, firms that achieve relatively higher productivity than in previous years or in comparison to competitors, are likely to be able to dedicate relatively greater resources toward their innovation activities. Further complexity is added to the relationship between productivity and innovation by the fact that both variables may be jointly affected by the same factors internal and external to the firm. For example, internal firm effects such as the specific business strategy of the firm can affect both firm productivity and the level of innovation activity. External effects can come in the form of differences between industry sectors. Pakes and Schankerman (1984) note that sector-specific conditions—such as the product market demand, technological opportunities, and the conditions for appropriating the returns from innovations—are important determinants of the firms' innovation activity within the sector. Such "contextual factors" (Becheikh, Landry, and Amara 2006) can simultaneously influence the average level of productivity within the sector. Furthermore, it can be considered to what extent time-lagged effects play a role. While it is to be assumed that past innovations can affect current productivity (for example, by patent protection of past innovations), past productivity can also affect current innovation activity.

Figure 2-2 schematically depicts these relationships between productivity and innovation considered in this thesis.

The studies in chapters 3 and 4 focus on aggregate productivity and technical change. Hereby, the link between firm-level productivity and the sector level as indicated in figure 2-2 becomes relevant. Improvements in production technology at the firm level are the driving force behind an outward shift of the production frontier at the sector level, i.e., technical change. They also influence the average level of productivity in the sector, which is examined in chapter 3 (besides the effect of reallocation of production resources).

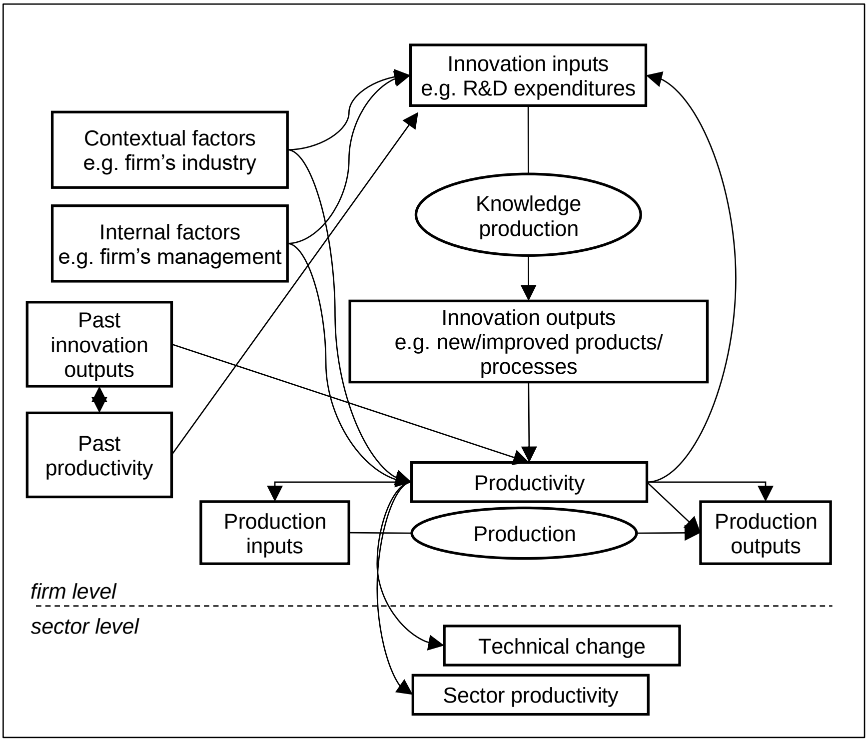

Figure 2-2. Illustration of considered links between productivity and innovation

Source: Own depiction following Crépon, Duguet, and Mairesse (1998), Becheikh, Landry, and Amara (2006)

The studies in chapters 5 and 6 directly focus on the effect of innovation on productivity. Chapter 5 examines this relationship for the food sector in comparison to two exemplary high-tech sectors. To this end, it makes use of a stepwise estimation procedure proposed by Crépon, Duguet, and Mairesse (1998). This model has the advantage of considering the entire innovation process, that is, the knowledge production process, as illustrated by figure 2-2. The study in chapter 6 considers contemporaneous effects and also lagged effects of innovation output on firm efficiency for the case of dairy processors.

Researchers' interests usually lie in establishing causal relationships between the two variables of interest. This task is complicated by the manifold relationships between innovation and productivity illustrated here. The next section discusses the econometric challenge and a possible remedy in more detail.

2.3. Econometric challenges

All empirical studies in this thesis apply regression analysis. A major concern in the regression analysis of observational data is the treatment of endogenous variables appearing on the right-hand side of the regression equation. The basic problem and instrumental variable estimation as a remedy are outlined below.

A simple linear regression equation with multiple independent variables can be represented by

$$y_1 = \beta_0 + \beta_1 y_2 + \beta_2 z_1 + u, \qquad (2\text{-}19)$$

with y_1 as the dependent variable, two independent variables y_2, z_1, and β_0, β_1, β_2 as (unobserved) parameters to be estimated. u represents an (unobserved) disturbance term. The primary interest lies in the identification of the slope parameters β_1 and β_2, which measure the partial effect of y_2 and z_1 on y_1. If all independent variables are exogenously determined, this can be achieved with Ordinary Least Squares (OLS) by minimizing the sum of squared residuals, or by a method of moments based approach (Wooldridge 2013, 72). However, one crucial assumption for this method to yield unbiased estimators is that the value of u does not depend on the independent variables. Formally,

$$E(u|y_2, z_1) = 0 \qquad (2\text{-}20)$$

(Wooldridge 2013, 70), that is, both y_2 and z_1 must be uncorrelated with u. Correlation between an independent variable and the error term can arise from the dependent and the independent variable being jointly determined (simultaneity), from unobserved variables affecting both the dependent and independent variable (omitted variable bias), or from measurement error. In this case, the affected independent variable is called an endogenous explanatory variable and, as a consequence, the OLS estimators for the parameters of the regression model are rendered biased and inconsistent (Wooldridge 2013, 87).

One prominent remedy to obtain consistent estimates is the instrumental variables approach. Assuming that y_2 is suspected to be an endogenous variable, this approach requires a third variable z_2 that is partially correlated with the endogenous variable but uncorrelated with the error term ($Cov(z_2, u) = 0$). Partial correlation of z_2 with y_2 is given when in the reduced form equation

$$y_2 = \pi_0 + \pi_1 z_1 + \pi_2 z_2 + v, \tag{2-21}$$

which expresses the endogenous variable as a function of all exogenous variables in the model, it holds that

$$\pi_2 \neq 0 \tag{2-22}$$

(Wooldridge 2013, 525). Under these conditions, z_2 serves as an instrumental variable for y_2 and consistent estimators for the model in equation (2-19) can be computed using a method of moments approach (Wooldridge 2013, 524). More generally, and especially when more than one variable is available as an instrumental variable, researchers can resort to the method of two stage least squares. Using this method encompasses in a first step the regression of the endogenous variable on all exogenous variables in the model, that is, a regression following equation (2-21). From this regression, the fitted values for the endogenous variable $\hat{y}_2$ can be obtained. In a second step, $\hat{y}_2$ is used in place of y_2 in the OLS estimation of the structural equation (2-19), which allows obtaining consistent estimators for the parameters in the original regression equation.

The problem of endogeneity frequently arises in economics since in many research settings and given the data observed, the independent variables themselves are variables chosen by individuals and are therefore not exogenously determined. For the identification of parameters in production functions, this issue has been recognized as early as by Marschak and Andrews, Jr. (1944). Specifically, the problem arises since the levels of production inputs are likely adjusted by production managers according to the expected efficiency observed by the manager but not the researcher. In the past, various remedies for this problem of endogenous input choice have been proposed (van Beveren 2012). Olley and Pakes (1996) suggested an estimation procedure that uses investment as a proxy for firm productivity. Levinsohn and Petrin (2003) built on this approach but proposed intermediate inputs instead of investment as the proxy variable. This strategy was questioned by Ackerberg, Caves, and Frazer (2006) due to collinearity problems in the estimation routine. Wooldridge (2009) suggested a modification of the approach by Levinsohn and Petrin (2003) and showed that the method reduces to a rather simple instrumental variable setup. Following a different approach, Blundell and Bond (2000) demonstrated how their earlier developed system GMM approach (Blundell and Bond 1998), which makes use of lagged regressors as instrumental variables, can be applied in the production function context.

As indicated by considerations in the previous section (2.2), the endogeneity problem also arises when incorporating innovation activity into the production function. Simultaneity is plausible by innovation activity affecting productivity and at the same time productivity affecting innovation activity. For example, entrepreneurs might decide on higher research and development budgets due to higher profits but, simultaneously, research and development output is suspected to be a determinant of firm profits. Secondly, it is likely that there are unobserved factors that affect productivity (and hence firm output) and innovation activity alike (omitted variable bias), for example, the specific business strategy the firm chooses. To study the effect of innovation on firm performance, a remedy for the endogeneity problem was proposed by Crépon, Duguet, and Mairesse (1998). Their estimation strategy builds on separate estimations of several stages of the innovation process, depicting the whole innovation process starting from the decision to conduct formal research and development up until the effect of innovation output on firm performance. For each estimation stage, the model makes use of instrumental variables available within the dataset.

The first, third, and fourth empirical studies in this thesis consider endogeneity-robust estimation strategies. The first study (chapter 3) considers endogenous input choice and employs the control function approach proposed by Wooldridge (2009). The third study (chapter 5) uses the estimation approach following Crépon, Duguet, and Mairesse (1998) to tackle endogeneity of innovation inputs in the knowledge production function as well as innovation output in the labor productivity function. The fourth study (chapter 6) employs a system GMM approach following Blundell and Bond (1998) and thereby tackles the endogeneity of both variable production inputs and innovation activity in the production function.

Part II. Empirical Studies

3. Deregulation and Productivity: Empirical Evidence on Dairy Production

This is a pre-copyedited, author-produced version of an article accepted for publication in the American Journal of Agricultural Economics following peer review. The version of record (Frick, Fabian, and Johannes Sauer. 2018. "Deregulation and Productivity: Empirical Evidence on Dairy Production." Amer. J. Agr. Econ. 100 (1): 354–78) is available online at: https://doi.org/10.1093/ajae/aax074

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3.1. Abstract

We investigate productivity development and its relation to resource reallocation effects in the dairy sector in southeast Germany during the phasing-out of the European Union milk quota. We hypothesize that both extreme output price levels and market deregulation fostered efficient reallocation of production resources. We use a farm-level dataset containing financial accounting data for a period of 15 years. Farm-level productivity is estimated by a proxy variable approach which is robust to endogenous input choice. We compare this approach to other estima-

tion techniques as well as an index based analysis. After aggregation we decompose sector productivity into unweighted mean productivity and a covariance term measuring the allocation of resources toward more productive farms. We observe an increase in the covariance term coinciding with a period of deregulation efforts and volatile milk prices. We seek to find support for our hypotheses by a regression analysis linking the measure for the potential covariance between resource reallocation and productivity on the one hand and deregulation as well as price variability on the other. In this analysis we find some empirical evidence for the hypotheses.

3.2. Introduction

In a well-functioning and free market, firms that cannot keep up with competitors are forced to reduce their market share or even cease their market participation. Thereby these firms release the resources bound by their production activity and make them available for production by more productive firms. This process contributes to a more efficient production at the sector level (i.e. aggregate productivity). Market regulation, however, is suspected to hinder this resource flow by keeping firms with low productivity in the market. This suspicion can also be applied to the case of the European Union (EU) milk quota system. The milk quota was introduced by the European Community in 1984 to restrict production volumes and avert high production surpluses that could only be removed from the market by high intervention costs. Originally introduced as only a temporary instrument for five years, the use of the quota was prolonged several times. With the quota regime in place, the expansion of a dairy operation was, in general, hindered by the additional costs of quota acquisition and ownership that can be seen as a source of additional rents for less productive farms. European dairy farmers were restricted to a certain output level by imposition of the "superlevy", a farmer was usually obliged to pay for production volumes exceeding the farm's quota. The final date of the abolition of the quota was introduced in the CAP reform of 2003 and confirmed in 2008. A phasing-out was performed by a stepwise increase of the quota volumes (soft landing approach). It can be expected that in the first years the distortionary effect imposed by the quota was strong considering the large additional costs expanding producers faced due to high quota prices. Toward the end of the quota system, the market disturbing effect might have become less significant since quota volumes were increased to an extent where milk quotas exceeded production on the EU level, and quota prices decreased (European Commission 2012).

Deregulation cannot be regarded as the sole driver for resource reallocation among farms. An important exogenous factor for a farmer's investment decision is the output price. The 2015/16 "milk crisis" in Europe and other parts of the world showed how susceptible farmers are to output price risk. Insisting calls for financial aid illustrate the possibly serious effect on the farm structure and indicate that price plunges are potentially followed by significant resource reallocation in the sector.

The research question we seek to answer by our analysis relates to in how far both these important factors—deregulation and output price risk—triggered efficient resource reallocation in the dairy sector in southeast Germany. Our work offers two contributions to the existing literature. First, on the methodological side, similar to van Biesebroeck (2008) and Petrick and Kloss (2013) we employ different approaches to productivity measurement and provide evidence on the relative performance of these estimators. And second, with significantly increased price volatility and more recently implemented deregulation measures, we examine two major events in the EU dairy sector whose recent effects on sector productivity have not been explicitly studied before to our knowledge.

3.3. Background

Restuccia (2016) described the underlying idea behind resource misallocation within an industry sector. The optimal reallocation of input resources among farms is given, when resources flow from farms with the smaller to farms with the greater marginal product. Any policy that dissuades an industry sector from reaching an optimal point of resource allocation will compromise aggregate output and productivity. Numerous studies confirm this principle by finding policy distortions predominantly negatively related to firm or sector performance. Outside of the agricultural economics literature examples include the work of Restuccia and Rogerson (2008) on a growth model calibrated with US data; the study by Eslava et al. (2004) on labor market, trade, financial, and social security reforms in the Colombian manufacturing sector; Hsieh and Klenow (2009), who found a positive effect of reforms on allocative efficiency for China, however, ambiguous results for India; and Guner, Ventura, and Xu (2008) who found rather negative effects of policies that restrict production of large firms or encourage production by small firms. As the agricultural sector is influenced by various policy measures in many countries, the effect of (de-)regulation on sector performance is of wide interest in the agricultural economics literature. An example of intensive policy control is the European Common Agricultural Policy and the implied subsidies and production quotas. If production quotas hinder the resource flow from less to more productive farms, this should be connected to decelerated structural change. It might therefore be expected that the abolition of the milk quota system will increase dynamics in the EU dairy sector (e.g. Boere et al. 2015). The empirical results for the EU are not unambiguous, however. Huettel and Jongeneel (2011), for example, showed that quotas do not necessarily dampen structural change. In their Markov chain model application on aggregate data for Dutch and German dairy farms they found that overall mobility of dairy farms increased rather than decreased with the milk quota in place. They attributed this effect to the stronger interdependency between growing and shrinking farms. On the other hand, they found exit mobility to be decreased under the quota regime, indicating that small and possibly less efficient farms were kept in the market. In contrast to these results, Kersting, Hüttel, and Odening (2016) indicated that, compared to a situation with no quota restrictions, the exit probability of less productive dairy farmers could be increased under a tradable quota regime since the selling of quota rights increased the liquidation value of farms. In their model, this resulted in higher mean productivity of farms in the sector. Zimmermann and Heckelei (2012) explored the determinants of Markov transition probabilities between size classes in various European regions. Partly, they found evidence that more liberal quota transfer mechanisms promote structural change (e.g. exit probabilities increased for smaller farms and decreased for the largest farms), and partly the effects could not be confirmed (e.g. negative effect of more liberal quota transfer on farm growth).

Results of studies explicitly focusing on the quotas' effect on sector performance point in the direction that production quotas negatively impact efficiency and productivity in the sector, however, the negative effect is reduced with increasing quota tradability. This result is e.g. confirmed in the study by Gillespie et al. (2015). In a stochastic frontier framework they applied a Malmquist productivity index on a panel of Irish dairy farmers reaching back to the pre-quota period. High productivity growth rates before the quota implementation, low growth rates in the first years of the quota regime, and increasing growth rates following policy reforms, reflect the hypothesized effect of the quota implementation and a liberalized quota trade on sector productivity. Colman (2000) showed that tradability of quota rights reduced sector inefficiency in the UK as quota could be transferred from less to more efficient farms. However, he demonstrated that in the case of the UK (in 1996/97), the optimal allocation of quota was not achieved, therefore, some inefficiency remained in the market. Furthermore, he argued that with high quota prices, the quota cost amounted to a significant share of total production cost, thereby posing a barrier for expanding farmers. A similar conclusion is drawn by Hennessy et al. (2009), who concluded that overall cost inefficiency of milk production in Ireland could be reduced by a national quota trading system compared to the existing regional trading system. With the abolition of the milk quota system the EU takes another step toward a more liberalized agricultural market already in place in other industrialized regions. Gray, Oss-Emer, and Sheng (2014), for example, examined productivity dynamics in the Australian broadacre agriculture in the context of policy reforms. They concluded that facilitated by comprehensive policy reforms, reallocation significantly influenced sectoral productivity gains and helped offset farm-level total factor productivity (TFP) decline. Kirwan, Uchida, and White (2012) examined the effect of the termination of production quotas in the tobacco sector in Kentucky. After the sudden elimination of quotas they found considerable resource reallocation flows accompanying the restructuring process in the sector and showed their positive effect on aggregate productivity.

Another factor that we take into account in our study is output price risk. That decreased price volatility in general helps farms to stay in business was found e.g. by Foltz (2004) for Connecticut dairy farms. Milk prices in the EU showed substantial fluctuations in the second half of our study period. After a phase of low prices from 2003 until 2007, the milk price reached a high in 2008, then declined sharply until 2010 before regaining the price level of 2008 in 2014. One hypothesis of our study builds on the assumption that higher output price risk encourages disinvestment decisions particularly of less productive farms. This assumption follows from the principle that with competitive input markets, less productive farms show higher average costs, and hence, with increasing output price volatility, the exit trigger is reached more easily for these farms. In this vein, Tauer (2006) illustrated for New York dairy farms how different milk price threshold levels can be set for the exit decision of farms in various size classes. Larger farms showed lower unit variable cost and hence were less likely to exit the market. Zimmermann and Heckelei (2012) found an overall negative effect of price volatility on investments by farms and especially small farms. They showed that by increasing milk price variation, exit probability was increased for small farms and decreased for large farms, farm size growth was negatively affected, and farm size decline positively affected. On the other hand, they also found a positive effect of price volatility on entry probabilities. Stokes (2006) found exit probability to be increased by higher price volatility for dairy farms of all size classes in Pennsylvania. In contrast to this, Pieralli, Hüttel, and Odening (2017) argued that irrespective of a farm’s efficiency, increasing output price volatility reduces the exit probability of farms. Deducing from a real options model they ascribed this effect to the increased value of waiting effected by increased volatility.

Both the deregulation and the output price effect on resource reallocation hinge on the assumption that, as a reaction to the exogenous stimulus, more productive farms are more likely to increase their production and less productive farms are more likely to reduce production or exit the market completely. This assumption seems reasonable given the basic assumption that competitive markets enforce "survival of the fittest" (Lambarraa, Stefanou, and Gil 2015), as well as empirical evidence from the existing literature. Lambarraa, Stefanou, and Gil (2015) e.g., found that in the case of Spanish olive farmers less efficient farmers are more likely to postpone investments. Pieralli, Hüttel, and Odening (2017) found that under given price volatility more efficient West German dairy farms are less likely to exit the market. Areal, Tiffin, and Balcombe (2012) showed that dairy farmers in Wales and England who acquired quota were likely to be also the more efficient ones.

Our article aims at contributing to the literature examining the influence of the EU milk quota on the efficiency of production. Similar to Kirwan, Uchida, and White (2012) we examine the effect of the removal of the production quota on reallocative efficiency and hence aggregate productivity. As shown before, there are numerous studies examining the impact of the EU milk quota on farm efficiency. Apart from Kimura and Sauer (2015) we are not aware of studies that quantify the contribution of efficient resource reallocation to aggregate productivity in the context of the abolition of the EU milk quota. A second aspect that we take into account in our analysis is the influence of volatile milk prices. Our article hence contributes by transferring the implications of the EU milk quota abolition and price volatility, which have been discussed in the aforementioned and other studies, from the micro to the macro level.

Before closing this section, a remark is in order about what is measured by the effect of resource misallocation on sector productivity. With productivity we examine predominantly the technical aspects of production and neglect other aspects that are of importance for agricultural production. In the context of resource reallocation this might be most prominently farm structure. If returns to scale are increasing, then efficient resource reallocation impacts farm structure. In Bavaria, where the data for our study stems from, structural change in the agricultural sector is primarily considered an unwanted development by many policy makers and sector representatives as small family businesses are regarded as an essential characteristic for the region highly valued by consumers. In the wider context of the EU, the intention of fostering small and medium sized farms can also be seen with the recent reform of the common agricultural policy 2014-2020. A simplified support scheme for small farmers was put in place, and the option of reallocating direct payments toward small and medium sized farms was given to the member states (European Commission 2013). Germany makes use of this option, with which the first 46 hectares of a farm are allocated a larger amount of direct payments (BMEL 2015). The inclusion of this reform in EU legislation is seen as a success also by Bavarian agricultural policy (StMELF 2014).

3.4. Theoretical framework and hypotheses

We start to outline our conceptual framework by briefly discussing the underlying theoretical framework and the derived hypotheses for our empirical study. We assume farmers to be risk-averse utility maximizers whose utility is a function of the distribution of profits for the farming operations. Farmers maximize the expected utility of the present value of future and present profits. By assuming that farms operate in competitive input and output markets we can proxy farm profitability by farm productivity. In each production period, farmers decide whether to increase, decrease, or maintain their production level. Ideally, profit-maximizing farmers increase their production until the marginal value products of inputs equal the respective input prices. We consider investment decisions in dairy farming as in general risky, since they are often linked to investments in fixed property like animal housing or milking technology and hence are nonreversible (or only costly reversible, see Hüttel, Mußhoff, and Odening 2010). Hence, fixed capital costs combined with volatile output prices pose a considerable risk to the future liquidity of the farm. As input markets are competitive, input prices (e.g. for farm equipment like animal housings, materials, etc.) can be expected to be the same for all farms, i.e. investment costs are the same at a given scale of operation and level of productivity. We can express production output of farm i in year t as a function of K production inputs X_{ikt} using a common technology $f(.)$. Furthermore, production output depends on a technology shift factor A_{it}:

$$Q_{it} = A_{it} f(X_{i1t}, X_{i2t}, \ldots, X_{iKt}) \quad \text{with} \quad t = 1,2,\ldots,T \quad \text{and} \quad i = 1,2,\ldots,N. \tag{3-1}$$

We adopt A_{it}, which contains technical efficiency and technical change, as a productivity measure. We acknowledge, however, that A_{it} is only equal to productivity in the absence of scale efficiency effects.[2] The marginal physical product (MPP) and the marginal value product (MVP) of the kth input for farm i and year t are given by, respectively,

$$MPP_{ikt} = A_{it} \frac{\partial f(X_{i1t}, X_{i2t}, \ldots, X_{iKt})}{\partial X_{ikt}} \quad \text{and} \quad MVP_{ikt} = \eta_{it} A_{it} \frac{\partial f(X_{i1t}, X_{i2t}, \ldots, X_{iKt})}{\partial X_{ikt}}, \tag{3-2}$$

with the output price η_{it}. Equations (3-2) show that A_{it} is positively related to both MPP and MVP. In the case of constant returns to scale and under the assumption that inputs are used in fixed proportions (as it would be given under allocatively efficient behavior and constant input price ratios) the variation in MPP and MVP can even be fully explained by variation in A_{it} (keeping the output price fixed). We therefore propose that discrepancies in A_{it} are a sufficiently precise measure of heterogeneity in MPPs and MVPs. Conforming with the results

[2] As will be seen in the results of our analysis, the productivity growth rates generated from this measure are highly correlated with productivity growth rates calculated by a Törnqvist index approach which naturally accounts for scale effects. We are therefore confident that negligence of scale effects does not compromise the productivity measure generated by A_{it}.

by Lambarraa, Stefanou, and Gil (2015) as well as Areal, Tiffin, and Balcombe (2012), we assume that, as a reaction to deregulation (increasing availability of quota rights), more profitable i.e. more productive farms (above average A_{it}) are more likely to invest as they show on average greater marginal value products and hence expect greater payoff for in general risky investment steps. At the same time, as more production resources are reallocated toward farms with the greater MPPs, this contributes positively to sector productivity. This leads us to Hypothesis 1:

Hypothesis 1: Efficient resource allocation and hence sector productivity is positively affected by increasing deregulation of the dairy sector.

One inherent influence on the investment decision is the marketing risk expected by farmers. On the one hand, since farmers are to behave as risk-averters, we expect that increased price volatility discourages all farmers (irrespective of whether they show above-average or below-average productivity) from investing in new farm equipment (compare to Zimmermann and Heckelei 2012). On the other hand, we expect that in times of uncertain future revenues, farmers are encouraged to further optimize their production practices toward input-saving techniques, hereby using the widening of profit margins as a risk management strategy for output price risk. Both these effects have an influence on mean productivity growth of farms and hence, on sector productivity. As we expect for these effects both a negative and positive influence, respectively, we do not further consider the sum of these effects on mean farm productivity. Instead, we focus on another mechanism: In line with the conclusions by Pieralli, Hüttel, and Odening (2017), we expect increased price risk to put more financial pressure on less productive farms, therefore encouraging them to exit the market, and hereby freeing resources that can be absorbed by more productive farms that have a more solid financial basis to cope with price volatility. Again, more production resources are reallocated toward more productive farms which results in improved sector productivity. We therefore hypothesize:

Hypothesis 2: By fostering reallocation of production resources toward more productive farms, output price risk contributes positively to overall sector productivity.

The empirical implementation of the hypotheses is shown in section "Empirical Modelling".

3.5. Endogenous input choice

The methodological difficulties of estimating production functions are known since Marschak and Andrews, Jr. (1944) but have received renewed interest in more recent years as new techniques became available to overcome the problem of endogenous input choice. A comprehensive overview of techniques that have been proposed is provided by van Beveren (2012). The problem arises because firms choose production inputs according to factors potentially unobservable by the econometrician. Assuming a Cobb-Douglas technology a firm's production process can be formalized as

$$q_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + v_{it}, \tag{3-3}$$

that is, firm i's output y in year t is described by the production inputs capital k, labor l, and intermediates m, all in logarithmic values. Besides the stochastic error, v captures the firm's productivity and a simple way of measuring productivity seems to consist of estimating (3-3) by OLS and calculate productivity as

$$p_{it} = \hat{\beta}_0 + \hat{v}_{it} = q_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it} \tag{3-4}$$

(see van Beveren 2012). However, it must be assumed that v is not only determined by random effects but rather has two components which can be shown by rewriting (3-3),

$$q_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \epsilon_{it}, \tag{3-5}$$

where ϵ represents a stochastic component due to measurement error or random shocks experienced by the production process. Factors such as managerial ability, expected weather events or livestock related characteristics are captured by ω. Both terms are not observed by the econometrician, however, ω may be known or predicted by the farmer prior to choosing levels of variable inputs. If this is the case, then variable inputs and ν are not independent and estimation of (3-3) using OLS yields biased results. To counter this, Olley and Pakes (1996) developed a two-stage procedure where in a first stage a reduced production function is estimated with investment used as a proxy for the productivity shocks observed by the firm and correlated with variable inputs (for details see Olley and Pakes 1996; Ackerberg, Caves, and Frazer 2006; van Beveren 2012; Ackerberg et al. 2007). Levinsohn and Petrin (2003, "LP") pointed out that the approach suggested by Olley and Pakes (1996) can be problematic due to the fact that capital is an input costly to adjust, probably leading to lumpy investment and datasets with a considerable share of zero investments. In this case, the assumption that investment is strictly increasing in unobservable productivity shocks does not hold, thus, ω cannot be formulated as a function of capital and investment. This problem can also be expected to affect the estimation of production functions of farms, considering that farms are small firms and acquisitions in machinery, animal housing, or milking equipment are major investments which are usually undertaken only once every few years. LP modified the approach and suggested intermediate inputs rather than investment as the proxy for unobserved productivity shocks.

The approaches by both Olley and Pakes (1996) and LP are challenged by Ackerberg, Caves, and Frazer (2006). They pointed out that without additional assumptions, the labor coefficient cannot be identified in the first stage of the algorithms due to collinearity between labor input and the non-parametric function used to substitute for productivity shocks. Wooldridge (2009) showed how the two-step approaches by Olley and Pakes (1996) and Levinsohn and Petrin (2003) can be reduced to an instrumental variable procedure. This approach has two main advantages: It is robust to the criticism of Ackerberg, Caves, and Frazer (2006) and standard errors can be easily obtained. As we apply this approach as the reference methodology in our study, we give a formal representation. Wooldridge (2009) as well as LP and Olley and Pakes (1996) describe the productivity process as

$$\omega_{it} = E(\omega_{it} | \omega_{i,t-1}) + \xi_{it}, \tag{3-6}$$

that is, as the sum of a first-order Markov process and the "innovation component" of productivity, ξ_{it}, which comprises productivity deviations independent from past productivity. Production inputs are divided into freely variable ones and the state variable capital which is fixed at the time of production. It is assumed that the state variable, as well as all past realizations of the freely variable inputs labor and intermediates are uncorrelated with ξ_{it}. Current realizations of the freely variable inputs are allowed to be correlated with ξ_{it}. The core assumption of the approach is that ω_{it} can be expressed as a function of the state variable and a proxy variable (intermediates in the methodology of LP). Equation (3-6) can then be rewritten as

$$q_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + g[h(k_{i,t-1}, m_{i,t-1})] + \xi_{it} + \epsilon_{it}, \tag{3-7}$$

where $g[h(k_{i,t-1}, m_{i,t-1})] \equiv E(\omega_{it} | \omega_{i,t-1})$, i.e. $h(.)$ describes contemporaneous ω_i and $g(.)$ accounts for the component of ω_i transmitted through time. This corresponds to equation (2.11) in Wooldridge (2009). Wooldridge (2009) specifies a second equation that identifies the coefficients of interest to improve efficiency in a system estimation. However, the coefficients of interest can already be extracted by estimating equation (3-7) by using appropriate lagged values as instruments. Specifying the composite error as $\phi_{it} = \xi_{it} + \epsilon_{it}$, the necessary orthogonality conditions are given by

$$E(\phi_{it} | k_{it}, k_{i,t-1}, l_{i,t-1}, m_{i,t-1}, \dots, k_{i1}, l_{i1}, m_{i1}) = 0, \qquad t = 2, \dots, T \tag{3-8}$$

(see equation 2.12 in Wooldridge 2009). The form of the control function $g[h(.)]$ is unknown and therefore implemented by a polynomial of high enough order of

$k_{i,t-1}$, and $m_{i,t-1}$, with the contained variables able to act as their own instruments. Also, k_{it} acts as its own instrument, and the endogenous regressors l_{it} and m_{it} are instrumented by $l_{i,t-1}$ and $m_{i,t-2}$, respectively.

Several applications of the described approaches exist in agricultural economics. Kazukauskas, Newman, and Thorne (2010) applied a modified approach of Olley and Pakes (1996) on a sample of Irish dairy farms. Kazukauskas et al. (2013) did not estimate productivity but included in their estimation model a control function based on LP. Rizov, Pokrivcak, and Ciaian (2013) extended the approach of Olley and Pakes (1996) to estimate the effect of subsidies on farm-level productivity in the EU-15. Kirwan, Uchida, and White (2012) used the LP estimator to generate production function estimates used then to construct aggregated industry productivity. Petrick and Kloss (2013) applied the LP approach on European crop farms comparing different estimators. They concluded that the LP estimator offers a viable approach to productivity measurement also with respect to agricultural applications. In a second article, Kloss and Petrick (2014) also found the Wooldridge (2009) LP modification to be a viable alternative. However, they noted that the control function approach incorporating intermediates as a proxy to control for productivity shocks may be questionable in the agricultural context, as a farmer's reaction to a positive productivity shock might be to use fewer instead of more intermediate inputs (e.g. favorable weather or livestock conditions requiring less intensive chemical plant protection or veterinary input).

Another widely applied approach to measure productivity at firm level consists of estimating stochastic production frontiers. Productivity change can then be calculated indirectly applying a Malmquist index comprising technical efficiency change, technical change, and possibly a scale efficiency change effect. The error term is divided into a random noise component and a stochastic inefficiency component. Endogenous regressors can be correlated with either of these two components (see e.g. Mutter et al. 2013). Therefore, standard stochastic frontier approaches to productivity measurement are expected to yield similarly biased results as obtained by OLS based estimation approaches. However, there are several studies concerned with endogeneity-robust estimation of production frontiers (Kutlu 2010; Shee and Stefanou 2015; Tran and Tsionas 2013; Kazukauskas, Newman, and Thorne 2010).

3.6. Dataset

We employ a dataset on Bavarian dairy farms that is part of the European Farm Accountancy Data Network (FADN). Bavaria is a German federal state (NUTS 1 region) located in the southeast of Germany. Agriculture in Bavaria is still characterized by relatively small family farms. In 2013, the average farm in Bavaria cultivated about 33.6 hectares of land (European Commission 2015a). As already mentioned, a major goal of the Bavarian state government is to slow down the pace of structural change for reasons of social and regional policy as well acceptance of modern agricultural production in society; a relatively low yearly rate of 1.5% of all farms closing in the period 2010 to 2013 is regarded as mid-term goal for regional agricultural policy (see StMELF). The data is collected by the Bavarian State Research Center for Agriculture (LfL). The dataset is designed as a stratified sample according to farm location, size classes, and specialization of the farms. The data contain financial records and additional socio-economic information on the use of family labor or education of the farm manager. One major advantage of the dataset is that physical output quantities and output prices are consistently reported. This allows us to accurately deflate revenues to arrive at quantity indices that do not include price effects. The dataset covers a period of 15 years (2000-2014). In large part (42%) the farms in the dataset are included over the whole time span. On average, in each year 3% respectively of the farms exit or enter the panel. Descriptive statistics of output and input variables and details on their construction are discussed in the Appendix. Although our dataset is based on a regional sample of farms, the results of the study are highly relevant in a larger European context: (i) Bavaria is the largest milk producing region in Germany and accounts for a significant proportion of the milk production in the EU, and (ii) dairy farming in Bavaria is characterized by a large share of small family farms and slow structural change and, therefore, is representative for many other European regions. The following numbers illustrate these two points. In 2004, Bavaria produced approximately 27 and 5% respectively of the milk in Germany and the EU-27 (European Commission 2015a). External workers, i.e. workers that are not family-related, are employed in only 8.5% of the observations in our dataset. Concerning the pace of structural change, using numbers from the Eurostat database (European Commission 2015a) aggregated for NUTS 1 regions, it can be shown that from 2005 to 2013 the number of specialized dairy farms in the European regions decreased at an average yearly rate of −4.8%. The average yearly rate of −3.5% for Bavaria lies close to this value. Speaking of farm sizes (2005-2013, 4 years available), the regions show an average of 94.4 livestock units (LSUs) per farm, whereas in Bavaria the farms are smaller with an average of 52.4 LSUs per farm. Still, it lies close to the average of 58.1 LSUs per farm of the group of regions with an average farm size up to 120 LSU per farm which represents 75% of all regions in the database. On average, from 2005 to 2013 LSUs per farm grew by 4.7% per year in all regions while in Bavaria specialized dairy farms grew at a similar rate of 3.3% per year.

3.7. Empirical modelling

In this section we describe the methods we apply to estimate farm-level productivity levels, how we aggregate farm-level productivity to sector productivity, and how we aim to explore the determinants of the reallocation effects.

3.7.1. Production function estimation

To verify the robustness of our estimation results and to compare the performance and robustness of different methodologies we measure productivity in various ways. We apply (i, ii) two specifications of the Wooldridge (2009) LP modification approach ("WLP"), (iii) an OLS approach based on fixed effects modelling ("FE"), (iv) a conventional stochastic frontier approach ("SFA"), where we calculate a Malmquist TFP index as a result of technical efficiency change, technical change, and scale effects, (v) a second SFA approach using a reduced set of inputs and outputs to address problems due to input aggregation, and (vi) a deterministic approach using a Törnqvist TFP index. In all regression-based approaches we include in general the same production inputs and controls as well as a quadratic time trend. For the fixed effects and stochastic frontier models, we apply translog production functions. For the WLP models, we apply Cobb-Douglas production functions to avoid identification problems due to multicollinearity between the production inputs and the control function variables. In general, we estimate production functions in the form

$$q_{it} = \beta_0 + x'_{it}\beta_1 + eco'_i\beta_2 + org_{it}\beta_3 + edu_{it}\beta_4 + age_{it}\beta_5 + \mathrm{sec}_{it}\,\beta_6 + \beta_t t + \beta_{tt}t^2 + e_{it}, \quad \text{(3-9)}$$

where q_{it} is the logarithmic output, row vector x'_{it} contains either only linear (for the Cobb-Douglas specifications), or linear, interaction, and squared terms (for the translog specifications) of the logarithmic production inputs *cows*, *capital*, *labor*, and *intermediates*, and we include a quadratic time trend as well as controls for agro-ecological zone (*eco'*), organic production (*org*), education (*edu*) and age (*age*) of the farm manager, and a dummy variable indicating that farm income is only secondary income for the farm household (*sec*). In case of the WLP and FE approaches we calculate estimated productivity as

$$p_{it} = \hat{\beta}_0 + eco'_i\hat{\beta}_2 + org_{it}\hat{\beta}_3 + edu_{it}\hat{\beta}_4 + age_{it}\hat{\beta}_5 + \mathrm{sec}_{it}\,\hat{\beta}_6 + t\hat{\beta}_t + t^2\hat{\beta}_{tt} + \hat{e}_{it} = q_{it} - x'_{it}\hat{\beta}_1, \quad \text{(3-10)}$$

where compared to equation (3-1), $p_{it} \equiv \ln A_{it}$. Treatment of the error term (e) and the constant (β_0) differs between the WLP and FE approaches, thus, we report details in the appendix, along with details on the estimation and calculation of p_{it} for the SFA and the index approaches. We follow a static representation of the production function in a sense that only this year's inputs are relevant for this year's output (as many other empirical applications on dairy farms also assume, see e.g. Gillespie et al. 2015; Emvalomatis, Stefanou, and Oude Lansink 2011; Areal, Tiffin, and Balcombe 2012; Brümmer, Glauben, and Thijssen 2002;

Kumbhakar, Tsionas, and Sipiläinen 2009). However, the WLP approach can be considered as dynamic insofar as the framework allows for serial correlation of unobserved productivity (see equation 6).

For the WLP approach the question of a suitable proxy to control for productivity shocks must be considered. As mentioned before, not every category of intermediate inputs might be correlated with productivity shocks at farm level. We apply two different proxies: (1) deflated costs for concentrated feed only, and (2) deflated costs for all intermediates by following the "standard" LP approach. We argue that the first model is based on a more realistic approach since in dairy farming additional milk output caused by productivity shocks must be balanced out with additional energy equivalents in feed rations (in simple words: if a cow produces more milk, it needs to have greater feed intake to balance energy output and input, see e.g. House 2011). We imagine a situation where a farmer achieves a greater milk output relative to another or the same farmer in the previous year through greater managerial effort; then, the more productive herd needs to have the greater feed intake. Hence, assuming equal capital and labor endowments of the two farms, feed consumption should be correlated with TFP. This might not be the case for other intermediate inputs—take as an example veterinary costs, which might even be negatively correlated with productivity (assuming that good managerial ability leads to greater milk output and better health status of the herd). We also find a counter-argument for the feed proxy. Consider two farms with the same feed inputs, and one farmer with greater managerial ability; then, there is no connection between productivity and feed input if the farmer with inferior managerial ability does not adapt his feeding strategy (or if lower feed intake of the herd is not reflected in the accounting data, e.g., because of storage of concentrates). As the choice of proxy is not straightforward, we employ two different proxies: the feed proxy and the total intermediates proxy based on the "standard" LP approach, which enables us to compare the outcomes of both specifications.

Table 3-1 compares the approaches applied in this study. Details for all estimated models and calculations are given in the Appendix. The first WLP specification is our preferred model since it is robust to potential endogeneity and allows the estimation of TFP levels rather than growth rates.

Table 3-1. Comparison of approaches to productivity measurement

Approach	Paramet-ric/ Non-paramet-ric	TFP	Endogeneity-cor-rected?
Wooldridge-Levinsohn-Petrin	Paramet-ric	TFP level: estimated input coefficients and rearrange-ment of the production func-tion following equation (3-10)	If farm-level produc-tivity is assumed to be a function of proxy variable
Fixed Effects panel estimation	Paramet-ric	TFP level: estimated input coefficients and rearrange-ment of the production func-tion, following equation (3-10)	If farm-level produc-tivity is assumed to be time-invariant
Stochastic Fron-tier Analysis	Paramet-ric	TFP growth rate: result of technical change, technical efficiency change and scale efficiency change	No
Törnqvist TFP index approach	Nonpara-metric	TFP growth rate: growth of output index less growth of an input index	Deterministic ap-proach, endogeneity not relevant

Source: own compilation

3.7.2. Aggregate productivity

Following Baily, Hulten, and Campbell (1992) and Olley and Pakes (1996), we first aggregate individual productivity levels to sector productivity as the output share weighted mean

$$p_t = \sum_{i=1}^{N} \lambda_{it} p_{it}, \tag{3-11}$$

where p_t denotes aggregate sector productivity and p_{it} is individual productivity. λ_{it} represents farm i's sample share of physical milk output in year t. Sector productivity is then further decomposed according to

$$p_t = \bar{p}_t + \sum_{i=1}^{N} (\lambda_{it} - \bar{\lambda}_t)(p_{it} - \bar{p}_t), \tag{3-12}$$

where bars over variables denote unweighted means. The first term on the right-hand side of equation (3-12) is the unweighted mean productivity in year t and accounts for sector productivity growth generated within farms ("within effect"). We denote the second term on the right-hand side as covariance-type term (cov) as it resembles the calculation of the sample covariance without division by sample size.[3] This term accounts for contribution to sector productivity by reallocation effects ("between effect"). In comparison to other decomposition approaches that have been proposed, this method has the advantage that correct measurement of farm entry and exit is not crucial (Foster, Haltiwanger, and Krizan 2001). Our dataset is not free from attrition and does not include an indicator of whether farms are exiters or entrants to the market or just to the sample.

Petrin and Levinsohn (2012) indicate that such a definition of aggregate industry productivity is problematic. They argue that the definition of industry productivity and reallocation effects used by Baily, Hulten, and Campbell (1992) and Olley and Pakes (1996) might not correspond exactly to the true aggregate productivity and reallocation dynamics. Instead, they propose to calculate aggregate productivity growth as the change in aggregate value added less aggregate changes in primary input use. Then, aggregate productivity growth can be decomposed into

[3] Omitting division by sample size makes the covariance measure sensitive to changes in the sample size. Our sample indeed experiences growth in size to a level of 119% in 2006 compared with 2000. However, we do not assume this to be a problem for the results of our study since the sample size decreases after 2006 and the fluctuation in the number of observations does not coincide with variation in the covariance term.

the respective contributions of firm-level productivity growth and reallocative efficiency. Petrin and Levinsohn (2012) show how their reallocative efficiency measure is based on wedges between input revenue shares and output elasticities. In theory, profit maximizing firms keep these wedges as small as possible. As a robustness check, we applied the methodology of Petrin and Levinsohn (2012). However, we faced difficulties in obtaining reliable results due to the fact that the farms in our dataset are characterized by a large share of family labor, for which wages are not reported. For the calculation of labor costs we therefore have to rely on standard wage rates reported by an official agency. The same applies to capital as farmers in our dataset employ a large share of proprietary capital (the mean of the ratio bank loans to proprietary capital is only 15% for our sample) for which interest rates (reflecting opportunity costs) are not reported. When applying the method of Petrin and Levinsohn (2012) we saw that our results are sensitive to the definition of the costs of primary inputs. We therefore resorted to the definition of aggregate productivity used by Baily, Hulten, and Campbell (1992), Olley and Pakes (1996), and others. We report the results of the Petrin and Levinsohn (2012) decomposition in the appendix. We cannot reject that our results might be flawed by the discrepancy between the calculated aggregate productivity and the true aggregate productivity as explained by Petrin and Levinsohn (2012). Nevertheless, we still consider the method used in our study to be a valid index suitable for quantifying sector productivity and reallocation effects. Finally, we do not experience problems with large and volatile reallocation terms as Petrin and Levinsohn (2012) do with respect to their data on manufacturing firms. In the appendix (table 3-11), we report results of a robustness check that was proposed by an anonymous reviewer. There, we aggregate inputs and outputs by summing them up for each year and calculate an aggregated Törnqvist TFP index with the use of mean cost shares. The results for this measure of aggregate productivity closely follow the measure we have calculated following Baily, Hulten, and Campbell (1992) and Olley and Pakes (1996).

3.7.3. Explaining productivity dynamics

In a second part of our study, we further explore the determinants of reallocation events. We examine the hypothesized links in a panel estimation set-up. The model aims at uncovering the policy-induced effect and the effect of price risk on efficient resource reallocation while controlling for other factors. As dependent variable we use the farm-level covariance term, given as

$$cov_{it} = \left(\lambda_{it} - \bar{\lambda}_t\right)\left(p_{it} - \bar{p}_t\right), \tag{3-13}$$

with variables defined as before. Herewith, we focus on the individual farm level with respect to the covariance term. A farm shows positive cov_{it} (i.e. contributes positively to sector productivity), if it is more productive than average and holds an above-average market share, or if it is less productive than average and has a below-average market share. Following our hypotheses, two influencing factors are of special interest in this context: The milk quota's regulatory power and output price risk. To quantify the regulatory power of the milk quota, several possible measures come to our mind. First, the price of quota rights that was set on quota exchanges can act as a measure of the regulatory power of the quota regime. The lower the price for quota rights, the lower the investment barrier for more productive farmers willing to expand their production. Hence, the market share of more productive farms should increase, and lower quota prices should be associated with a higher farm-specific covariance term. This also corresponds to the hypothesis stated by Huettel and Jongeneel (2011): If the quota regime keeps the production volumes of farms tied together, decreasing quota prices would only further accelerate resource reallocation toward more productive farms. Second, the milk quota volumes were increased from 2006 until 2008 by 0.5% per year, in 2008 by an additional 2% and from 2009 until 2013 by 1% per year. These increases are also mirrored in the quota growth rates of farms in our dataset (see table 3-6). We consider these increases to be important deregulation steps that had—as already formulated in Hypothesis 1—a positive effect on efficient resource reallocation. Third, we cannot rule out that the confirmation of the abolition of the milk quota in 2008 had a psychological impact on farmers' (dis)investment decisions. Fourth, another deregulation effort was the restructuring of the quota trade system. Until March 2007, quota rights could only be traded within the seven administrative districts in Bavaria, i.e. the quota balance of the districts was even. Starting from April 2007, quota rights could be traded between Bavarian regions and also between the German federal states. As both these events coincide with the quota increases, we expect these additional policy-induced effects to be controlled for by the quota growth variable we include in our regression model. Other non-quota related policy effects could stem from the decoupling of direct payments and the reduction of intervention prices. The decoupling of direct payments was already effected in 2005/06. We can therefore credibly assume that if the decoupling had an effect on resource reallocation, it was only a delayed effect that commingled with the quota effect. Additionally, intervention prices for milk products were decreased starting from 2004. This might have had an indirect impact on dairy farmers by contributing to the increased price volatility in the subsequent years, which we explicitly take into account in our analysis as a separate factor. The variables that we include in the analysis as deregulation measures are the quota volume increases and the quota exchange price. The variable "quota increase" (*inc*) is the yearly median of quota growth we observe in our dataset and hence does not vary across farms. The variable "quota price" (*pri*) varies across years and seven regions within Bavaria until 2007 (if also with high correlations), as prices were set on separate exchanges. After 2007, only one price was set for all of Germany, hence, quota prices do not vary across regions for this period in our study.

The second important component of our analysis is output price risk. We quantify output price risk with milk price volatility which we measure as the standard deviation of the milk price the farmer received in the current and the preceding years. Corresponding to Hypothesis 2, we expect farm-level milk price volatility to have a positive impact on the covariance term cov_{it}: We postulate that less productive farms ($p_{it} - \bar{p}_t < 0$) show increasing cov_{it} with increasing price volatility, as they are forced to reduce their market share (decreasing $\lambda_{it} - \bar{\lambda}_{it}$). In this vein, also the above-average productive farms ($p_{it} - \bar{p}_t > 0$) show increasing cov_{it} as they can passively increase their market share (increasing $\lambda_{it} - \bar{\lambda}_{it}$). The question is how many lags of the farm-level milk price are to be considered with respect to the volatility measure, i.e. whether only the last year's milk price change or also volatility in earlier years has an influence on the farmer's present behavior. We calculated several standard deviations with differing time horizons from two years up to the last five years. To avoid collinearity in the model (as the standard deviations show high correlation coefficients) we decided to run separate regressions, each including a different lag of the standard deviation of the last three years' milk price ($SD3$). Also, the quota exchange price shows high correlation with its lagged values. We include only last year's quota price to account for the possibly delayed effect of the quota price on investments.

Besides deregulation and output market effects we can also think of other possible reasons for an increase or decrease in the covariance term. First, one may consider weather as an important factor in agricultural production that influences productivity and therefore also cov_{it}. However, we think that in our study weather is not a significant factor as it is concerned with specialized dairy farms which are less dependent on weather conditions. Second, in dairy production, animal health issues might play a role. One important cattle disease that was still a problem in the early 2000s is the mad cow disease. However, the number of confirmed cases in Germany declined steadily until reaching zero in 2010. As will be seen in the results section, we cannot relate this to the pattern of the productivity covariance increase we observe and hence we do not include animal health issues in our analysis. Speaking of market effects, we also have to consider shocks on input markets as possible determinants of cov_{it}. Indeed, also prices for intermediates, e.g. concentrated feed, showed fluctuations and followed a similar trend as the milk prices. Yet feed costs are only a fraction of the total costs of dairy farms and hence we attribute superior significance to milk prices and neglect intermediate price fluctuations in our analysis. Also, prices of capital and labor can be expected to have a negligible influence since our dataset contains farms with a large share of proprietary capital and family labor force, as already described. We control for further farm-specific effects by the following variables: The availability of a farm successor (*suc*, a dummy variable indicating that there is at least one child with agricultural education in the farmer's household); a dummy variable indicating that farm income is only secondary income for the farmer's household (*sec*); and a dummy variable for organic farming (*org*). "Availability of a farm successor" and "farming as secondary income" are incorporated to control for the willingness of farm investments. "Organic farming" is incorporated to control for differing investment behavior when acting on output markets of organic products. The full specification for the first model is given by

$$cov_{it} = \gamma_0 + SD3_{it}\gamma_1 + inc_t\gamma_2 + pri_{it}\gamma_3 + suc_{it}\gamma_4 + sec_{it}\gamma_5 + org_{it}\,\gamma_6 + a_i + u_{it}, \tag{3-14}$$

with variables explained above. We assume a linear relationship as we lack an underlying theoretical framework that would suggest an alternative functional form for the relationship investigated. $SD3_{it}$ is replaced by $SD3_{it-1}$ and $SD3_{it-2}$ in the second and third model, respectively. We expect that many other unobserved factors important for the willingness to invest (e.g. availability of production alternatives given by environmental conditions) are captured by a_i. We prefer a fixed effects over a random effects regression as it is robust to possible correlations between these unobserved factors and the regressors. Considering the persistent nature of farm-level productivity as well as farm size, one reasonable option seems to be the inclusion of the lagged dependent variable as additional explanatory. If we still were to consider fixed effects in such a revised setting, appropriate estimation routines would include the models introduced by Arellano and Bond (1991) or Blundell and Bond (1998). We applied such estimation routines and obtained results far less robust (in terms of varying coefficients' magnitudes and statistical significance) than those obtained by the fixed effects estimation (we suspect this might be due to rather weak performance of instruments).

We therefore consider it as most efficient to use the fixed effects estimation framework. We are confident all important factors are controlled for in this part of our study and that the effects that we observe are indeed related to policy and output market influences. Separating the policy and the output market effect is a difficult if not impossible task since both coincide in time and both vary over time rather than between farms. Furthermore, we can expect that price volatility is partly also influenced by deregulation efforts. Although the model allows therefore only cautious conclusions, it nevertheless offers some valuable insights.

3.8. Results and discussion

All estimated production function models show a satisfactory statistical significance at parameter and overall model level. Estimation results for the first WLP specification are shown in table 3-2. Detailed estimates for the other models can be found in a supplementary appendix online. Estimated partial elasticities for the various model specifications are given in table 3-3. Returns to scale (rts) for all models are close to constant rts and vary from about 0.96 (decreasing rts) to about 1.12 (increasing rts) at the sample mean.

Table 3-2. Estimation results for the Wooldridge-Levinsohn-Petrin specification I

Variable	Estimate		Variable	Estimate	
$cows_t$	0.560***	(0.021)	org_t	0.003	(0.014)
$capital_t$	0.002	(0.031)	edu_t	0.011	(0.014)
$labor_t$	0.113***	(0.016)	age_t	−0.001**	(0.000)
$intermediates_t$	0.214***	(0.015)	sec_t	0.006	(0.021)
$concentrates_t$	0.131***	(0.027)	t	0.015***	(0.002)
eco2	0.028**	(0.012)	t^2	0.000***	(0.000)
eco3	0.035**	(0.014)	$capital^3_{t-1}$	0.006	(0.004)
eco4	0.061***	(0.017)	$concentrates^3_{t-1}$	−0.002	(0.002)
eco5	0.036	(0.029)	$capital^2_{t-1} \times concentrates_{t-1}$	0.007	(0.004)
eco6	0.001	(0.027)	$capital_{t-1} \times concentrates^2_{t-1}$	−0.018***	(0.006)
eco7	0.000	(0.016)	$capital^2_{t-1}$	−0.289**	(0.129)
eco8	−0.025*	(0.015)	$concentrates^2_{t-1}$	0.321***	(0.107)
eco9	−0.001	(0.021)	$capital_{t-1} \times concentrates_{t-1}$	0.108	(0.152)
eco10	0.011	(0.017)	$capital_{t-1}$	3.472***	(1.137)
eco11	0.042	(0.049)	$concentrates_{t-1}$	−3.545**	(1.732)
eco12	−0.069*	(0.037)	*constant*	omitted from regression	
R^2	0.92				
N	11,789				

Note: Subscript *i* as farm identifier is omitted. Endogenous regressors are $cows_t$, $labor_t$, $intermediates_t$, and $concentrates_t$. All other variables listed in the table are included instruments. Excluded instruments are $cows_{t-1}$, $labor_{t-1}$, $intermediates_{t-1}$, and $concentrates_{t-2}$. Significance levels are: ***1%, **5%, and *10%. Standard errors in parentheses are clustered for 1,292 farms.

Table 3-3. Partial elasticities per model specification

Input	WLP1	WLP2	FE	SFA1	SFA2	Törnqvist
cows	0.560	0.557	0.542	0.578	0.774	0.036
capital	0.002	−0.024	0.112	0.060		0.359
labor	0.113	0.111	0.046	0.096	0.086	0.287
intermediates	0.214	0.406	0.264	0.378	0.262	0.318
concentrates	0.131					
Scale elasticity	1.021	1.049	0.963	1.113	1.122	1.000

For the Törnqvist index approach, calculated cost shares are reported in table 3-3. The WLP specifications show low elasticities for "other capital" which could be explained by multicollinearity with respect to the lagged value used in the control function.The coefficients for the two WLP specifications are of similar magnitude, indicating that the results are not sensitive to the choice of the proxy variable. Comparing the output elasticities estimated by the WLP, FE, and SFA1 models, we find differences between the estimators, however, there is no clear evidence that the estimators of the FE and SFA models are biased by endogenous input choice. Theory predicts that output elasticities should equal the calculated cost shares, reported in the last column of table 3-3. In our case we find considerable discrepancies. One has to keep in mind, however, that for costs of cows, other capital, and mostly labor, no cash outflows are reported in our data. Therefore, we have to rely on standard wage and interest rates for the calculation of labor and capital costs that might not correspond exactly to reality. For productivity calculation with the Törnqvist approach this is less of a problem since we calculate growth rates of inputs and output, and the weighting of growth rates by cost shares is less sensitive to such errors.

3.8.1. Productivity growth rates

Unweighted mean productivity growth rates are given in table 3-4. Growth rates for the WLP models start from 2003 since lags of up to order two are used to estimate productivity levels. Relatively high values are obtained for the SFA2 model specification. For all models, growth rates are positive apart from the last year in the time period considered, further the levels of the estimated growth rates are similar across all models. Also here, we fail to identify explicit differences between the models not corrected for potential endogeneity (SFA and FE) and the ones that are robust (the WLP and the index approach).

Table 3-4. Unweighted mean productivity growth rates

Year	WLP1	WLP2	FE	SFA1	SFA2	Törnqvist
2001	-	-	0.025	0.014	0.029	0.032
2002	-	-	0.018	0.012	0.007	0.006
2003	0.003	0.003	0.003	0.007	0.009	−0.004
2004	0.011	0.009	0.011	0.012	0.017	0.017
2005	0.009	0.005	0.002	0.010	0.013	0.010
2006	0.006	0.007	0.005	0.009	0.011	0.001
2007	0.023	0.018	0.019	0.013	0.022	0.018
2008	0.018	0.016	0.008	0.008	0.008	0.013
2009	0.012	0.019	0.018	0.013	0.015	0.025
2010	0.005	0.002	0.004	0.010	0.005	0.010
2011	0.020	0.017	0.016	0.012	0.018	0.020
2012	0.029	0.016	0.024	0.009	0.010	0.013
2013	0.009	0.009	0.003	0.008	0.005	0.012
2014	−0.017	−0.023	−0.014	0.002	0.004	−0.027

Note: Productivity growth rates for the WLP approaches start in 2003 since lags up to order two are used in their estimation.

Table 3-5 reports correlation coefficients of the estimated farm-level productivity growth rates between the different models. Strong correlations are observed between the WLP and FE models (despite differing functional form of the production function) as well as the index approach. Rather weak correlations are observed between the second SFA specification and all other models, questioning the results obtained by this specification based on a reduced set of inputs and outputs.

Table 3-5. Correlation matrix for productivity growth rates

	WLP1	WLP2	FE	SFA1	SFA2	Törnqvist
WLP1	1.00					
WLP2	0.96	1.00				
FE	0.94	0.96	1.00			
SFA1	0.72	0.75	0.78	1.00		
SFA2	0.43	0.46	0.51	0.52	1.00	
Törnqvist	0.85	0.87	0.90	0.72	0.47	1.00

3.8.2. Productivity levels and covariance

In table 3-6 we report sector and mean productivity levels and covariance terms for the preferred model specification (WLP1). The second column shows that sector productivity increased by approximately 15% over the total period, corresponding to an average annual growth of approximately 1.1%. This is well in line with annual growth rates of productivity in dairy production found by other studies (e.g. Kazukauskas, Newman, and Thorne 2010). The results suggest that in large part this increase in sector productivity was caused by an increase in mean productivity of farms (the “within effect”, third column of table 3-6). It can be seen that especially high growth rates of mean productivity are observed in the first years of quota volume increases (2007-2009), but also in 2011 and 2012. As mentioned earlier, we focus on the contribution of reallocation effects to sector productivity (the “between effect”). The fourth column suggests that the covariance term amounts to 4.1 percentage points in 2014. Compared to a covariance term of 2.6 in 2002 this means that more efficient resource allocation contributed 1.5 percentage points to sector productivity growth.

Table 3-6. Sector productivity, mean productivity, and covariance term for WLP specification I and mean output price, quota price, quota stock growth per year

Year	p_t	$\bar{p}_t$	cov_t	Milk price[a] (EUR/kg)	Milk quota price[b] (EUR/kg)	Median of farm-level quota stock growth[c] (%)
2002	1.000	0.974	0.026	0.38	0.76	0.0
2003	1.002	0.977	0.025	0.35	0.50	0.0
2004	1.013	0.988	0.025	0.33	0.52	0.0
2005	1.021	0.997	0.024	0.33	0.48	0.0
2006	1.028	1.003	0.025	0.33	0.55	0.0
2007	1.054	1.027	0.028	0.33	0.37	0.5
2008	1.079	1.045	0.034	0.44	0.37	0.5
2009	1.095	1.057	0.038	0.36	0.24	2.5
2010	1.102	1.063	0.039	0.32	0.10	1.0
2011	1.123	1.084	0.038	0.38	0.11	1.0
2012	1.156	1.115	0.040	0.40	0.09	1.0
2013	1.171	1.126	0.046	0.39	0.04	1.0
2014	1.147	1.106	0.041	0.45	0.11	1.0

[a] Milk prices are yearly averages of farm-level prices observed.
[b] Milk quota prices are provided by the Bavarian State Research Center for Agriculture (Bayerische Landesanstalt für Landwirtschaft 2015).
[c] The EU-wide quota increases are mirrored with a delay of one year in our dataset since e.g. 2007 refers to business year 2006/2007 and hence includes the quota increase of 0.5% in 2006.

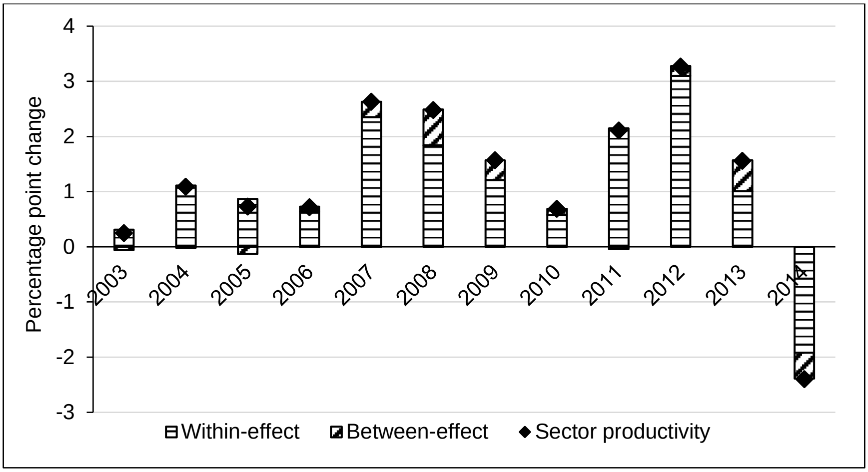

Figure 3-1. Contributions of farm-level productivity growth (within-effect) and resource reallocation (between-effect) to sector productivity growth

Contributions of farm-level productivity growth and resource reallocation to sector productivity growth are illustrated in figure 3-1. Notably, the covariance term lingers on a steady level in the first years and then shows a significant increase starting from 2007. Sector and mean productivity as well as the covariance term based on the alternative models are given in table 3-12 in the Appendix. The magnitude of the reallocation effect differs between models, but, in general, we find the same pattern of an increasing reallocation effect from 2007 onwards. We reinforce the finding of an increasing covariance term during this period by a regression-based robustness check (results given in table 3-7). Running separate probit regressions for each year, we can show that especially in the years of an increasing covariance term, it is the more productive farms which invested in new farm equipment. This is consistent with evidence suggested by the covariance term: on average more productive farms increase their production efforts. The model offers additional evidence as it explicitly links farm-level productivity to input choices rather than to output shares as is the case for the estimated covariance term.

Table 3-7. Separate Probit regressions per year linking an investment decision with farm-level TFP and further control variables

	2003	2004	2005	2006	2007	2008
p_{t-1}	−0.014	0.034	0.018	0.044	0.156*	0.160**
	(0.093)	(0.083)	(0.088)	(0.087)	(0.085)	(0.083)
Farm successor	0.036	0.066***	0.068**	0.060**	0.047*	0.048*
	(0.027)	(0.026)	(0.028)	(0.026)	(0.026)	(0.027)
Share of grassland	0.023	0.040	−0.012	0.017	−0.009	0.066
	(0.047)	(0.044)	(0.048)	(0.047)	(0.046)	(0.048)
Age of farmer	−0.005***	−0.005***	−0.002	−0.004***	−0.005***	−0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Farming as secondary income	−0.001	−0.084	−0.009	−0.074	−0.073	−0.022
	(0.062)	(0.071)	(0.064)	(0.069)	(0.069)	(0.067)
Organic farming	0.111**	0.081*	0.054	0.042	−0.028	−0.018
	(0.051)	(0.048)	(0.049)	(0.045)	(0.047)	(0.047)
N	874	896	961	999	1,018	1,020
	2009	**2010**	**2011**	**2012**	**2013**	**2014**
p_{t-1}	0.215***	0.204**	0.139*	0.144	−0.047	0.080
	(0.077)	(0.081)	(0.081)	(0.090)	(0.071)	(0.077)
Farm successor	0.076***	0.034	0.084***	0.106***	0.030	0.063**
	(0.026)	(0.026)	(0.027)	(0.027)	(0.026)	(0.027)
Share of grassland	−0.015	−0.001	0.113**	0.054	−0.002	−0.039
	(0.049)	(0.049)	(0.050)	(0.049)	(0.048)	(0.051)
Age of farmer	−0.002	−0.001	−0.004***	−0.001	−0.003**	−0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Farming as secondary income	−0.105	0.028	−0.124*	0.004	0.010	−0.025
	(0.070)	(0.062)	(0.075)	(0.064)	(0.058)	(0.068)
Organic farming	0.046	0.085**	0.002	0.008	0.026	0.113***
	(0.045)	(0.042)	(0.045)	(0.043)	(0.040)	(0.041)
N	1,006	976	954	942	975	968

Note: Reported are marginal effects at sample means and robust standard errors in parentheses. Significance levels are: ***1%, **5%, and *10%. The binary dependent variable indicates an investment step and equals one if the delta between this year's and last year's original value of buildings and structures is positive, and zero, if not. To account for the fact that new equipment is likely to be more productive, we use the one-period lag of farm-level productivity (p_{t-1}). Further, we control for the availability of a farm successor, the availability of production alternatives (measured as the share of grassland), the age of the farmer, a dummy indicating that farming income is only secondary income for the farmer, and organic production.

3.8.3. Explaining productivity dynamics

In this section we explore the reasons for the pattern of the covariance term that we observe. As shown in table 3-6, quota prices showed more of a steady decrease rather than experiencing sudden price shocks. We can therefore rule out that plumping quota prices posed a sudden investment incentive to farmers. We nevertheless keep quota prices as an explanatory variable in the subsequent regression analysis as a gradual decrease of quota prices still lowers the investment barrier for farmers. The increases in quota volumes seem to offer greater explanatory power. Comparing the quota growth rates (table 3-6) and the growth in the covariance term, we find that the increases in quota volumes is mirrored well in the growth of the covariance term. The first increase in quotas in 2007 coincides with a first increase in the covariance term, and the following quota expansions are also accompanied by further increases in the covariance term. We seek to strengthen this result in the fixed effects models. The results of the models are summarized in table 3-8.

Despite the relatively modest model fit which we attribute to measurement error rather than the omittance of important variables, the regression results provide support for our hypotheses. As expected, the estimates for quota prices carry the expected negative signs, indicating that the effect of a decreasing investment barrier possibly dominates the effect of lower liquidation value of farms. This result of an increasing sector productivity with an increasing tradability of the quotas is in line with the conclusions drawn by Gillespie et al. (2015; Colman), Colman (2000), and Hennessy et al. (2009). Also, the median of quota growth shows significant positive influence on the covariance term. Both results support the hypothesis that declining regulatory power is associated with an increasing significance of resource reallocation for sector productivity. The coefficient of milk price volatility shows the expected sign, supporting our hypothesis of a positive effect of price risk on efficient resource reallocation, if also not statistically significant.

Table 3-8. Estimates of the Fixed Effects regression to explain the farm-level covariance term

Variable	Model I	Model II	Model III
$SD3_t$	4.5×10^{-7}		
	(3.7×10^{-7})		
$SD3_{t-1}$		4.4×10^{-7}	
		(4.5×10^{-7})	
$SD3_{t-2}$			3.4×10^{-7}
			(4.3×10^{-7})
Quota increase	3.6×10^{-4} ***	3.7×10^{-4} ***	4.4×10^{-4} ***
	(9.3×10^{-5})	(1.1×10^{-4})	(1.0×10^{-4})
Quota exchange	-1.7×10^{-5}***	-1.8×10^{-5}***	-2.3×10^{-5}***
$price_{t-1}$	(4.7×10^{-6})	(4.8×10^{-6})	(5.9×10^{-6})
Farm successor	-9.2×10^{-7}	-9.2×10^{-7}	-8.4×10^{-7}
	(3.1×10^{-6})	(3.1×10^{-6})	(3.0×10^{-6})
Farming as secondary in-	8.8×10^{-6}	6.0×10^{-6}	5.0×10^{-6}
come	(1.5×10^{-5})	(1.6×10^{-5})	(1.8×10^{-5})
Organic farming	4.9×10^{-6}	6.0×10^{-6}	8.7×10^{-6}
	(1.2×10^{-5})	(1.3×10^{-5})	(1.3×10^{-5})
Constant	3.6×10^{-5} ***	3.6×10^{-5} ***	3.7×10^{-5} ***
	(2.9×10^{-6})	(3.0×10^{-6})	(3.4×10^{-6})
N	11,806	10,408	9,160
Within R^2	0.010	0.012	0.014

Note: *SD3* is the standard deviation of the farm-level milk price in the last three years. Robust standard errors are reported in parentheses. Significance levels are: ***1%, **5%, and *10%.

We can show that the coefficients of the deregulation variables are also of economic significance. For interpretation of the magnitude of the coefficients, we have to reconvert the effects on the individual covariance term cov_{it} into the effects on the aggregate measure cov_t. We can do this by summing up the respective coefficient across the 1,014 observations that are included in the regression on average per year. Thus, using the results of the first model in table 3-8, an increase of quota volumes by one percent in a single year resulted in a mean increase of the aggregated covariance term cov_t (and hence sector productivity, p_t)

by ($0.01\times3.6\times10^{-4}\times1{,}014\approx$) 0.4 percentage points. An increase in sector productivity by a similar magnitude is caused by a decrease of the quota exchange price by 20 eurocents. This reflects well the pattern we observe in cov_t. Purely hypothetical, to quantify the price volatility effect, if we assume that farmers were affected by a mean milk price drop where they receive 40 eurocents per kilogram in two subsequent years and 20 eurocents in the third year, this would result in an increase of sector productivity by 0.002 percentage points—reflecting the low significance of price risk according to our results.

Kimura and Sauer (2015) examined TFP development in dairy farms in the Netherlands, Estonia, and the UK for a similar time period as we do in our study. For the Netherlands, they found that sector input and output both increase from 2008 on, possibly as a reaction to the confirmation of the phasing-out of the milk quota by the European Commission. The starting point of this increase coincides with the increase of the covariance term in our study. However, the reallocation effects found in their study show a different pattern than our results. For the Netherlands, they found a stagnating reallocation effect over the whole time period, whereas for the UK the reallocation effect was declining due to a decreasing TFP gap between farms. Only for Estonia, the reallocation effect was on a high level and increasing from 2003 to 2009, however, it declined again thereafter.

3.9. Conclusions

Using a sample of specialized dairy farms in southeast Germany, we find empirical evidence that the reallocation of resources toward more productive farms increased gradually during the phasing-out of the EU milk quota. Regarding deregulation as the sole driver of resource reallocation might be too shortsighted, however. During the period of the quota volume increases, farmers faced considerable output price risk. We know that many dairy farms were brought to the brink of existence by the price lows during that time. Although we cannot provide statistically significant results of a positive influence of milk price risk on reallocative efficiency, we suspect that it was an interplay of deregulation and price volatility that drove efficient resource reallocation during our study period. Having in mind also recent events when dairy farmers were brought into financial distress by milk price drops, we conclude that extremes in milk market prices can function as an ignition for major reallocation events that are after the abolition of the milk quota no longer restricted in their extent. In light of the recent “milk crisis” in 2015 and 2016, evidence supporting this view might be found in future studies. The results have important policy implications. If the exclusive objective of agricultural policy was efficient production in the sector, deregulation is one mean of achieving this, as already found by numerous other studies. Since also price volatility shows a positive effect on efficient resource allocation, it likewise appears to be beneficial for non-wasteful production in the sector. However, as we already mentioned, one aim of regional agricultural policy in Bavaria is the slow-down of structural change. If increased price volatility triggers more efficient resource allocation, this is most likely connected to greater churning and more frequent farm exits in the sector. Then, regional policy measures should focus on the stabilization of the income of farms. This result is also transferable to other countries or regions where the aim is to preserve traditional farming structures. The challenge for European agricultural policy would then be to find the appropriate tools for achieving this aim without falling back to outdated price support schemes. In our sample, resource reallocation notably contributed to sector productivity. Hence, the price for the preservation of farming structures would be less efficient production as a whole. On the other hand, continuing promotion of within-farm productivity growth could help offset these sector efficiency losses, since our results show that large part of the sector productivity gains in our study period was effected by productivity growth within farms.

Methodologically, our study shows how the recently emerged endogeneity-robust WLP approach to productivity estimation can also be applied in an agricultural context. The results of the WLP model are insensitive to the choice of the specific proxy variable and are validated by a comparison with other estimation techniques. Given the relatively straightforward implementation based on existing software packages its importance for productivity measurement in agricultural economics should increase in the future.

3.10. Appendix

3.10.1. Data preparation

To define our sample of specialized dairy farms, we include only farms that generate at least two thirds of their output from milk sales. We use the farms' sales share averaged over the whole sample period to avoid the exclusion of observations for which the farm operates below this threshold in single years. On average, the farms in our sample generate 92% of their sales from dairy activities (revenues from milk sold as well as calves, heifers, and milk cows sold), i.e. they are highly specialized. As a single output we define total sales of the farm. Different output categories are aggregated by deflating total sales using a Törnqvist price index, calculated by weighting price changes in various output categories (e.g., milk, cereals, cattle, etc.) by the farm's individual sales shares. The price changes are calculated based on reported farm-individual prices and also based on price indices provided by the German statistics agency (Destatis 2019), for the few cases where prices are not reported. For the second stochastic frontier model we only use physical milk as output. Apart from the first WLP and the second SFA specification, we distinguish four different input categories. Intermediates (*intermediates*) are calculated as total expenditures deflated by a Törnqvist price index, again consisting of price changes for intermediates categories weighted by expenditure shares. Since individual prices for inputs are not reliably reported, we use price indices reported by the German statistics agency. For the first WLP specification, we exclude costs for concentrated feed from intermediates and use concentrated feed as a separate input (*concentrates*). The number of milk cows is included as a separate input (*cows*). Other capital (buildings, machinery/equipment, and other animals) is aggregated to one input by cumulating deflated investments and treating the capital stock in the first year as initial investment. Land (owned and rented) is also incorporated here by multiplying the number of hectares of cultivated land with an initial per hectare value and adding the value to the capital variable (*capital*). Labor is given by reported amounts of employed full-time equivalents (*labor*). As control variables we include dummy variables indicating the agro-ecological zone where the farm is located (*eco*), a dummy variable for organic production (*org*), a dummy variable for agricultural education of the farmer (*edu*), age of the farmer (*age*), and a dummy variable indicating that farming is only secondary income for the farm household (*sec*).

3.10.2. Wooldridge-Levinsohn-Petrin estimator

In the first model we estimate part of the Wooldridge-Levinsohn-Petrin GMM framework described in Wooldridge (2009). The estimation equation for the first WLP specification is represented by

$$\begin{aligned} q_{it} = x'_{it}\beta_1 + c'_{it-1}\beta_2 + eco'_{i}\beta_3 + org_{it}\beta_4 + edu_{it}\beta_5 + age_{it}\beta_6 \\ + \mathrm{sec}_{it}\,\beta_7 + t\beta_t + t^2\beta_{tt} + \phi_{it}. \end{aligned} \tag{3-15}$$

This corresponds to equation (2.11) in Wooldridge (2009). q is the logarithmic output. ϕ_{it} comprises random shocks not correlated with inputs, and the productivity innovation component that is possibly correlated with variable inputs (for further details see Wooldridge 2009). Row vector x' contains linear logarithmic terms of the production inputs *cows*, *capital*, *labor*, *intermediates*, and *concentrates*. c' represents the variables of the control function which consists of an intercept and a polynomial of order three of the one-period lags of the state variable (*capital*) and the proxy variable (*concentrates*). Apart from the state variable *capital*, all other contemporaneous production inputs are assumed to be possibly correlated with the productivity innovation component contained in the error ϕ_{it}, and hence require proper instrumentation. *Labor*, *intermediates*, and *cows* are instrumented by their one-period lags. Since the one-period lag of the proxy variable *concentrates* is used in the control function, its two-period lag is employed as an instrument. For the second WLP specification, *concentrates* is included in *intermediates*, and hence *intermediates* replaces *concentrates* as the proxy variable. In principle, also the estimation of a translog production function is compatible with the WLP methodology by specifying the corresponding admissible lags also as instruments for the interaction terms. We attempted such a specification with the result that the estimators showed to be very sensitive to the specification of the control function. We suspect that this is due to multicollinearity between the state and proxy variables included in both the control function and the vector of production inputs. Therefore, although it is more restrictive, we resorted to the Cobb-Douglas functional form. Despite the loss in flexibility, the Cobb-Douglas functional form is widely used in empirical studies (out of the studies already mentioned, see e.g. Shee and Stefanou 2015; Petrin and Levinsohn 2012; Kazukauskas, Newman, and Thorne 2010; Rizov, Pokrivcak, and Ciaian 2013; Eslava et al. 2004). However, one important restriction of the Cobb-Douglas production function is that output elasticities and the elasticity of scale are invariant with respect to input levels. We expect this not to be a crucial restriction as we observed for the translog fixed-effects specification and the stochastic frontier approaches that output elasticities do not vary much with respect to varying input levels. For example, for the first stochastic frontier estimation the output elasticity with respect to cows is 0.60 for the 25% of the largest and 0.54 for the 25% smallest farms (measured in terms of herd size). GMM estimation is performed in Stata 13 using the command *ivregress*. Productivity levels are calculated as

$$\ln p_{it}^{wlp} = c'_{it-1}\hat{\beta}_2 + eco'_i\hat{\beta}_3 + org_{it}\hat{\beta}_4 + edu_{it}\hat{\beta}_5 + age_{it}\hat{\beta}_6 + \sec_{it}\hat{\beta}_7 + t\hat{\beta}_t + t^2\hat{\beta}_{tt} + \hat{\phi}_{it} = q_{it} - x'_{it}\hat{\beta}_1, \tag{3-16}$$

i.e. the residual of the production function, including technical change and the influences of the variables that can be changed by the farmer in the medium or long run (where we assume that with *age* we measure not purely the age of the farmer but rather the attitude of the farmer or employment of out-of-date production techniques).

3.10.3. Fixed effects

The fixed effects model yields estimators robust to endogenous input choice if we are willing to assume that individual deviations (ω) from mean productivity (β_0) are time-invariant. Then, the production function can be represented as

$$q_{it} = \beta_0 + x'_{it}\beta_1 + eco'_i\beta_2 + org_{it}\beta_3 + edu_{it}\beta_4 + \sec_{it}\beta_5 + t\beta_t + t^2\beta_{tt} + \omega_i + v_{it}. \quad (3\text{-}17)$$

Since production inputs are assumed to be correlated with unobserved productivity, the random effects assumption does not apply and we must resort to the fixed effects model. The time invariant factors β_0, eco'_i, and ω_i will be captured by the farm-specific time invariant effect. We exclude age from this regression as inclusion would not be meaningful in a fixed effects setup and we think that factors related to age (e.g. employment of out-of-date production techniques) are captured by the fixed effect. We include org, edu, sec to account for farms that switch between production schemes, for changes in education of the farm manager, and for farmers that switch from full-time to part-time farming or vice versa. We estimate (3-17) in translog form, with the row vector x'_{it} including linear, quadratic, and interactions of logarithms of *cows*, *capital*, *labor*, and *intermediates*. org, edu and sec enter the equation as dummy variables. v_{it} is an i.i.d. error term with $N(0, \sigma_v^2)$. We use the Stata command *xtreg* and the within regression estimator. Estimated productivity levels are then given by

$$\ln p_{it}^{fe} = \hat{\beta}_0 + eco'_i\hat{\beta}_2 + org_{it}\hat{\beta}_3 + edu_{it}\hat{\beta}_4 + \sec_{it}\hat{\beta}_5 + t\hat{\beta}_t + t^2\hat{\beta}_{tt} + \hat{\omega}_i + \hat{v}_{it} = q_{it} - x'_{it}\hat{\beta}_1. \quad (3\text{-}18)$$

3.10.4. Stochastic frontier models

We estimate stochastic frontier models in translog form with the Stata command *sfpanel* following the model of Battese and Coelli (1995) as

$$q_{it} = \beta_0 + x'_{it}\beta_1 + t\beta_t + t^2\beta_{tt} + v_{it} - u_{it}. \quad (3\text{-}19)$$

The row vector x'_{it} again contains logs of all linear, squared, and interaction terms for the inputs (with a reduced set of inputs in the second model), as well as the time trend, represented by a linear and squared term. v_{it} is an i.i.d. error component with $N(0, \sigma_v^2)$. Technical efficiency is quantified by $u_{it} \sim N^+(z'_{it}\delta, \sigma_u^2)$. We include in z'_{it} the same variables that were part of the inefficiency also in the WLP and FE models, namely *eco*, *org*, *edu*, *age*, and *sec*. Productivity change (pc) is then calculated as

$$\ln pc_{it}^{sfa} = \ln \widehat{tec}_{it} + \ln \widehat{tc}_{it} + \ln \widehat{sec}_{it}, \tag{3-20}$$

with technical efficiency change $\ln \widehat{tec}_{it} = \ln\left(e^{-\hat{u}_{it}}/e^{-\hat{u}_{it-1}}\right)$, technical change $\ln \widehat{tc}_{it} = \frac{1}{2}\left(\frac{\partial q_{it-1}}{\partial t} * \frac{\partial q_{it}}{\partial t}\right)$, and scale efficiency change $\ln \widehat{sec}_{it} = \frac{1}{2}\sum_{k=1}^{K}\left[\left(\frac{\hat{\mathrm{E}}_{it}-1}{\hat{\mathrm{E}}_{it}} * \hat{\epsilon}_{ikt} + \frac{\hat{\mathrm{E}}_{it-1}-1}{\hat{\mathrm{E}}_{it-1}} * \hat{\epsilon}_{ikt-1}\right)(x_{ikt} - x_{ikt-1})\right]$, with K inputs and scale elasticity $\hat{\mathrm{E}}_{it} = \sum_{k=1}^{K} \hat{\epsilon}_{ikt}$ and partial elasticity of the kth input $\hat{\epsilon}_{ikt} = \frac{\partial q_{it}}{\partial x_{ikt}}$. Productivity levels are calculated by setting $\ln p_{it=2000} = 0$ and cumulating growth rates as $\ln p_{it}^{sfa} = \sum_{s=2}^{t} \ln pc_{it}^{sfa}$. Data gaps in single years are assigned the sample average growth rate. Farms entering the dataset at a later point in time start with the sample average productivity level.

3.10.5. Törnqvist index

We calculate a Törnqvist TFP growth index in logarithmic form for farm i in year t as

$$\ln pc_{it}^{törn} = (q_{it} - q_{it-1}) - \frac{1}{2}\sum_{k=1}^{4}(s_{ikt} + s_{ikt-1})(x_{ikt} - x_{ikt-1}), \tag{3-21}$$

where y denotes logarithmic output, x the four logarithmic inputs as used in the other approaches, and s the cost share of the kth input. Similar as for the SFA approach, starting values are set and growth rates are cumulated to generate productivity levels as $\ln p_{it}^{törn} = \sum_{s=2}^{t} \ln pc_{it}^{törn}$. Data gaps and "latecomers" are treated in the same way as in the SFA approach. For easier comparison, productivity levels (p_{it}) of all models are adjusted to normalize industry productivity to 1 in 2002.

3.10.6. Sector productivity calculation and decomposition following Petrin and Levinsohn (2012)

We calculated aggregate productivity growth and estimated reallocation effects following equations (12) and (13) in Petrin and Levinsohn (2012). In table 3-9 we report sector productivity (AP_t^a) and reallocative efficiency (RE_t^a) following the methodology of Petrin and Levinsohn (2012) and using the same inputs as for the first WLP approach (WLP1).

Table 3-9. Comparison of results based on the methodology by Petrin and Levinsohn (2012)

Year	p_t^{wlp1}	cov_t^{wlp1}	AP_t^a	RE_t^a	AP_t^b	RE_t^b
2002	1.000	0.026	1.000	0.000	1.000	0.000
2003	1.002	0.025	0.993	−0.018	0.997	−0.008
2004	1.013	0.025	1.009	−0.023	1.020	−0.005
2005	1.021	0.024	1.022	−0.030	1.037	−0.007
2006	1.028	0.025	1.021	−0.040	1.043	−0.011
2007	1.054	0.028	1.053	−0.054	1.081	−0.017
2008	1.079	0.034	1.081	−0.046	1.116	−0.009
2009	1.095	0.038	1.119	−0.027	1.164	0.018
2010	1.102	0.039	1.130	−0.057	1.185	0.010
2011	1.123	0.038	1.158	−0.058	1.222	0.021
2012	1.156	0.040	1.176	−0.070	1.250	0.028
2013	1.171	0.046	1.218	−0.062	1.294	0.036
2014	1.147	0.041	1.175	−0.107	1.257	0.033

Note: p_t^{wlp1} and cov_t^{wlp1} are sector productivity and the covariance term as already given in table 3-6. AP_t^a, AP_t^b, RE_t^a, and RE_t^b are aggregate (or sector) productivity and reallocative efficiency (corresponding to the covariance term) calculated following the methodology by Petrin and Levinsohn (2012), before (a) and after (b) adjustment of cost shares. Growth rates of AP and RE were converted to discrete growth rates and cumulated accordingly.

As can be seen, sector productivity follows a similar trend, whereas reallocative efficiency is negative and decreases even further. In this calculation, we calculated revenue shares of costs (expenditures for inputs as shares of revenue) that sum up to unrealistic 142% of revenue. When we scale the cost shares (as already mentioned we have unreliable data for costs of primary inputs) to equal theoretical correct 100%, the result is AP_t^b and RE_t^b. Then, the spread between p_t and AP_t widens. However, reallocative efficiency (RE_t^b) now follows a similar trend as cov_t with the characteristic increase starting from 2008.

3.10.7. Descriptive statistics and additional results

Table 3-10. Descriptive statistics of variables used in the production function estimations

	2000			
Variable	Mean	Std. Dev.	Min	Max
Output (EUR)[a]	82,399	38,642	10,393	286,020
Cows (number)	33.0	13.4	7.0	135.0
Other capital (EUR)	866,320	422,515	152,443	6,052,293
Labor (FTE[b])	1.53	0.44	0.35	3.12
Intermediates (EUR)[a]	23,328	13,970	2,819	116,659
Concentrated feed (EUR)	9,591	6,911	52	61,247
Number of observations	917			
	2014			
Variable	Mean	Std. Dev.	Min	Max
Output (EUR)[a]	144,315	92,251	12,911	611,942
Cows (number)	47.2	25.1	2.0	182.2
Other capital (EUR)	1,329,918	701,978	199,943	5,850,496
Labor (FTE[b])	1.65	0.53	0.30	4.97
Intermediates (EUR)[a]	37,004	26,298	2,791	225,347
Concentrated feed (EUR)	14,764	11,506	55	109,749
Number of observations	992			
Number of observations (all years)	14,978			
Number of farms (all years)	1,470			

[a] Shown are deflated values (implicit quantity index, monetary value less price changes).
[b]FTE = full-time equivalent

Table 3-11. Robustness check for sector productivity calculation

Year	p_t^{agg}	p_t^{wlp1}
2002	1.000	1.000
2003	1.003	1.002
2004	1.006	1.013
2005	1.018	1.021
2006	1.021	1.028
2007	1.049	1.054
2008	1.067	1.079
2009	1.084	1.095
2010	1.098	1.102
2011	1.120	1.123
2012	1.156	1.156
2013	1.173	1.171
2014	1.147	1.147

Note: Both measures are sector productivity normalized to one in 2002. p_t^{wlp1} is sector productivity calculated following equation (3-12), see also table 3-6. p_t^{agg} is sector productivity calculated by summing up inputs and output per year over farms and using these aggregate measures along with mean cost shares to calculate a Törnqvist TFP index.

Table 3-12. Industry productivity, mean productivity, and covariance term per model

Year	WLP2			FE			SFA1		
	p_t	$\bar{p}_t$	cov_t	p_t	$\bar{p}_t$	cov_t	p_t	$\bar{p}_t$	cov_t
2002	1.000	0.978	0.022	1.000	0.960	0.040	1.000	0.997	0.003
2003	1.002	0.981	0.021	1.001	0.962	0.039	1.009	1.004	0.005
2004	1.012	0.990	0.022	1.012	0.973	0.039	1.020	1.017	0.004
2005	1.015	0.995	0.020	1.012	0.975	0.037	1.031	1.027	0.004
2006	1.022	1.002	0.021	1.018	0.980	0.038	1.041	1.037	0.004
2007	1.043	1.019	0.023	1.038	0.998	0.040	1.055	1.050	0.005
2008	1.065	1.035	0.029	1.052	1.006	0.046	1.065	1.058	0.007
2009	1.085	1.054	0.031	1.072	1.024	0.048	1.080	1.072	0.009
2010	1.088	1.056	0.032	1.078	1.028	0.050	1.092	1.082	0.009
2011	1.105	1.074	0.031	1.094	1.045	0.050	1.106	1.095	0.010
2012	1.121	1.091	0.030	1.117	1.070	0.047	1.116	1.106	0.010
2013	1.134	1.101	0.033	1.125	1.073	0.052	1.126	1.114	0.012
2014	1.103	1.076	0.027	1.105	1.058	0.047	1.130	1.117	0.013

Table 3-13. Industry productivity, mean productivity, and covariance term per model (Continued)

Year	SFA2			Törnqvist		
	p_t	$\overline{p_t}$	cov_t	p_t	$\overline{p_t}$	cov_t
2002	1.000	0.996	0.004	1.000	0.991	0.010
2003	1.013	1.005	0.007	0.998	0.987	0.011
2004	1.029	1.022	0.007	1.014	1.004	0.011
2005	1.041	1.035	0.007	1.024	1.015	0.011
2006	1.054	1.046	0.008	1.029	1.016	0.014
2007	1.077	1.069	0.008	1.053	1.035	0.017
2008	1.088	1.077	0.010	1.074	1.048	0.026
2009	1.108	1.094	0.014	1.104	1.075	0.029
2010	1.115	1.100	0.015	1.120	1.085	0.035
2011	1.137	1.120	0.015	1.149	1.107	0.041
2012	1.147	1.131	0.015	1.161	1.122	0.038
2013	1.156	1.137	0.018	1.181	1.135	0.046
2014	1.166	1.141	0.023	1.148	1.105	0.042

Note: The starting point of the reallocation term differs for the SFA models and the index approach since we are bound to calculate productivity levels from growth rates. Therefore, both industry and mean productivity start with a common value in 2000 and the covariance effect is accordingly zero in the first year.

4. Technological Change in Dairy Farming with Increased Price Volatility

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4.1. Abstract

Accompanied by steps towards market liberalization, dairy farmers in the European Union have been confronted with increased price risk in recent years, which might have affected their innovation behavior. We examine technical change and technical efficiency of specialized dairy farms before and during a phase of volatile milk prices. Additionally, we compare the results with mixed dairy farms, which might have achieved an advantage by diffusing price risk through diversification. Our results indicate a slowdown in technical change in specialized as well as in mixed dairy farming coinciding with the start of a volatile market phase.

4.2. Introduction

Dairy farmers in the European Union have faced several changes in the production environment in recent decades. The implementation of labor-saving technologies has allowed herd sizes to grow continuously while the overall number of dairy farms has declined, resulting in considerable structural changes. Under the quota regime, total milk production has remained fairly stable, but from 2000 to 2013, the number of dairy farms in the three largest milk-producing countries declined by approximately 36 %, 39 %, and 53 % in Germany, France, and the United Kingdom, respectively. Accordingly, average herd sizes increased in these countries by approximately 64 %, 46 %, and 58 % (Eurostat 2018a). This development was accompanied by efforts of the European Commission to lead the dairy sector towards deregulation by lowering intervention price levels, eliminating export subsidies, liberalizing milk quota transfers, gradually increasing quota volumes, and finally, abolishing the milk quota in 2015. Even before this date, dairy farmers in Europe were confronted with increased volatility of milk prices. While for a long period milk price levels had been dominated by seasonal variation, a disruptive pattern began in 2007 (figure 4-1). Strong domestic and worldwide demand led to a price high in 2007 that was followed by a sharp decrease due to lower demand and a rebound in supply, which resulted in the (first) dairy sector crisis in 2009 (USDA 2007, 2008).

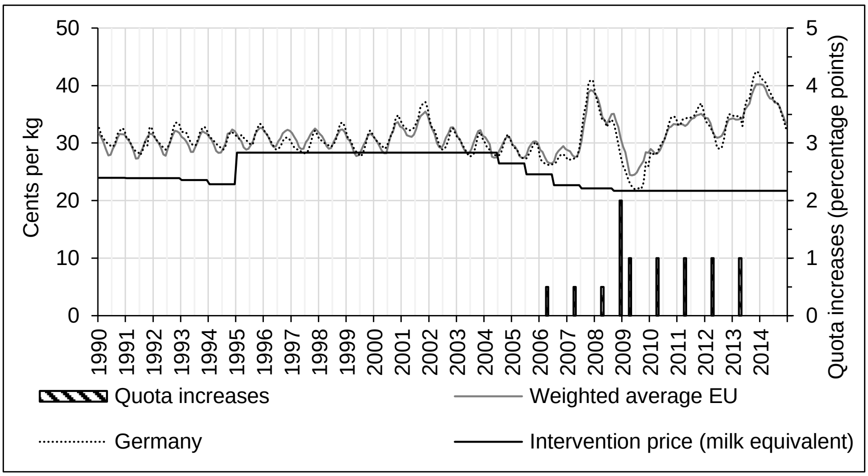

Figure 4-1. Development of milk prices and intervention price levels in the EU and Germany

Source of data: EU Milk Market Observatory (2019)

Farm family income and a farm's financial resources for maintaining and expanding business activities are directly dependent on output prices. Increased price volatility therefore translates into increased risk for the financial well-being of farms. The financial distress of dairy farmers is well documented by financial aids granted by the European Commission in 2009 (European Commission 2009b).

This article aims to shed light on how the realization of technological advancement in the sector has been affected by this emerging price uncertainty. Technical change as well as the level of technical efficiency within an industry depend on producers' willingness and ability to invest in new equipment and production techniques (Sauer and Latacz-Lohmann 2015). It must be considered whether increased output price volatility had negative implications for innovation adoption and consequently technology in the dairy sector. For example, risk-averse farmers might abstain from or postpone investments because of the fear of not being able to meet future credit obligations. Although a link between price risk and innovation behavior has been established by other authors (Sauer and Zilberman 2012), we are not aware of any other empirical studies directly examining technical change in view of the recent price turbulences in the European dairy sector.

To examine this link, we study the rate of technical change and technical efficiency change in West German dairy farming before and during a period of volatile milk prices. Additionally, we compare the results for specialized farms with the results for dairy production on mixed farms. Diversification in output activities is a means of countering output price risk. Therefore, mixed dairy farms might show advantageous innovation behavior during phases of uncertain output markets owing to their greater financial leeway for investing in new technologies.

The article is structured as follows. In the next section, we summarize some of the related literature motivating our study. We then examine average levels of net investment as an indicator for innovation activity in the sector during our study period. In the following two sections, we turn to the methodological framework and dataset used, before presenting the results separately by farm type and concluding in the last section.

4.3. Related literature

In this section, we focus on existing knowledge about determinants of the technology adoption behavior of farms. Although this discussion was originally built on profitability as a determinant of the rate of technology diffusion (Griliches 1957), it became apparent that education, learning, scale effects, credit constraints, and risk also play important roles (Foster and Rosenzweig 2010). Risk in general is expected to influence the investment decisions of farmers, because farmers are risk-averse and therefore react cautiously to the risk inherent in new and unfamiliar technology by postponing adoption and gathering further information (Jensen 1982; Just and Zilberman 1983). Similar consequences are predicted by the real options framework, where increasing uncertainty generally increases the value of waiting and delays investment decisions even for risk-neutral decision makers (Floridi et al. 2013).

For dairy farmers, low milk prices can critically diminish the liquidity of the farm, leading to constrained access to credit markets. If a farm has sufficient funds of its own or might be able to provide the necessary assets as collateral (e.g., by owned land), it might still refrain from investment if a combination of additional loan payments and increased milk price volatility puts the future liquidity of the farm at stake. Schulte, Musshoff, and Meuwissen (2018) showed that increased milk price volatility can considerably affect the profitability of investment decisions if farmers behave in a risk-averse manner. A negative effect of milk price volatility on the investment propensity of dairy farms was confirmed by Zimmermann and Heckelei (2012) for a dataset on European farms. For Pennsylvanian dairy farms, Stokes (2006) found that as output price volatility increased, the number of farm exits increased, the number of farm entries decreased, and farm size growth rates decreased. A study especially relevant to our context was performed by Sauer and Zilberman (2012), who investigated, among other factors, the role of profit risk in the decision to adopt automated milking systems amongst Danish dairy farms. They showed that both decreasing mean profit and increasing profit variability negatively impacted the probability of adoption.

A contrasting line of reasoning highlights that investing in more advanced technology could be a strategy to encounter output price risk by increasing overall farm productivity. For example, Kim and Chavas (2003) found indications that technical change decreases risk exposure in corn production. For Louisianan dairy farming Rahelizatovo and Gillespie (2004) found a positive effect of risk aversion on the probability of adoption of several best management practices. They explain this finding by the risk-reducing effect of best management practices.

Along with risk, frequently discussed determinants for technology adoption include financial constraints such as access to credit and the level of liquidity, since the adoption of new technologies or inputs depends on a farmer's ability to provide the necessary funds, either from their own assets or by borrowing (Foster and Rosenzweig 2010). Although there is no indication that the average European farmer faces capital market constraints (Petrick and Kloss 2012), individual farmers' behavior can be expected to be significantly influenced by credit constraints. Hüttel, Mußhoff, and Odening (2010) identified capital market frictions and irreversibility as determinants of the investment behavior of German farmers. Läpple, Renwick, and Thorne (2015) found a positive effect of credit accessibility on the degree of innovation for a sample of Irish farms. El-Osta and Morehart (1999) found that credit reserves are positively related to technology adoption decisions in U.S. dairy farms. These considerations are also relevant for the context of our study. Declining liquidity might pose additional barriers to credit markets for dairy farmers. On the other hand, the period of volatile milk prices coincided with the financial crisis beginning in 2008. Although the farming sector might have been only distantly impacted compared to other sectors, it marked the start of a phase with low capital market interest rates that has lasted until today. The effect of interest rates on investment can be twofold. On the one hand, decreasing interest rates decrease the cost of technology adoption and thereby increase the probability of adoption; on the other hand, in a dynamic setting, interest rates discount future risk, which leads to a negative effect of decreasing interest rates on the probability of adoption (Tsur, Sternberg, and Hochman 1990).

In summary, we identify three macroeconomic factors potentially influencing recent investment behavior in the dairy sector: milk price volatility, plunging interest rates, and a significant decline in government intervention. At the same time, reduced government intervention is a possible cause of milk price volatility, since decreased intervention price levels lowered the price floor, and the abolition of quotas can be expected to have a price-decreasing effect (Bouamra-Mechemache, Jongeneel, and Requillart 2008). Our main conjecture is that increased output price risk had significant implications for the innovation behavior of European dairy farmers. Consequently, the rate of technical change as well as the level of technical efficiency in the sector have been possibly affected. The comparison of specialized and mixed dairy farms is motivated by the assumption that, by specialized learning and scale effects, more specialized dairy farms might have an advantage with respect to more effectively implementing state-of-the-art technology. However, more diversified dairy farms are less vulnerable with respect to milk price changes, which could prove dairy production in mixed farms advantageous during volatile market phases.

4.4. Explorative indicators

In this section, we focus on net investment as an indicator for innovation activity to build up some intuition about farmers' reactions to recent market events. We calculate net investments as gross investment less depreciation in machinery and equipment as well as in buildings using the data at hand. Figure 4-2 presents mean net investment per annual work unit by farm type and in comparison to the average farm-gate milk price. It is evident that both specialized and mixed dairy farms adjusted net investment according to the level of milk prices. The milk price high from 2007 was accompanied by spikes in net investment, while, as expected, investments in buildings seem less flexible than investments in farm machinery. From this graphical analysis, milk price volatility seems not to have had a detrimental effect on the level of net investments: especially after 2009 and coincident with a recovery of milk prices, net investments increased substantially.

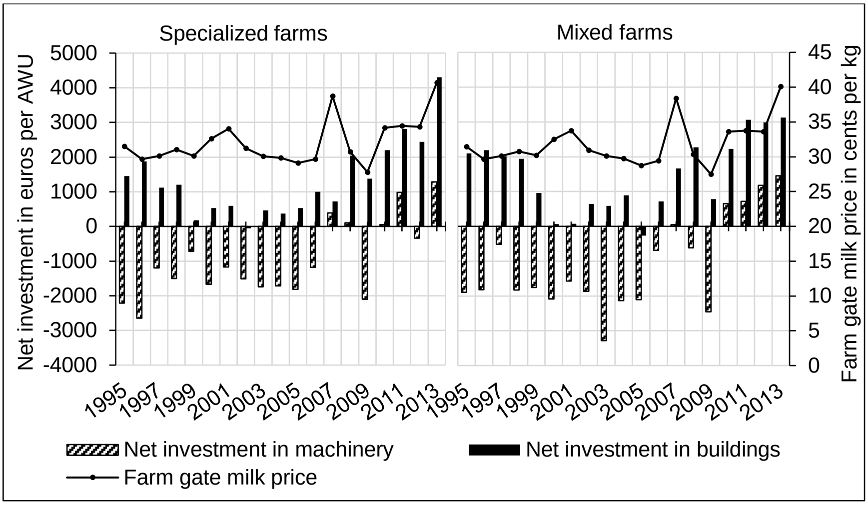

Figure 4-2. Development of net investment in machinery and buildings (per annual work unit, AWU) and average farm gate milk price by farm type

Source: Authors' calculations based on FADN data

Table 4-1 presents the results of fixed effects regressions for net investment (per annual work unit) on the prices of milk and wheat as well as on farm type. As expected from the visual analysis, milk and wheat prices were positively related to farm net investments. On average, the insignificant coefficients for the mixed farm dummies suggest no significant differences between specialized and mixed dairy farms.

Table 4-1. Estimation results of fixed effects regressions of net investment on output prices and farm type

Dependent variable	Net investment machinery		Net investment buildings	
	Coefficient	S.E.	Coefficient	S.E.
$D_{mixed\ farm}$	−155.96	(2525.62)	1310.02	(3352.83)
Milk price	185.99***	(38.05)	−26.37	(50.51)
Wheat price	5.12*	(3.10)	10.68***	(4.12)
$D_{mixed\ farm}$ × milk price	−37.57	(57.90)	27.07	(76.87)
$D_{mixed\ farm}$ × wheat price	2.48	(4.58)	−7.97	(6.08)
Milk price (t−1)	13.72	(43.77)	43.94	(58.10)
Wheat price (t−1)	4.48	(3.34)	4.48	(4.44)
$D_{mixed\ farm}$ × milk price (t−1)	43.83	(66.86)	−43.83	(88.75)
$D_{mixed\ farm}$ × wheat price (t−1)	−4.81	(4.85)	3.54	(6.43)
Constant	−8767.11***	(1668.01)	−1275.60	(2214.34)
Observations	16,305		16,305	
Within−R^2	0.006		0.001	

In addition, the small and statistically insignificant coefficients for interactions between farm type and output prices support the impression from the visual analysis that mixed farms do not react less sensitively to output prices than specialized dairy farms with respect to their investment decisions. These numbers do not raise suspicion of a negative effect of milk price volatility on technological advancements in the sector. Contrary to our initial expectations, high levels of net investments could be observed, especially after 2007, for both specialized and mixed dairy farms. From this result, it seems that the investment decisions of most dairy farms were not negatively influenced by increased price volatility and possibly even followed a strategy of new investments to counter increased output price risk. It is, however, not guaranteed that the relatively high levels of net investment resulted in positive technical change or an increase in technical efficiency. It could be that the investments were used for expansion of farm activities or for replacing equipment and not necessarily investment in innovative technology. In the following section, we therefore turn to the analysis of the production technology in a distance function framework, which allows the direct measurement of technical progress and technical inefficiency.

4.5. Methodology

We now turn to the methods we applied for the estimation of the production technology, technical change, technical efficiency, and related measures.

4.5.1. Distance function framework

To account for multiple outputs and multiple inputs in both specialized and mixed dairy farms, we adopt a distance function framework. The output distance function is defined by the maximum possible amount by which a farmer can increase outputs with given production inputs while still remaining in the production possibility set (Färe and Primont 1995). Formally, $D^O(X,Y,T,Z) = \min\{\Theta : (Y/\Theta) \epsilon P(X,T,Z)\}$, where X and Y denote input and output vectors, respectively, T contains technical change as one external shift factor, and Z denotes changes in environmental conditions. For empirical implementation, the distance function can be described in translog form. Imposition of linear homogeneity with respect to outputs and defining $\ln D^O = -u$ results in the estimable equation

$$\begin{aligned}
-\ln y_{1it} = \alpha_0 &+ \sum_{m=2}^{M} \alpha_m \ln y^*_{mit} + \frac{1}{2}\sum_{m=2}^{M}\sum_{n=2}^{M} \alpha_{mn} \ln y^*_{mit} \ln y^*_{nit} \\
&+ \sum_{k=1}^{K} \beta_k \ln x_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \ln x_{kit} \ln x_{lit} \\
&+ \frac{1}{2}\sum_{k=1}^{K}\sum_{m=2}^{M} \gamma_{km} \ln x_{kit} \ln y^*_{mit} + \ln T + u_{it} \\
&+ \sum_{p=1}^{2} \eta_p z_{pit} + v_{it}.
\end{aligned} \tag{4-1}$$

v_{it} is a normally distributed random error and with z_{pit} we introduce additional variables accounting for environmental conditions. Inefficiency is quantified by u_{it} following a truncated normal distribution. $\ln T$ denotes the technical change component and will be discussed below. We impose linear homogeneity in outputs by dividing other outputs by the farm's milk output, that is, $y^*_{mit} = y_{mit}/y_{1it}$. The symmetry conditions are imposed by $\alpha_{mn} = \alpha_{nm}$ $(m, n = 2, \dots, M)$ and $\beta_{kl} = \beta_{lk}$ $(k, l = 1, \dots, K)$.

Useful measures can be derived from the distance function in the form of derivatives. Distance elasticities with respect to inputs $(\partial \ln D^O/\partial \ln x_k = \partial(-\ln y_1)/\partial \ln x_k = -\epsilon_{y_1 x_k})$ represent the percentage change in y_1 by a one-percent change in x_k while holding the output ratios y^*_m constant i.e., a change in total output, and are therefore equivalent to output elasticities with respect to inputs in a production function framework. In contrast, derivatives with respect to the normalized outputs $(\partial \ln D^O/\partial \ln y^*_m = \partial \ln y_1/\partial \ln y^*_m)$ are output m's share in total production and indicate its relative importance in production (Morrison Paul and Nehring 2005).

4.5.2. Formulation of technical change

We aim to evaluate the rate of technical change for milk production by specialized and mixed dairy farms. For specialized farms, which only realize a minor share of their output in the form of non-milk products, we can rely on the standard time trend approach to measure technical change. That is, in equation (4-1) we let

$$\ln T = \delta_t t + \frac{1}{2}\delta_{tt} t^2 + \sum_{m=2}^{M} \alpha_{mt} t \ln y^*_{mit} + \sum_{k=1}^{5} \beta_{kt} t \ln x_{kit} \qquad (4\text{-}2)$$

where the first two terms account for neutral technical change and the last two terms for output and input biases in technical change. The rate of technical change can then be evaluated as

$$\dot{T}_t \equiv \frac{\partial(-\ln y_1)}{\partial t} = \frac{\partial \ln T}{\partial t} = \delta_t + \delta_{tt}t + \sum\nolimits_{m=2}^{M} \alpha_{mt} \ln y_{mit}^* + \sum\nolimits_{k=1}^{5} \beta_{kt} \ln x_{kit}. \tag{4-3}$$

Since (4-2) includes a term quadratic in t, $\dot{T}$ depends on t and is sufficiently flexible to detect a possible slowdown (or speedup) in (neutral) technical change.

To allow for a more erratic pattern of technical change we additionally compare this specification to a time dummy variable specification; i.e., we let $\ln T = \sum_{t=1996}^{2013} \lambda_t D_t$ in equation (4-1). This specification allows a more flexible inspection of technical change (Sauer and Park 2009) and corresponds to the general technical change index formulation by Baltagi and Griffin (1988) with the assumption of Hicks-neutral technical change.[4]

For mixed farms, which generate a considerable share of their output from non-milk outputs, an evaluation of technical change in this manner would only yield an unprecise measure (in the context of our study) since this technical change measure shows frontier shifts in the aggregate output mix of the farm. Moreover, we want to evaluate product-specific technical change. One possibility to achieve this would be to estimate separate, product-specific production functions by allocating production inputs across production outputs according to, for example, observed revenue shares (Foster, Haltiwanger, and Syverson 2008) or by using estimates from single-product firms (Loecker et al. 2016). Examples for product-specific analyses of productivity and technical change with observed input allocations include Cherchye et al. (2013) and Walheer (2019). Because revenue shares fluctuate with output prices and we do not observe input allocations, we instead rely on measures that can be derived from an enhanced formulation of technical change based on the distance function. More specifically, we focus on

[4] We restrict technical change in this specification to be Hicks-neutral since the full specification by Baltagi and Griffin (1988) interrelates the neutral and biased technical change components, which is unsuitable for our analysis of mixed farms.

measures of technical change biases. In general, technical change biases with respect to an input contain information about whether technical change is relatively input-saving or input-using, meaning that new technology allows to use less or requires more of one specific input in relation to the other inputs in order to produce the same amount of output. Transferring this idea to outputs, a bias towards one output implies that with the same amount of inputs, a relatively greater amount of this output can be produced. This, in turn, can be interpreted as relatively stronger technological advances realized in the production of this output.

In our formulation of technical change, we follow Stevenson (1980), who introduces additional third-order interaction terms (a truncated third-order Taylor-series expansion) into a cost function. While Stevenson (1980) uses terms of time multiplied with interactions across the other regressors (i.e. $t \times \sum_j \sum_k X_j X_k$), we use terms of quadratic time interacted with linear terms of inputs and outputs (i.e. $t^2 \times \sum_j X_j$), that is, we specify

$$\begin{aligned} \ln T = \delta_t t + \frac{1}{2}\delta_{tt} t^2 + \sum_{m=2}^{M} \alpha_{mt} t \ln y_{mit}^* + \sum_{k=1}^{5} \beta_{kt} t \ln x_{kit} \\ + \frac{1}{2}\sum_{m=2}^{M} \alpha_{mtt} t^2 \ln y_{mit}^* + \frac{1}{2}\sum_{k=1}^{5} \beta_{ktt} t^2 \ln x_{kit}. \end{aligned} \tag{4-4}$$

Therefore, the rate of technical change becomes

$$\begin{aligned} \dot{T}_t \equiv \frac{\partial \ln T}{\partial t} = \delta_t + \delta_{tt} t + \sum_{m=2}^{M} \alpha_{mt} \ln y_{mit}^* + \sum_{k=1}^{5} \beta_{kt} \ln x_{kit} \\ + \sum_{m=2}^{M} \alpha_{mtt} t \ln y_{mit}^* + \sum_{k=1}^{5} \beta_{ktt} t \ln x_{kit}. \end{aligned} \tag{4-5}$$

In contrast to (4-3), the technical change biases are now measured with two additional terms that are dependent on t. That is, whereas the usual formulation only allows for technical change biases in constant rates, we allow for changing rates in technical change biases. The relative importance of an output in the production process is then given by

$$\frac{\partial(-\ln y_{1it})}{\partial \ln y_{mit}^{*}} = \alpha_m + \alpha_{mm} \ln y_{mit}^{*} + \frac{1}{2}\alpha_{mn} \ln y_{nit}^{*} + \sum\nolimits_{k=1}^{5} \gamma_{km} \ln x_{kit} + \alpha_{mt} t + \frac{1}{2}\alpha_{mtt} t^2 \tag{4-6}$$

and this entity's change over time by

$$\frac{\partial}{\partial t}\left[\frac{\partial(-\ln y_{1it})}{\partial \ln y_{mit}^{*}}\right] = \alpha_{mt} + \alpha_{mtt} t, \tag{4-7}$$

where $\alpha_{mt} > 0 (< 0)$ indicates increasing (decreasing) significance of output m in the production process, that is, output-m-favoring (discriminating) technical change, at an increasing ($\alpha_{mtt} > 0$) or decreasing ($\alpha_{mtt} < 0$) rate. In this way, we can evaluate whether technical change in milk production by mixed farms decelerated or accelerated relative to other outputs during volatile market phases. A deceleration of technical change in milk production would correspondingly indicate a shift in innovation efforts towards other outputs.

4.5.3. Generalized Malmquist index

After the estimation of technical change, our analysis aims to explore possible reasons for the pattern of technical change we observe. Because farmers' primary interest lies in profitability (that is, productivity with given input and output prices), this entails examination of the components of productivity other than technical change and technical efficiency. An approach that lends itself to this purpose is proposed by Orea (2002). From discrete changes in the output distance function from one period to the next, a Malmquist productivity index can be calculated that separates total factor productivity into technical efficiency change (TEC), scale efficiency change (SEC), and technical change (TC). Starting from an output distance function as defined by equation (4-1), the index can be defined as

$$
\begin{aligned}
ln\, G_{it}^{O} \equiv\ & \frac{1}{2}\sum\nolimits_{m=1}^{M}\left(\frac{\partial \ln D_{it}^{O}}{\partial \ln y_{imt}} + \frac{\partial \ln D_{is}^{O}}{\partial \ln y_{ims}}\right)(\ln y_{mit} - \ln y_{mis}) \\
& -\frac{1}{2}\sum_{k=1}^{K}\left(\frac{\partial \ln D_{it}^{O}/\partial \ln x_{kit}}{\sum_{k=1}^{K}\partial \ln D_{it}^{O}/\partial \ln x_{kit}} + \frac{\partial \ln D_{is}^{O}/\partial \ln x_{kis}}{\sum_{k=1}^{K}\partial \ln D_{is}^{O}/\partial \ln x_{kis}}\right)(\ln x_{kit} - \ln x_{kis}) \\
& = \frac{1}{2}\sum_{k=1}^{K}\left[\left(-\sum\nolimits_{k=1}^{K}\frac{\partial \ln D_{it}^{O}}{\partial \ln x_{kit}} - 1\right)\frac{\partial \ln D_{it}^{O}/\partial \ln x_{kit}}{\sum_{k=1}^{K}\partial \ln D_{it}^{O}/\partial \ln x_{kit}}\right. \\
& \left. + \left(-\sum\nolimits_{k=1}^{K}\frac{\partial \ln D_{is}^{O}}{\partial \ln x_{kis}} - 1\right)\frac{\partial \ln D_{is}^{O}/\partial \ln x_{kis}}{\sum_{k=1}^{K}\partial \ln D_{is}^{O}/\partial \ln x_{kis}}\right](ln\, x_{kit} - ln\, x_{kis}) \\
& -(ln\, T_t - ln\, T_s) - (u_t - u_s) \\
& -\frac{1}{2}\sum_{p=1}^{2}\left(\frac{\partial \ln D_{it}^{O}}{\partial z_{ipt}} + \frac{\partial \ln D_{is}^{O}}{\partial z_{ips}}\right)(z_{ipt} - z_{ips}) - (v_t - v_s) \\
& = SEC - TC - TEC - ZC - VC.
\end{aligned}
\tag{4-8}
$$

The terms right after the identity sign represent a total factor productivity (TFP) index with normalized output elasticities as weights for the aggregation of input changes. This corresponds to the generalized Malmquist index by Orea (2002) with the difference that we formulate technical change in a general form (where technical progress is observed when $ln\, T_t < ln\, T_s$), and we add changes in environmental variables (ZC) and idiosyncratic errors (VC).

As an extension and for the purpose of exploring changes in inputs and outputs underlying technical change, we restate the index equation as

$$
\begin{aligned}
-TC = & \left[\frac{1}{2}\sum\nolimits_{m=1}^{M}\left(\frac{\partial \ln D_{it}^{O}}{\partial \ln y_{imt}} + \frac{\partial \ln D_{is}^{O}}{\partial \ln y_{ims}}\right)(\ln y_{mit} - \ln y_{mis})\right. \\
& -\frac{1}{2}\sum_{k=1}^{K}\left(\frac{\partial \ln D_{it}^{O}/\partial \ln x_{kit}}{\sum_{k=1}^{K}\partial \ln D_{it}^{O}/\partial \ln x_{kit}}\right. \\
& \left.\left. + \frac{\partial \ln D_{is}^{O}/\partial \ln x_{kis}}{\sum_{k=1}^{K}\partial \ln D_{is}^{O}/\partial \ln x_{kis}}\right)(\ln x_{kit} - \ln x_{kis})\right] \\
& - SEC + TEC + ZC + VC.
\end{aligned}
\tag{4-9}
$$

In a way similar to a growth accounting approach, technical change can be 'decomposed' into separate (weighted) growth rates of inputs and outputs, while still considering scale and technical efficiency effects. This allows us to track movements in outputs and inputs that are intermediately responsible for the observed technical change patterns. That is, although we do not observe changes in production techniques originally responsible for technical change, comparing growth rates of inputs and outputs allows us to gain some further insight into the symptoms of technical change.

4.6. Data and estimation

We use data from the EU's Farm Accountancy Data Network on West German farms for the period 1995–2013. We exclude East German farms from the analysis because of structural differences in the form of the presence of very large mixed farms in the East German dataset, which would impair the comparison between specialized and mixed farms. For specialized dairy farms, we distinguish two farm outputs: 'milk' and 'other output' (i.e., $M = 2$ in equation (4-1)) and five production inputs 'dairy cows', 'intermediates', 'labor', 'land', and 'other capital'. Milk output (y_1) is defined as the physical quantity of milk produced on-farm. By using the physical quantity, we use an output measure free of any price biases possibly not fully accounted for by deflating revenues with a national price index. 'Other output' consists of all other goods produced on the farm, aggregated by summing up the deflated value of production in various categories. For mixed farms, we disaggregate this output category into two outputs ($M = 3$): 'plant production' and 'other animal production'. Inputs are defined in the same way for specialized and mixed farms. Input 'cows' (x_1) is measured by the average number of dairy cows, and 'intermediates' (x_2) are defined by expenditures for feed, animal purchases, other livestock specific inputs, energy, and crop specific inputs, each deflated by suitable price indices from Eurostat's online database. Input 'labor' (x_3) is the farm's annual work units (AWU), 'land' (x_4) is the amount of land used in production, and 'capital' (x_5) is measured by deflated depreciation for farm buildings and machinery. For both samples, we removed observations where the farm did not produce milk anymore or has not yet produced any milk.

Table 4-2. Descriptive statistics

		Specialized dairy farms		Mixed farms	
Variable	Unit	Mean	Std. Dev.	Mean	Std. Dev.
Output value shares					
Milk	%	72.5	13.1	37.9	17.1
Other animal production	%	19.2	10.4	35.1	23.6
hereof: cattle sales	%	93.8	16.3	56.8	38.0
hereof: pig sales	%	4.3	14.5	39.6	38.3
Plant production	%	8.3	9.2	27.0	16.3
Outputs					
Milk	kg	348,773	316,465	185,999	164,521
Other output	Euros	37,237	34,066		
Other animal output	Euros			67,969	90,949
Plant output	Euros			36,876	42,844
Inputs					
Cows	Number	50.2	36.3	28.1	19.5
Labor	Annual work units	1.8	0.8	1.8	0.9
Intermediates	Euros	50,594	45,902	74,548	75,166
Land	Hectares	60.1	39.8	68.7	52.6
Capital (depreciation)	Euros	19,238	13,875	19,025	13,460
Number of observations		31,079		11,485	

Note: Output value shares are shown for illustration purposes and are not used for estimation. Monetary values are in constant 1995 prices.

We further control for environmental conditions by including weather data from 22 weather stations, where each observation is assigned the data of the likely nearest weather station.[5] We include two proxies for weather shocks: the number of days per year with a maximum air temperature above 30°C to account for heat stress of dairy cows (z_1), and the log of the cumulative rainfall per year to account for beneficial growing conditions (z_2).

Descriptive statistics of the two samples are given in table 4-2. Specialized and mixed farms are on average of similar size in terms of labor and capital endowments. Inspecting output value shares reveals that the output of specialized farms mainly consists of milk and cattle sales, while mixed farms source, on average, almost equal parts of their output from milk, other animal production, and plant production.

As additional regressors we include 27 region dummy variables (NUTS 2 level). For estimation of the distance functions, we rely on the stochastic frontier model formulation of Battese and Coelli (1995) since it allows for flexible temporal variation of farm efficiency.[6] All calculations were performed in Stata 15 with the help of 'sfpanel' (Belotti et al. 2012).

4.7. Results and discussion

Prior to frontier estimations, OLS regressions were performed, and these showed a statistically significant positive skew of predicted residuals, justifying a stochastic frontier formulation. Overall, the model fit of the distance functions for both the specialized and the mixed farm sample was satisfactory with 64% (specialized farms) and 48% (mixed farms) of the coefficients showing statistical significance

[5] The data are publicly available from the German meteorological service DWD (www.dwd.de).

[6] We decided not to use a frontier model that separates unobserved heterogeneity from efficiency (e.g., by Greene 2005 or Kumbhakar, Lien, and Hardaker 2014) because of our data, which is an unbalanced panel. Therefore, for farms that are in the dataset only a few years, (time-invariant) heterogeneity might be overstated.

at the 10% level or lower. The full model estimation results are given in in the appendix in table 4-8.

4.7.1. Specialized farms

Average estimated distance elasticities for the sample of specialized farms are given in table 4-3. Because of the distance function formulation with negative output as the dependent variable, elasticities with respect to outputs are expected to have a positive sign and elasticities with respect to inputs a negative sign. As expected from output value shares, the distance elasticity with respect to other output amounts to approximately 18 %, signifying that specialized milk farms generate most of their output from milk production. All elasticities with respect to inputs show the expected negative sign with milk cows being the most important production input. The sum of the elasticities with respect to inputs suggests that specialized farms on average operate at slightly increasing but close to constant returns to scale.

Table 4-3. Average estimated marginal effects in specialized farming

	Average marginal effect	S.E.
Other output	0.183***	0.004
Cows	−0.559***	0.009
Intermediates	−0.375***	0.006
Labor	−0.042***	0.006
Land	−0.028***	0.007
Capital	−0.054***	0.004
Returns to scale	−1.059	
Time	−0.013***	0.000

Note: Standard errors are calculated using the delta method.

Our main interest lies in the estimates of technical change. On average for the whole sample period, specialized farms realized technical progress at a rate of

1.3 % per year (table 4-3), which is in line with the results of other studies (Cechura et al. 2017; Emvalomatis 2012; Kellermann and Salhofer 2014). As indicated by the negative coefficient for the quadratic time term (δ_{tt}, see table 4-8 in the appendix), however, there is a slowdown in estimated neutral technical change. To illustrate, the second column of table 4-4 gives average predicted growth rates by year. Technical change decelerated over time with growth rates of 1.8 % at the beginning and 0.8 % at the end of the study period. To investigate further, we illustrate in figure 4-3 the results of the distance function estimation with year dummies in place of the continuous year variable. The graph plots the year dummy coefficients λ_t alongside the predicted frontier from the baseline model (equations (4-1) and (4-2), with inputs and outputs held constant at the sample mean and normalized to 1995 = 0).

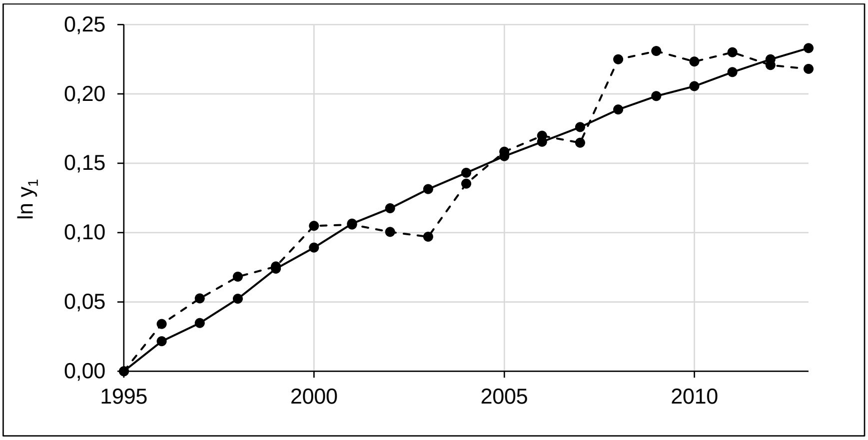

Figure 4-3. Technology levels estimated by models with a time trend (solid line) and a time dummy formulation (dashed line)

Although both specifications capture the same long-term trend, the dummy variable specification uncovers a plateau in the technology level after 2008. This pattern is further confirmed by allowing for differing rates of neutral technical change starting from 2009 in the baseline model. We incorporate this by interacting the neutral technical change terms with a dummy variable, assuming the value of 1 for the years 2009 to 2013, that is, we add $\delta_{Dt} D_{t \geq 2009} t + \delta_{Dtt} D_{t \geq 2009} t^2$ in equation (4-2). The two additional coefficients are both statistically significant. The predicted technical change rates are given in the third column of table 4-4 and suggest that yearly technical progress remained at a stable level of around 1.4 % per year until 2008, whereas the rates were close to zero for the period after 2008. After 2010, even statistically significant positive change rates are observed, indicating (slow) technical regress.

The estimates for technical inefficiency (last column of table 4-4, calculated on the basis of a common TC trend) reveal that the level of mean inefficiency remained fairly stable at around 10 %. This low level of inefficiency is remarkable, especially considering that our model does not consider farm heterogeneity other than region-specific effects. The largest change in inefficiency occurred in 2008, when mean inefficiency is estimated to be reduced by 1.7 %age points. The frontier shift visible in the time dummy specification and the drop in inefficiency in the time trend formulation in 2008 were preceded by a spike in milk prices in 2007 (see figure 4-2). Recalling the spike in farm machinery and equipment observed in figure 4-2, this suggests that farmers used additional revenue to update their equipment, which translated into productivity growth either ascribed to increased technical change (in the time dummy specification) or reduced inefficiency (in the time trend specification). However, the continuing stagnation in technical change and technical inefficiency after 2008 is not in line with increasing levels of net investment observed after 2009. In general, one would expect farmers to need some time to adjust to newly implemented techniques. For example, the construction of new farm buildings requires additional attention from the farmer, and herd management must be adjusted to the new conditions. Therefore, some latency until major investments manifest themselves in increased productivity is plausible. Yet the peculiarity of our observation lies in the endurance of the technical change stagnation. That is, the high levels of net investment from 2009 onward did not result in technical progress during the following four years.

Table 4-4. Average rates of technical change and predicted inefficiency by year for specialized farms

Year	$\dot{T}_t$ Common TC trend for all years		$\dot{T}_t$ Allowing for break in neutral TC in 2009		Inefficiency (u)
1995	−0.018***	(0.001)	−0.012***	(0.001)	0.093
1996	−0.018***	(0.001)	−0.012***	(0.001)	0.092
1997	−0.017***	(0.001)	−0.012***	(0.001)	0.091
1998	−0.016***	(0.001)	−0.013***	(0.001)	0.094
1999	−0.016***	(0.001)	−0.013***	(0.001)	0.093
2000	−0.015***	(0.000)	−0.014***	(0.001)	0.092
2001	−0.015***	(0.000)	−0.014***	(0.000)	0.097
2002	−0.014***	(0.000)	−0.014***	(0.000)	0.104
2003	−0.013***	(0.000)	−0.014***	(0.000)	0.103
2004	−0.013***	(0.000)	−0.015***	(0.000)	0.100
2005	−0.012***	(0.000)	−0.015***	(0.001)	0.099
2006	−0.012***	(0.000)	−0.015***	(0.001)	0.097
2007	−0.011***	(0.000)	−0.016***	(0.001)	0.108
2008	−0.010***	(0.000)	−0.016***	(0.001)	0.091
2009	−0.010***	(0.000)	−0.002**	(0.003)	0.094
2010	−0.009***	(0.001)	0.000	(0.002)	0.094
2011	−0.009***	(0.001)	0.002**	(0.001)	0.099
2012	−0.008***	(0.001)	0.004***	(0.001)	0.101
2013	−0.008***	(0.001)	0.006***	(0.001)	0.104
Total	−0.013***	(0.000)	−0.009***	(0.000)	0.097

Note: The numbers show average estimated marginal effects by year based on the estimation for the whole sample and based on an estimation allowing for a structural break in 2009 by incorporating dummy variable interactions with neutral technical change. Standard errors in parentheses and significance levels were calculated using the delta method.

This contrasts with results from earlier studies that established shorter time lags between investment activity and productivity effects (Sauer and Latacz-Lohmann 2015). To gain additional insights, we explore possible reasons for the observed pattern in the following subsection.

Exploring the technical change stagnation

Several explanations for the pattern of technical change we observe come to mind. First, during uncertain market phases, farmers might shift their focus towards implementing already established techniques by imitating peers but neglect new (unknown and therefore riskier) techniques that are able to push the frontier outward. This behavior would explain technical change stagnation and would be observable in increased technical efficiency. Second, especially towards the end of the milk quota system, farmers might have tried to position themselves for a prospective increase in market share by shifting to growth strategies and using scale effects, for which a consequence would be increased scale efficiency. Third, high feed prices that were observed starting in 2007 might have dampened cow productivity. Lastly, one might wonder whether specialized dairy farms showed no technical progress *although* or *because* they showed high levels of net investment after 2008—that is, positive output growth could have been outweighed by extraordinarily high capital input growth.

To explore the plausibility of these explanations, we show in table 4-5 results for the Malmquist index decomposition as described by equation (4-8) and based on the time dummy specification. While we report the average changes for each year in table 4-10 in the appendix, we show in table 4-5 averages for the two periods before and starting from 2009. Overall, the numbers indicate technical change to be the most important driver of productivity, leading to synchronous progressions of technical change and total factor productivity change. Technical efficiency change is estimated as close to zero, suggesting that the average dairy farmer did not move closer to the frontier after 2009, which was already indicated by the low and stable levels of technical inefficiency shown in table 4-4 for the time trend formulation. This contradicts the presumption that farmers shifted their attention to the adoption of established technologies.

In addition, the influences of weather effects (ZC) and unobserved factors (VC) seem to be of minor importance. Similarly, scale efficiency gains are close to zero. The likely explanation is given by the estimates of returns to scale, which indicated slightly increasing but close to constant returns to scale (table 4-3), with 90% of the observations lying in the range of −1.10 to −1.02. This leaves little room for productivity improvement by a growth strategy.

Table 4-5. Results for the Malmquist index decomposition

		Output and input changes						
Period	−TC	Milk	Other output	Cows	Materi-als	Labor	Land	Capital
1996−2008	0.017	0.015	0.003	0.003	−0.002	0.000	0.000	−0.001
2009−2013	−0.002	0.016	0.003	0.007	0.009	0.000	0.000	0.000

Period	TFP	SEC	−TEC	−ZC	−VC
1996−2008	0.017	0.000	−0.001	0.000	0.001
2009−2013	0.003	0.001	0.000	0.001	0.002

Note: The negative of TC, TEC, ZC, and VC is shown for ease of interpretation, positive numbers (in all columns apart from input growth rates) contribute positively to TFP. Growth rates of outputs and inputs are weighted by corresponding elasticities.

Nevertheless, positive growth rates of outputs show that farms consistently grew in size throughout the two periods. Especially after 2009, this was likely facilitated by the increases in quota volumes. Additionally, after 2009, farm milk output grew faster than average herd size, which means that average cow productivity still increased during the period of technical change stagnation (if at slightly smaller rates). This contradicts a potential negative effect of high feed prices or a possible stagnation in improvements in cow genetics on technical change. Looking at growth rates of capital input reveals that capital is accredited only a minor share in production (as can be seen by low average distance elasticities in table

4-3), and hence the observed high levels of investment can be ruled out as a cause of the low technical change rates.

Apparently, the technical change stagnation after 2008 was associated with high growth rates in cow and material inputs. Dairy farms still achieved output growth rates at least similar in magnitude to those before 2009, but this output growth was consumed almost completely by growth in cow and material inputs. In general, growth in milk output and materials input seems more interrelated after 2008: growth in milk output was accompanied by synchronous growth in materials input (see table 4-10 in the appendix). From the yearly growth rates in cow input, it can also be seen that, coinciding with a milk price spike, average herd size growth was especially high in 2007, close to zero at the price low in 2009, and higher with recovering milk prices starting in 2010.

All of this suggests that dairy farmers reacted to changing output prices and increased price volatility and entered an adjustment phase starting in 2007, which was characterized by an overall increasing scale of operations. The stagnation in technical progress during this phase indicates that many of the net investments were aimed at an expansion of operations and not necessarily at improving production techniques. Additionally, the potential for improvements in productivity by increases in technical efficiency or scale efficiency were limited by the already high levels of technical efficiency and returns to scale close to unity.

4.7.2. Mixed farms

Average estimated distance elasticities for mixed farms are given in table 4-6. As for specialized farms, all elasticities show the expected sign. Animal and plant output are estimated to represent approximately 41 % of total production, which is slightly less than their calculated revenue shares (table 4-2). Over the whole sample period, mixed farms showed technical progress of 1.0 % per year, which is less than the 1.3 % estimated for specialized farms.

Table 4-6. Average estimated marginal effects in mixed farming

	Average marginal effect	S.E.
Animal output	0.230***	0.005
Plant output	0.183***	0.006
Cows	−0.497***	0.013
Intermediates	−0.425***	0.010
Labor	−0.054***	0.010
Land	−0.037***	0.010
Capital	−0.049***	0.005
Returns to scale	−1.062	
Time	−0.010***	0.001

Note: Standard errors calculated with the delta method.

We explore the shape of technical change in the same way as for specialized farms in table 4-7. The numbers show that in general, technology progressed more slowly over the whole study period for these farms as compared to specialized farms, supporting the assumption that specialized farms have a greater ability to acquire state-of-the-art technology. Allowing for a structural break in technical change in 2009 shows that, contrary to our expectation, we observe the same pattern of stagnating technical change after 2008: While growth rates hover closely around values of 1 % per year in the period 1995-2008, no technical progress is realized during the years 2009-2013. Compared to specialized farms, mixed farms show a similar level of average technical inefficiency of 9.0 %. As in specialized farms, mean inefficiency decreased in 2008, however, this change is not too different in magnitude from the changes observed in other years. The more fluctuating nature of technical inefficiency might be due to the greater influence of weather conditions on plant production not controlled for by the weather proxies in our model.

Table 4-7. Average rates of technical change and predicted inefficiency by year for mixed farms

	$\dot{T}_t$				Inefficiency (u)
Year	Common TC trend for all years		Allowing for break in neutral TC in 2009		
1995	−0.010***	(0.002)	−0.010***	(0.002)	0.091
1996	−0.010***	(0.002)	−0.010***	(0.002)	0.086
1997	−0.010***	(0.002)	−0.010***	(0.001)	0.085
1998	−0.010***	(0.002)	−0.010***	(0.001)	0.087
1999	−0.011***	(0.002)	−0.011***	(0.001)	0.091
2000	−0.011***	(0.002)	−0.011***	(0.001)	0.085
2001	−0.011***	(0.002)	−0.010***	(0.001)	0.088
2002	−0.010***	(0.002)	−0.010***	(0.001)	0.089
2003	−0.011***	(0.002)	−0.010***	(0.001)	0.096
2004	−0.010***	(0.002)	−0.010***	(0.001)	0.087
2005	−0.010***	(0.002)	−0.010***	(0.001)	0.088
2006	−0.010***	(0.002)	−0.010***	(0.001)	0.094
2007	−0.010***	(0.002)	−0.010***	(0.001)	0.103
2008	−0.009***	(0.002)	−0.009***	(0.002)	0.080
2009	−0.009***	(0.002)	−0.003*	(0.002)	0.085
2010	−0.009***	(0.002)	−0.002	(0.002)	0.098
2011	−0.008***	(0.002)	−0.001	(0.002)	0.083
2012	−0.007***	(0.002)	0.001	(0.002)	0.096
2013	−0.007***	(0.002)	0.003	(0.003)	0.096
Total	−0.010***	(0.001)	−0.008***	(0.001)	0.090

Note: The numbers show average estimated marginal effects by year and in total from the estimation on the whole sample and from an estimation allowing for a structural break in 2009 by incorporating dummy variable interactions with neutral technical change. Standard errors in parentheses and significance levels were calculated by the delta method.

To further explore the technical progress realized in specific outputs, we evaluate the coefficients of the technical change bias terms with respect to the outputs (α_{mt} and α_{mtt}). These coefficients are estimated to be close to zero but statistically significantly different from zero for animal production (at the 10 % level, see table 4-8 in the appendix). With $\alpha_{2t} > 0$ and $\alpha_{2tt} < 0$, the share of animal output shows a flat, n-parabolic shape over time. This is illustrated in figure 4-4. If technical change were to favor animal output, we would expect an upward-sloping shape of the share of animal output. The results therefore suggest that neither output was favored by technical change and that mixed farms allocated their innovation efforts independently from price developments in the individual output categories. The low growth rates in overall technical change observed in mixed farms after 2008, however, suggest that like specialized farms, mixed farms did not realize substantial technological progress in either output activity. An explanation for this might possibly be found by scrutinizing output prices of the different agricultural outputs in recent years.

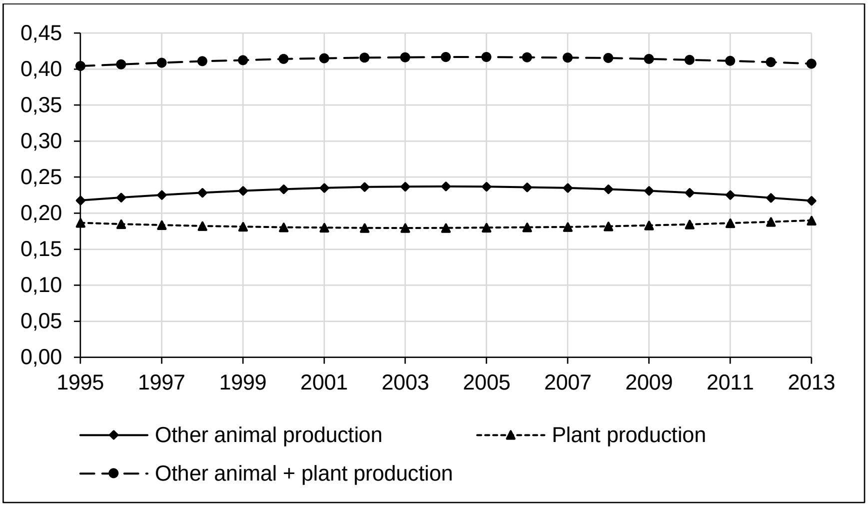

Figure 4-4. Predicted shares of other animal production and plant production over time for mixed farming

As can be seen in figure 4-5, not only did milk show increased volatility since 2007 but the prices for cash crops did so as well. Moreover, the prices moved in a more concerted pattern.[7] With increased positive correlation between prices of different outputs, diversified farms lose their risk-spreading advantage over specialized farms (Merener and Steglich 2018).

Inspecting further the series for pig prices in figure 4-5 raises the question of whether farms with pig production had an advantage over farms without pig production, since pig prices seemed more stable after 2007. For brevity, we do not report separate estimation results, but note that further analyses showed that this was not the case. The distance function for mixed farms active in pig production equally showed no shifts significantly different from zero when estimated for the period after 2008. This shows that also farms with a high degree of diversification showed no different innovation behavior.

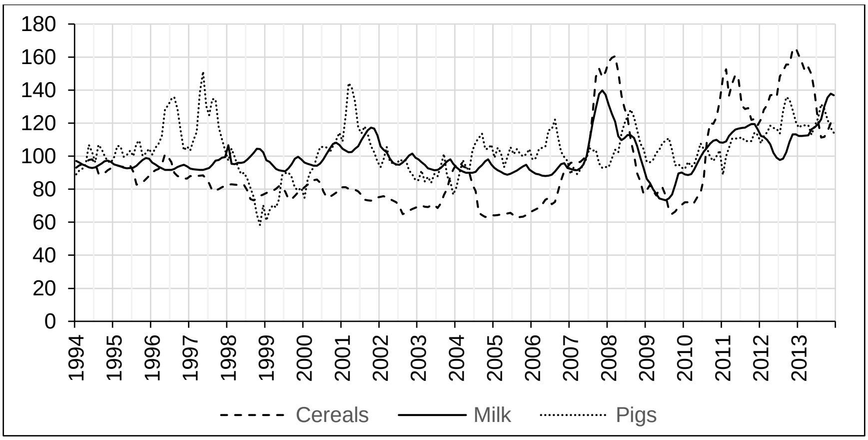

Figure 4-5. Indices of output prices for cereals, milk, and pigs in Germany

Source of data: German National Statistical Office (Destatis 2019)

[7] This can be illustrated by looking at correlation of the price series: For the monthly prices shown in figure 4-5, correlation coefficients before/after January 2007 amounted to –0.10/0.71, –0.02/0.30, and 0.19/0.40 for milk and cereals, milk and pigs, and cereals and pigs, respectively.

4.8. Conclusions

When estimating distance functions for dairy farms, we observe a slowdown in technical change during a phase of volatile milk prices. Our analysis also shows that mixed dairy farms did not exhibit different innovation behavior than specialized dairy farms. We suspect that the reason for this can be found in the correlation between prices of different agricultural commodities during recent years by which diversification partly lost its risk-spreading advantage.

While the recent changes in the regulatory environment are likely a determinant of milk price volatility—for example, by lowering intervention price levels—they might have also had a direct effect on dairy farmers' investment behavior by influencing their confidence in future business opportunities. Because of the simultaneity of the regulatory changes and milk price volatility, and since variation in prices happens across time rather than across farms, the two effects are hard to separate. Hence, asserting a causal effect of price volatility on technical change is difficult. However, milk price volatility was one—if not the most—important determinant of dairy farmers' financial well-being in recent years and several empirical studies confirmed that price volatility impacts famer's investment decisions. Therefore, it is plausible to assume that price volatility played at least a partial role in the technological stagnation we observe.

Further, our results indicate that the stagnation in technical change happened despite the considerable willingness of dairy farmers to invest in new equipment, which questions our original expectation of a direct negative effect of price volatility on technical change. More likely, a combined effect of price volatility and phasing-out of the quota led farmers into a turbulent adjustment period, where—as indicated by the high growth in average herd size and milk output—dairy farmers positioned themselves for a market free of quota limitations and an alignment to world market prices. Considering the rather steep increase in the technology level in 2008 following a year of high milk prices, it remains unclear whether the slowdown we observe is enduring or just a temporary rest—a question that should be addressed in future analyses. If the stagnation we observe turns out to be an adjustment period, improvements in technical change as a consequence of the previous high levels of net investment are a likely scenario for the following years.

Another conclusion is that if we do not observe the effect of a lack of willingness to invest, we might observe a lack of technological opportunities that were able to push the state of technology in the sector. Implemented technologies might put greater emphasis on progress we do not observe in the data, for example, on advancements in product quality, such as in animal welfare. Further research should also focus in more detail on this missing link between farm net investments and technical change.

4.9. Appendix

Table 4-8. Estimation results

	Specialized farms		Mixed farms	
Parameter	Coefficient	S.E.	Coefficient	S.E.
Other output α_2	−0.4511***	(0.0685)		
α_{22}	0.0780***	(0.0072)		
Animal output α_2			−0.5619***	(0.0751)
α_{22}			0.0523***	(0.0035)
Plant output α_3			0.1804**	(0.0824)
α_{33}			0.0347***	(0.0037)
α_{23}			0.0060	(0.0069)
Cows β_1	−0.8475***	(0.1659)	−1.1298***	(0.1590)
β_{11}	0.1254***	(0.0294)	0.0089	(0.0163)
Intermediates β_2	−0.1450	(0.1161)	0.4766***	(0.1219)
β_{22}	−0.0114	(0.0097)	−0.0535***	(0.0087)
Labor β_3	−0.3181***	(0.1161)	−0.1019	(0.1611)
β_{33}	0.0077	(0.0108)	0.0231	(0.0162)
Land β_4	0.0535	(0.1107)	−0.4632***	(0.1586)
β_{44}	0.0010	(0.0097)	−0.0078	(0.0163)
Capital β_5	0.0145	(0.0484)	0.1951**	(0.0789)
β_{55}	−0.0032*	(0.0019)	−0.0016	(0.0039)
β_{12}	−0.0237	(0.0300)	0.0410*	(0.0215)
β_{13}	−0.0828***	(0.0261)	−0.0006	(0.0298)
β_{14}	−0.0242	(0.0268)	0.0237	(0.0292)
β_{15}	−0.0703***	(0.0124)	−0.0494***	(0.0132)
β_{23}	0.0381**	(0.0170)	0.0093	(0.0200)
β_{24}	−0.0179	(0.0171)	0.0282	(0.0180)
β_{25}	0.0264***	(0.0081)	0.0082	(0.0095)
β_{34}	0.0041	(0.0167)	−0.0365	(0.0230)
β_{35}	0.0246***	(0.0094)	0.0191	(0.0152)
β_{45}	0.0169*	(0.0087)	0.0135	(0.0138)
γ_{12}	0.0968***	(0.0259)	0.0518***	(0.0141)
γ_{22}	−0.0208	(0.0133)	0.0346***	(0.0100)
γ_{32}	−0.0193**	(0.0093)	−0.0159	(0.0103)
γ_{42}	−0.0000	(0.0115)	−0.0370***	(0.0105)
γ_{52}	−0.0223***	(0.0051)	−0.0219***	(0.0054)

Table 4-9. Estimation results (continued)

	Specialized farms		Mixed farms	
Parameter	Coefficient	S.E.	Parameter	Coefficient
γ_{13}			0.0450***	(0.0160)
γ_{23}			−0.0473***	(0.0108)
γ_{33}			−0.0060	(0.0121)
γ_{43}			0.0429***	(0.0156)
γ_{53}			−0.0202***	(0.0069)
Time δ_t	−0.0014	(0.0055)	−0.0086	(0.0273)
δ_{tt}	0.0003***	(0.0000)	0.0001	(0.0015)
α_{2t}	−0.0011**	(0.0005)	0.0044**	(0.0021)
α_{3t}			−0.0018	(0.0025)
α_{2tt}			−0.0002**	(0.0001)
α_{3tt}			0.0001	(0.0001)
β_{1t}	−0.0038***	(0.0012)	−0.0033	(0.0050)
β_{2t}	−0.0009	(0.0008)	−0.0012	(0.0033)
β_{3t}	0.0013	(0.0008)	0.0013	(0.0043)
β_{4t}	0.0026***	(0.0007)	−0.0034	(0.0039)
β_{5t}	0.0001	(0.0004)	0.0018	(0.0023)
β_{1tt}			0.0001	(0.0003)
β_{2tt}			0.0000	(0.0002)
β_{3tt}			−0.0000	(0.0002)
β_{4tt}			0.0000	(0.0002)
β_{5tt}			−0.0000	(0.0001)
Region	(0.000)		(0.000)	
Heat η_1	0.0005***	(0.0001)	0.0009***	(0.0002)
Rain η_2	−0.0075	(0.0047)	−0.0116	(0.0083)
Constant	0.6978	(0.4686)	−2.3184***	(0.6529)
σ_u	−6.70e+03***		5.8313***	
σ_v	6.4812***		−4.2236***	
Log-Likelihood				
Observations	31,079		11,485	

Note: Significance levels are ***0.01, **0.05, and *0.10. Standard errors in parenthesis are clustered within farms. Coefficient estimates for the region dummies are not reported, but the numbers in parentheses show p-values of a test on joint significance.

Table 4-10. Detailed results for yearly TFP components of specialized dairy farms

		Output and input changes						
Year	−TC	Milk	Other output	Cows	Materials	Labor	Land	Capital
1996	0.033	0.023	−0.002	0.005	−0.007	−0.001	0.000	−0.001
1997	0.018	0.007	0.001	−0.002	−0.010	0.000	0.001	−0.003
1998	0.016	0.012	0.004	−0.002	0.005	−0.001	0.000	0.000
1999	0.007	0.032	0.004	0.009	0.011	0.000	0.000	0.001
2000	0.030	0.032	0.002	0.015	−0.008	0.000	0.001	0.000
2001	0.000	0.001	0.008	−0.001	0.005	0.000	0.000	0.000
2002	−0.005	0.007	−0.008	−0.001	0.010	−0.001	0.000	−0.004
2003	−0.003	0.013	−0.002	0.002	0.005	0.000	0.000	−0.002
2004	0.038	0.013	0.007	0.001	−0.011	0.000	0.000	−0.002
2005	0.024	−0.005	0.012	−0.003	−0.007	0.000	0.001	−0.001
2006	0.008	0.024	−0.001	0.002	0.004	0.000	0.000	0.000
2007	−0.003	0.007	−0.004	0.012	0.002	0.000	0.000	0.000
2008	0.061	0.023	0.018	0.008	−0.024	0.000	0.000	−0.001
2009	0.006	0.011	0.007	0.002	0.008	0.000	0.000	−0.001
2010	−0.008	0.034	−0.006	0.009	0.013	0.000	0.000	0.000
2011	0.006	0.015	0.007	0.005	0.010	0.000	0.000	0.000
2012	−0.008	−0.011	−0.003	0.005	−0.014	0.000	0.000	0.000
2013	−0.005	0.033	0.009	0.012	0.026	0.000	0.000	0.001

Year	TFP	SEC	−TEC	−ZC	−VC
1996	0.025	0.000	0.001	−0.010	0.002
1997	0.023	−0.001	−0.001	0.006	0.001
1998	0.014	0.000	−0.004	0.002	−0.001
1999	0.016	0.001	0.003	0.002	0.002
2000	0.027	0.001	0.000	−0.007	0.004
2001	0.005	0.000	−0.003	0.008	0.000
2002	−0.006	0.000	0.000	−0.002	0.000
2003	0.006	0.000	0.000	0.009	0.000
2004	0.031	−0.001	0.000	−0.009	0.003
2005	0.017	−0.001	−0.003	−0.004	0.000
2006	0.016	0.000	−0.001	0.009	0.000
2007	−0.011	0.001	−0.002	−0.008	0.001
2008	0.057	−0.001	−0.001	−0.001	−0.001
2009	0.008	0.000	−0.001	0.001	0.003
2010	0.005	0.001	0.002	0.008	0.001
2011	0.007	0.001	0.002	−0.008	0.005
2012	−0.006	−0.001	−0.002	0.005	0.000
2013	0.002	0.003	0.000	0.001	0.002

Note: The negative of TC, TEC, ZC, and VC is shown for ease of interpretation; positive numbers (in all columns apart from input growth rates) contribute positively to TFP. Growth rates of outputs and inputs are weighted by corresponding elasticities.

5. Innovation and Productivity in the Food vs. the High-Tech Manufacturing Sector

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5.1. Abstract

The food sector is considered a mature industry characterized by low research and development (R&D) intensity. Nevertheless, food companies face numerous challenges and cannot do without innovation activity if they want to keep their competitiveness. In this study, we examine the impact of innovation on labor productivity in European food companies and compare it to results for firms operating in high-tech sectors. The central motivation of our study is that the low R&D intensity observed in the food sector should be mirrored in different productivity effects of innovation when compared to the high-tech sector. We use microdata from the European Union's 'Community Innovation Survey' (CIS) and apply an endogeneity-robust multi-stage model that has been applied by various recent studies. Our results point out major differences between the examined subsectors. While we find strong positive effects of innovation on labor productivity for food firms, we find insignificant effects in the high-tech sector. This might

suggest that the returns to innovation might be best evaluated separately by sector rather than for the manufacturing sector as a whole.

5.2. Introduction

The food sector is one of the most important subsectors of the European Union's (EU) manufacturing sector in terms of employment and aggregate value added (Eurostat 2017b). At the same time, it is regarded as a mature and therefore an industry with slow technological advances (Caiazza 2015; Galati, Bigliardi, and Petroni 2016). Nevertheless, food processing companies do not face fewer challenges from external sources than firms in other sectors, be it from input price volatility (European Commission 2016), product quality and safety requirements (Trienekens and Zuurbier 2008), changing consumer needs (Busse and Siebert 2018; Bigliardi and Galati 2013; Gormley 2018; Aguilera 2006), the implementation of new technologies (Menrad 2004), continuing consolidation of grocery retailers and competitors, globalization, as well as legislative requirements (Wijnands et al. 2008).

For these reasons, food companies cannot do without innovation activity if they want to remain competitive. We argue that the differences in research and development (R&D) intensity observed among subsectors of the manufacturing sector are primarily a result of differing returns to innovation and differing innovation behavior. Therefore, returns to innovation might best be studied separately by subsector. Our study contributes by uncovering these differences through the empirical analysis of the relationships between innovation inputs and outputs and labor productivity in the special case of the food sector and in comparison to two high-tech sectors (chemicals and pharmaceuticals as well as computer, electronic, and optical products). Although the model and data we employ have been used in various other studies, to the best of our knowledge, the research question has not been addressed before and our study therefore provides original insight into innovation behavior and innovation effects at the firm level in the food sector in contrast to the high-tech sector.

5.3. Background and related literature

5.3.1. Differences in innovation behavior

Eurostat (2018b) classifies the subsectors of the manufacturing sector according to their ‘technological intensity’ into high-technology, medium-high-technology, medium-low-technology, and low-technology. Along with various other traditional industries, the food sector is classified as a low-technology sector. At the level of the 2-digit NACE classification, the only two high-technology subsectors are the pharmaceutical industry and the manufacture of computer, electronic, and optical products. An example for a medium-high-technology sector is the manufacture of chemicals and chemical products. A similar classification is provided by the OECD (2011). Following Pakes and Schankerman (1984), the reasons for disparities in R&D intensity between industry sectors can be subsumed into three categories: product market demand, technological opportunity, and appropriability conditions. For the case of the European food sector, some characteristics are worth noting. The effect of market demand can be expected to be ambiguous: On the one hand, aggregate demand is large compared to other sectors.[8] On the other hand, with tendencies of saturation in the European market, growth rates are small (Menrad 2004; European Commission 2016). Important research areas that can provide technological opportunities to food firms are seen e.g. in biotechnology and nanotechnology (Juriaanse 2006; Bigliardi and Galati 2016). However, radically new product developments are restrained by conservative behavior of consumers (Galizzi and Venturini 1996; Garcia Martinez and Briz 2000).

Another aspect that determines product market demand as well as appropriability conditions is market structure. The European food sector is characterized by high market power of food retailers (Wijnands et al. 2008). It can be considered

[8] In terms of production value, the food sector was the largest subsector in EU manufacturing in 2015 (Eurostat 2018a).

whether pressure by food retailers forces food manufacturers to reduce their investments in new product developments (Weiss and Wittkopp 2005; Juriaanse 2006). For a study examining how this negative effect could be mitigated by vertical integration and network effects, see Karantininis, Sauer, and Furtan (2010). Triguero, Córcoles, and Cuerva (2013) uncover additional differences in the determinants of innovation in food firms in comparison to other manufacturing firms. For their sample of Spanish firms, they point out differences in the importance of environmental and market-related factors as well as regarding the persistence of product vs. process innovation.

Another point discussed in the literature is how far low-tech firms differ from high-tech firms in the way they generate innovation output from innovation input. Schiefer et al. (2009) remark that food firms tend to focus on process innovations and therefore source a significant share of their innovations from upstream industries, e.g. suppliers of equipment. The dependence of food firms on the acquisition of external technology is supported by Ciliberti, Carraresi, and Bröring (2016) in a comparison to the pharmaceutical sector. Galizzi and Venturini (1996) find a weak relationship between R&D and innovation activity for food firms and attribute it to the incremental nature of food product innovations. Mairesse and Mohnen (2005) examine the importance of R&D in the innovation production process of high-tech vs. low-tech (excluding food) firms. Contrary to Galizzi and Venturini, they find that, on average, R&D intensity can be attributed to a greater significance for innovation output of low-tech firms compared to high-tech firms.

Lastly, firms of different subsectors also differ in the way how innovation affects production output. In the end, it is this aspect that determines the dedication of firms to their innovation activity, since if firms behave as profit maximizers, the effort they put into their innovation activities should reflect the returns they expect from these investments (Pakes and Schankerman 1984). An important determinant are the appropriability conditions prevailing in the subsectors. The effectiveness of instruments available to firms to secure the benefits from their innovation activity varies by subsector, which explains the differing use of, for example, patent protection, secrecy, complexity of products or processes, or lead time advantages (Cohen 2010). With respect to product innovation, appropriability conditions relate to the shape of the typical product life cycle. While there is a consensus that high technology levels entail shorter product life cycles, the pharmaceutical sector can be seen as a special case. Estimates of development costs of new drugs range in a magnitude of several hundred million of US dollars (DiMasi, Grabowski, and Hansen 2016). For appropriating the return to their new product developments, pharmaceutical and also chemical manufacturers usually rely on the effectiveness of patents (Mansfield 1986). With a typical patent protection period of 20 years starting from application, this entails longer product life cycles than for food products, for example. In the case of cardiovascular drugs, Bauer and Fischer (2000) find typical growth phase durations of at least three years, while Fischer, Leeflang, and Verhoef (2010) report an average time to peak sales of more than six to almost ten years. Bauer and Fischer (2000) mention an effective payback period of 15 to 20 years. In this way, new product developments affect production output over a significantly longer period of time than in other sectors. Compared to this, food manufacturers frequently launch new products by changing their flavors or compositions or introduce ‘me too’ products and the failure rate is high (Juriaanse 2006; Stoneman, Bartoloni, and Baussola 2018, 47). Another distinct case is the electronics sector, where R&D intensity is high and at the same time product life cycles are short, see e.g. Broda and Weinstein (2010), who report some electronics products among the product groups with the lowest product creation and destruction rates.

What these findings show is that firms of different manufacturing subsectors supposedly differ with respect to the determinants of their innovation activity, the way how innovation inputs are transformed into innovation outputs, as well as the way how innovation affects production output. Hence, when the effects and determinants of innovation are empirically studied, coefficients in regression models should be allowed to vary between subsectors.

5.3.2. Measuring the productivity effects of innovation

Productivity can be defined by an index of output quantity relative to an index of combined input quantities used in production, i.e.,

$$\frac{Quantity\ index\ of\ output}{Quantity\ index\ of\ combined\ inputs}, \tag{5-1}$$

for the case of one output and several production inputs (OECD 2001). By relating production outputs to production inputs, productivity is a measure of effectiveness of the production process. Because innovation entails the introduction of products with increased quality as well as the implementation of improved techniques of production or business practices (OECD and Eurostat 2005), the hypothesis of its positive effect on productivity is inherent. This general relationship has been examined by numerous empirical studies which predominantly confirm a positive effect (Griliches 1998b; Hall, Mairesse, and Mohnen 2010; Klomp and van Leeuwen 2001; Lööf and Heshmati 2006). On the other hand, also strategic considerations play a role in the decision of a firm on its innovation activity, for example, when new products are used for entering new markets. For the U. S. pharmaceutical sector this is documented by Acemoglu and Linn (2004). Because such strategic decisions might require additional investments, innovation might not show positive correlation with contemporary productivity in these cases.

Empirically measuring the impact of innovation activity on productivity confronts researchers with some challenges. Apart from simultaneity between productivity and innovation (Griliches 1998a), one important question concerns the choice of measure of firm-level innovation activity. The general argument against R&D as an innovation indicator is that R&D efforts represent only a primary step (the innovation input) in the innovation process. An appropriate measure would somehow reflect innovation output, e.g. the number (and ideally innovative content) of new products and processes. To account for this, many studies adopted the model of Crépon, Duguet, and Mairesse (1998, CDM hereafter). This multi-stage model has the advantages of taking into account both selectivity and simultaneity issues and of picturing the whole innovation process from the decision to engage in R&D to the effect of innovation output on productivity. Examples of studies employing the CDM model on manufacturing firms (and services in some studies) include Griffith et al. (2006), Castellacci (2011), Hashi and Stojčić (2013), Lööf and Heshmati (2002), Raffo, Lhuillery, and Miotti (2008), Siedschlag and Zhang (2014), and Tevdovski, Tosevska-Trpcevska, and Disoska (2017). Most of these studies confirm a positive effect of innovation output on productivity. Some exceptions can be found by Griffith et al. (2006) and Raffo, Lhuillery, and Miotti (2008), who find negative but insignificant effects in some regressions. All the aforementioned studies focus on the manufacturing sector as a whole. An example of a CDM model specifically in the food sector can be found in the study by Acosta, Coronado, and Romero (2015). For Spanish firms, they find a positive elasticity of productivity with respect to innovation output of about 30% for various innovation output indicators.

We are not aware of other studies employing the CDM model in the food sector by separating it from other sectors. Various studies that work with the CIS dataset include sector dummy variables that allow for subsector-specific intercepts. This, however, does not allow for different slopes with respect to innovation related coefficients, which seems crucial considering the suspected heterogeneity in innovation behavior as well as the fundamental technological differences among subsectors of the manufacturing industry.

5.4. Theoretical model

Assuming Cobb-Douglas production technology, firm i's production output Q can be described as a function of, for example, the production inputs capital K, labor L, and materials M, alongside the corresponding output elasticities β:

$$Q_{it} = e^{A_{it}} K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it}^{\beta_m}. \tag{5-2}$$

We assume further that part of a firm's productivity level A can be explained by the firm's present and past innovation outputs g, i.e.,

$$A_{it} = f(g_{it}, g_{it-1}, g_{it-2}, \dots, g_{it-T}, \alpha, u_i, \epsilon_{it}). \tag{5-3}$$

Although not tested in our study, we expect T to vary by subsector due to differences in appropriability conditions and other factors discussed earlier. For example, with low effectiveness of patent protection or increasing ease of imitation of products and processes, we expect smaller T (e.g. in the food or electronics sector) and larger T with long product cycles due to the widespread use of patents (e.g. in the pharmaceutical sector). u_i is determined by other firm-specific factors influencing productivity like managerial ability that are not of particular interest to our study, and α represents average productivity across time and firms. ϵ_{it} comprises idiosyncratic shocks to productivity and measurement errors. With lower-case letters denoting natural logarithms of production output and inputs and assuming a linear form of $f(.)$, we can rewrite equation (5-2) as

$$q_{it} = \alpha + k_{it}\beta_k + l_{it}\beta_l + m_{it}\beta_m + \sum_{s=0}^{T} g_{it-s}\gamma_{t-s} + u_i + \epsilon_{it}, \tag{5-4}$$

With this specification we follow other examples where the firm's innovation activity enters the production function directly (see, e.g. Griliches 1998a). Of central interest to our study is the magnitude of the returns to innovation that can be defined as $\sum_{s=0}^{T} \gamma_{t-s}$. Under the assumptions of constant returns to scale and cost minimization, theory requires that output elasticities equal the cost shares of the respective inputs. If we treat innovation output in a similar manner than the traditional production inputs, we can express some intuitive expectations about differences in the effect of innovation on production output in different manufacturing subsectors. Similar to the traditional production inputs, firms can be expected to choose their R&D efforts according to the returns generated by innovation output, ceteris paribus. Specifically, if we regard R&D expenditures as the cost of innovation and keep in mind the high R&D intensity in high-tech sectors, we can assume that firms in high-tech sectors show, on average, larger returns to innovation than food firms. Considering long product life cycles in sectors like pharmaceuticals we acknowledge, however, that this hypothesis might not hold in the short run for all types of innovation in all sectors.

5.5. Data and empirical strategy

The EU's Community Innovation Survey (CIS), started in 1992, has since then been collecting data related to the innovation activity of European firms at approximately two-year intervals. National statistical offices conduct the survey following a harmonized questionnaire separately in their country and the datasets are compiled by Eurostat. The dataset contains general firm characteristics like turnover and number of employees along with data on the innovation activity of the firm, e.g. the number of new products and processes implemented as well as innovation inputs and information sources used. We employ data from the latest available CIS wave (CIS 2014), which refers to the study period of 2012 to 2014. We analyze the data as a cross-section since panel identifiers are not implemented in the CIS methodology.[9] For 2014, microdata from 21 member states were available for analysis in Eurostat's Safe Center in Luxemburg. For our study, we use data from Germany, Spain, France, and Italy. With this country selection, we aim at selecting a sample of manufacturing firms with a relatively homogeneous technology largely comparable across countries. Partly, this country selection is also driven by data availability, since not every member state included all variables in its national survey. Detailed descriptive statistics by sector and country are given in Table 5-9 in the appendix. What is apparent from the table is that although there is some variation within sectors across countries, key variables like turnover per employee, R&D expenditures per employee, or the share of firms that introduced

[9] To our knowledge, panel identifiers are implemented starting from CIS 2014 so that first panel data estimations will be possible with the consecutive CIS wave.

a product innovation are clustered by sectors rather than by countries. This observation further encourages our intention to analyze the data separately by sector rather than by country. Detailed variable descriptions can be found in the appendix.

In estimating the impact of innovation on productivity with the CIS dataset, one has to cope with potential endogeneity. It must be assumed that there are variables not included in the CIS survey that impact both innovation activity and productivity. Further, it is likely that productivity and innovation activity are simultaneously determined by influencing each other. Crépon, Duguet, and Mairesse (1998) propose a remedy to these endogeneity problems by estimating several subsequent equations depicting the whole innovation process of a firm. First, the determinants of the R&D intensity (the innovation inputs, expressed as R&D expenditure per employee) of a firm are evaluated. Because the structure of the CIS questionnaire determines that only the subsample of firms with any innovation activity provide information on R&D expenditures, this estimation step is performed as a Heckman selection model to avoid selection bias. In the following, we omit subscript t for simplicity and the cross-sectional structure of the data. Formally,

$$h_i^* = public_i'\beta_1 + x'_i\beta_2 + e_{1i} \tag{5-5}$$

represents the selection equation with the latent variable h_i^*, which takes a value larger than zero for firms deciding to invest in formal R&D and to report their R&D expenditures ($h_i = 1$). Analogously, $h_i^* \leq 0$ for firms not engaging in formal R&D and/or not reporting R&D expenditures ($h_i = 0$). The vector x_i' comprises a constant and control variables that we consider in all estimation steps. Specifically, it includes dummy variables for seven firm size classes according to the number of employees, sector and country dummy variables, as well as dummy variables indicating if a firm belongs to an enterprise group, has a foreign head office, or operates on local, national, or international markets. $public_i'$ represents dummy variables for the use of public funding at the local, national, or EU level.

The second equation of the Heckman model describes the intensity of R&D activities, with

$$r_i^* = public_i'\beta_3 + x'_i\beta_4 + e_{2i} \tag{5-6}$$

describing the R&D intensity expressed as the natural logarithm of R&D expenditures per employee, which is not observed when $h_i = 0$ and equal to r_i when $h_i = 1$. Because we cannot think of a reasonable exclusion restriction, we include with $public_i'$ and x_i the same variables as for the selection equation. However, we want to note here (and also empirically show later with a robustness check) that the interpretation of our results does not change with an alternative specification of the Heckman model. Apart from the public funding dummy variables, all variables are included in the subsequent estimation steps. That is, we rely on the public funding dummy variables as excluded instruments for the innovation input. Examples for other studies that use the public funding variables for at least one of the equations in the Heckman model include Acosta, Coronado, and Romero (2015), Griffith et al. (2006), Hashi and Stojčić (2013), Raffo, Lhuillery, and Miotti (2008), Tevdovski, Tosevska-Trpcevska, and Disoska (2017).

In the second step of the CDM model, the innovation inputs are connected to the innovation outputs in form of the knowledge production function. The CIS questionnaire incorporates several innovation output indicators, whereas most of them come in the form of binary variables indicating the introduction of a product or process innovation, for example. The knowledge production function can then be measured in the form of a probit estimation, described by

$$g_i = \widehat{r_i^*}\beta_5 + coop_i'\beta_6 + x'_i\beta_7 + e_{3i}, \tag{5-7}$$

where g_i is either the binary process or product innovation indicator. To encounter endogeneity in this step, the predicted R&D intensity $\widehat{r_i^*}$ is used here to approximate the observed innovation input. Following Griffith et al. (2006), we predict r_i^* for the whole sample and not just for the R&D reporting firms, implying that this measure covers the entirety of efforts a firm puts into its innovation process and not just the innovation inputs represented by formal R&D. We include with x_i' the same control variables as in the Heckman model. Dummy variables for innovation cooperation ($coop_i'$) serve as excluded instruments for the innovation output because we can safely assume that cooperation in innovation activities has an effect on the innovativity of a firm.

The last step consists of incorporating the innovation output in a production function, which allows the evaluation of the output elasticity with respect to innovation output. With the data at hand, we have to modify the production model in equation (5-4) in two ways. First, the cross-sectional nature of the data allows us to only link contemporaneous variables. We therefore include only contemporaneous innovation activity into the production function, assuming that with current innovation input and output we can effectively proxy past innovation input and output. This is a justifiable assumption since current innovation activity can be expected to be partly determined by past innovation activity and under the precondition that innovation activity does not show a cyclical pattern. Second, the CIS data does not provide proxies for capital nor materials. We therefore resort to a labor production function. Following the original CDM model and other applications (e.g. Griffith et al. 2006; Castellacci 2011; Acosta, Coronado, and Romero 2015), we estimate the production function in the (partial) productivity form, i.e. with labor productivity as the dependent variable. We control for deviations from constant returns to scale by incorporating firm size dummies as explaining variables. Again, since innovation output cannot be regarded as exogenous in this equation, the predicted innovation output (predicted probability) from the second estimation step is used as an explanatory variable. Formally, this step is described as

$$y_i = \hat{g}_i\beta_8 + x'_i\beta_9 + e_{4i}, \tag{5-8}$$

where y_i is the natural logarithm of turnover per employee, $\widehat{g_i}$ is the predicted innovation output, and x_i' contains the same control variables as in the previous steps.

In an explorative approach, we first perform the estimations separately by country for each pooled manufacturing sector. Then, we estimate the model pooled by countries and separately for each one of the three selected sectors, namely the food sector (division 10 of NACE Rev. 2) as a low-tech sector, and the chemical and pharmaceutical industry as representatives of the high-tech sector (divisions 20 and 21 of NACE Rev. 2) forming a pooled sample, along with the sector of computer, electronic and optical products (division 26 of NACE Rev. 2, henceforth the 'electronics sector'). This estimation strategy not only allows for differing returns to R&D and innovation across subsectors but also for possible differences in the parameters for the innovation determinants and control variables considered in the estimations. Table 5-1 gives an overview of the approach.

Table 5-1. Overview of the empirical approach

	Estimation 1: All manufacturing	Estimation 2: Separate subsectors
Sectors	All manufacturing pooled	Separate by selected subsectors: Food, Chemicals and Pharmaceuticals, Electronics
Countries	Separate by countries (Germany, Spain, France, Italy)	Countries pooled (Germany, Spain, France, Italy)

5.6. Results

We first present results for the CDM model applied to the pooled sample of the whole manufacturing industry separated by countries. We show that our results are similar to the results reported by other studies. Additionally, we point out differences between subsectors that become apparent from the estimated coefficients for subsector dummy variables. In the next step, we present the results for the CDM model applied to the separate sub-sector samples pooled for all countries.

5.6.1. Results for the pooled manufacturing sector

We report the full regression results in the appendix, in table 5-10 to table 5-15. Table 5-10 and table 5-12 show the results for the determinants of the decision to engage in formal R&D and for the determinants of R&D intensity. In general, most coefficients show the expected sign and confirm findings from earlier studies. In all countries, firms receiving public funding are more likely to invest in R&D and show a higher R&D intensity. Also, firms with a higher degree of international activity (selling products to countries outside of the EU) show a higher propensity and intensity of R&D activities (compared to firms not selling outside of the EU). As is to be expected, larger firms conduct R&D with a higher probability, but not necessarily with a higher intensity. Of special interest to us are the differences between sectoral innovation behaviors. Compared to the food sector, the chemical and pharmaceutical sector (NACE 20 and 21) as well as the electronics sector (NACE 26) show a significantly higher propensity for conducting R&D and a higher R&D intensity (with the exception of the German and French pharmaceutical sectors), underscoring their interpretation as high-tech sectors.

Results for the knowledge production can be found in table 5-14. While we conducted the analysis for product and process innovation in parallel, we present detailed results only for product innovation since the results in the knowledge production function and in the subsequent productivity equation were almost identical for the product and the process innovation indicator. [10] The estimates confirm theoretical considerations that R&D intensity is positively related to the probability of a product innovation. This holds for all countries. The coefficients of the cooperation dummies show mostly statistically significant positive signs, confirming the expected positive effect of innovation cooperation on the innovativity

[10] The likely reason for this is that the same instrumental variables are used for both innovation indicators and the relationships between instrumental variables and the innovation indicators are similar, leading to high correlation between the results. High correlation between the innovation indicators is also observed by Raffo, Lhuillery, and Miotti (2008), Acosta, Coronado, and Romero (2015), Tevdovski, Tosevska-Trpcevska, and Disoska (2017).

of firms. Remarkably, the chemical/pharmaceutical and the electronics sector show smaller propensity to introduce a product innovation at a given level of R&D intensity. A reason for this could be that following the CIS methodology, firms count as a product innovation any product that is new to the firm but not necessarily new to the market. One could suspect that food firms (especially food firms focused on consumer products) frequently introduce products which are only minor modifications of products already in the market (e.g. new flavors) but at the same time are new products for the firm. For the development of these products, relatively fewer R&D resources are required.

Table 5-15 shows the results for the productivity equation which provide the returns to innovation and are therefore of central interest to our study. Similarly as before, we only report results for the product innovation indicator since the results for the process innovation indicator do not differ substantially. The results for product and process differ only to a certain extent with respect to Germany, where the process innovation indicator shows an even more negative coefficient of −0.253, statistically significant at the 1% level. While most studies conclude in positive returns to innovation, a negative coefficient for innovation output in the productivity equation is not unprecedented in the literature. Griffith et al. (2006) report negative (but not statistically significant) returns to innovation for Germany (product innovation) and Spain (process innovation). Raffo, Lhuillery, and Miotti (2008) find a negative (not significant) coefficient for product innovation in the case of Argentina. From our point of view, a possible explanation for switching signs for the output elasticity of innovation across countries could be the result of differing subsector shares within countries as well as differences in innovation behavior observed in these subsectors. A logical next step in our analysis is therefore to estimate innovation behavior for each sector.

5.6.2. Results for separate sectors

In the following section, we report results for estimation models separated by sectors but pooled by countries. Table 5-2, table 5-3, and table 5-4 show the results for the Heckman selection model of the food sector and the two high-tech sectors. As expected, the public funding dummies show a positive (in most cases significant) effect on both the propensity and the intensity of R&D. Public funding at the local level seems to be of greater relevance for food firms compared to high-tech firms. In this vein, EU public funding show greater relevance for R&D intensity of high-tech firms, while the coefficient is insignificant in the case of food firms. The results also point out significant differences between countries to a certain extent. However, we are careful with respect to the interpretation of country differences, as these might be simply a result of differences in questionnaire design. The most prominent difference seems that firm size plays a much more important and consistent role as a determinant of R&D intensity in the food sector compared to the high-tech sectors. R&D intensity decreases almost monotonically with the size of the food firm, while this trend is not clear-cut for the high-tech sectors.

Table 5-2. Results of the Heckman selection model for the food sector

	Selection equation		Intensity equation	
	Coef.	S. E.	Coef.	S. E.
Public funding				
Local level	0.435***	(0.049)	0.439***	(0.129)
National level	0.569***	(0.049)	0.801***	(0.141)
EU	0.221**	(0.099)	0.126	(0.188)
Enterprise group	0.138***	(0.025)	0.347***	(0.093)
Foreign head office	−0.035	(0.046)	0.211	(0.154)
Markets				
Local	−0.015	(0.042)	−0.191	(0.148)
National	0.205***	(0.033)	−0.052	(0.165)
EU	0.060**	(0.030)	0.125	(0.121)
Other	0.100***	(0.028)	0.255***	(0.097)
Country				
Germany	reference		reference	
Spain	−0.272***	(0.045)	0.136	(0.190)
France	−0.189***	(0.046)	0.235	(0.196)
Italy	−0.138***	(0.049)	0.166	(0.203)
Firm size (number of employees)				
10−19	reference		reference	
20−49	0.077***	(0.027)	−0.588***	(0.126)
50−99	0.098***	(0.032)	−0.593***	(0.135)
100−249	0.204***	(0.037)	−1.096***	(0.141)
250−499	0.314***	(0.044)	−1.297***	(0.155)
500−999	0.351***	(0.063)	−1.197***	(0.201)
≥1000	0.525***	(0.082)	−1.217***	(0.255)
3−digit NACE	included		included	
Rho	−0.292	(0.188)		
Log−likelihood	−4217.4			
Number of observations	3334			

Notes: Standard errors (S. E.) are robust. Reported are marginal effects for the probability of positive R&D expenditures (selection equation) and marginal effects for the expected R&D intensity conditional on positive R&D (intensity equation). Levels of significance are ***1%, **5%, *10%.

Table 5-3. Results of the Heckman selection model for the chemicals and pharmaceuticals sector

	Selection equation		Intensity equation	
	Coef.	S. E.	Coef.	S. E.
Public funding				
Local level	0.239***	(0.043)	0.185*	(0.101)
National level	0.388***	(0.035)	0.351***	(0.078)
EU	0.194***	(0.065)	0.360***	(0.121)
Enterprise group	0.026	(0.022)	0.312***	(0.088)
Foreign head office	−0.040*	(0.023)	−0.201**	(0.090)
Markets				
Local	0.069***	(0.027)	−0.101	(0.112)
National	0.077**	(0.032)	0.182	(0.196)
EU	0.083***	(0.026)	−0.217	(0.141)
Other	0.089***	(0.022)	0.230**	(0.102)
Country				
Germany	reference		reference	
Spain	−0.178***	(0.041)	−0.419***	(0.129)
France	−0.191***	(0.044)	−0.190	(0.135)
Italy	−0.152***	(0.043)	−0.552***	(0.14)
Firm size (number of employees)				
10−19	reference		reference	
20−49	0.024	(0.023)	−0.109	(0.099)
50−99	0.027	(0.027)	−0.344***	(0.125)
100−249	0.077***	(0.030)	−0.265**	(0.119)
250−499	0.176***	(0.037)	−0.245*	(0.131)
500−999	0.223***	(0.053)	−0.014	(0.169)
≥1000	0.266***	(0.073)	0.393**	(0.175)
3−digit NACE	included		included	
Rho	−0.117	(0.152)		
Log−likelihood	−3483.1			
Number of observations	2111			

Notes: Standard errors (S. E.) are robust. Reported are marginal effects for the probability of positive R&D expenditures (selection equation) and marginal effects for the expected R&D intensity conditional on positive R&D (intensity equation). Levels of significance are ***1%, **5%, *10%.

Table 5-4. Results of the Heckman selection model for the sector of computer, electronic and optical products

	Selection equation		Intensity equation	
	Coef.	S. E.	Coef.	S. E.
Public funding				
Local level	0.013***	(0.003)	0.249***	(0.086)
National level	0.015***	(0.004)	0.470***	(0.088)
EU	0.068***	(0.022)	0.462***	(0.091)
Enterprise group	0.002	(0.002)	0.315***	(0.103)
Foreign head office	−0.001	(0.002)	−0.023	(0.128)
Markets				
Local	0.003	(0.002)	−0.314***	(0.106)
National	0.004	(0.003)	−0.971***	(0.199)
EU	0.003	(0.002)	0.128	(0.169)
Other	0.005***	(0.002)	0.539***	(0.150)
Country				
Germany	reference		reference	
Spain	−0.009***	(0.003)	0.046	(0.120)
France	−0.005**	(0.003)	0.159	(0.131)
Italy	−0.007**	(0.003)	−0.282**	(0.127)
Firm size (number of employees)				
10−19	reference		reference	
20−49	−0.002	(0.002)	−0.408***	(0.11)
50−99	0.001	(0.002)	−0.614***	(0.143)
100−249	0.000	(0.002)	−0.447***	(0.146)
250−499	0.004	(0.003)	−0.356**	(0.158)
500−999	0.009*	(0.005)	−0.116	(0.229)
≥1000	0.054***	(0.018)	0.106	(0.190)
3−digit NACE	included		included	
Rho	−0.105	(0.090)		
Log−likelihood	−1660.6			
Number of observations	1066			

Notes: Standard errors (S. E.) are robust. Reported are marginal effects for the probability of positive R&D expenditures (selection equation) and marginal effects for the expected R&D intensity conditional on positive R&D (intensity equation). Levels of significance are ***1%, **5%, *10%.

Table 5-5 reports the results of the knowledge production function for the product innovation indicator. As expected, R&D intensity is positively related to the introduction of a product innovation in all sectors. Contrary to the results by Galizzi and Venturini (1996) but in line with the results by Mairesse and Mohnen (2005), R&D intensity seems to be more important for a product innovation in the food than in the high-tech sectors. Again, firm size seems to play a more important role for the innovativity of a firm in the food sector compared to firms in the high-tech sectors: With a given level of R&D intensity, large food firms are far more likely to introduce a product innovation than smaller food firms, while this effect is less pronounced for firms in the high-tech sectors.

Table 5-5. Results of the knowledge production function by sector

	Food	
	Coef.	b. S. E.
R&D intensity	0.502***	(0.082)
Cooperation partners		
Other enterprise group members	0.237***	(0.048)
Suppliers	0.182***	(0.052)
Customers	0.106	(0.075)
Competitors	0.019	(0.067)
Consultants	0.154***	(0.059)
Universities	0.015	(0.055)
Government/public or private research institutes	0.078*	(0.045)
Enterprise group	−0.040*	(0.024)
Foreign head office	−0.091*	(0.050)
Markets		
Local	0.135***	(0.039)
National	0.205***	(0.030)
EU	0.043	(0.028)
Other	−0.011	(0.036)
Country		
Germany	reference	
Spain	−0.402***	(0.043)
France	−0.385***	(0.044)
Italy	−0.278***	(0.038)
Firm size (number of employees)		
10−19	reference	
20−49	0.371***	(0.059)
50−99	0.409***	(0.064)
100−249	0.737***	(0.106)
250−499	0.940***	(0.131)
500−999	0.929***	(0.139)
≥1000	1.016***	(0.157)
3−digit NACE	included	
Pseudo−R^2	0.235	
Log−likelihood	−1,601.2	
Number of observations	3,334	

Notes: Standard errors are bootstrapped (b. S. E.). Reported are marginal effects at sample means for the probability of the introduction of a product innovation. Levels of significance are ***1%, **5%, *10%.

Table 5-5. Results of the knowledge production function by sector (continued)

	Chemicals and pharma-ceuticals		Computer, electronic and optical products	
	Coef.	b. S. E.	Coef.	b. S. E.
R&D intensity	0.258***	(0.098)	0.302***	(0.049)
Cooperation partners				
Other enterprise group members	0.172***	(0.040)	0.170**	(0.073)
Suppliers	0.133***	(0.044)	0.046	(0.047)
Customers	0.106**	(0.052)	−0.020	(0.057)
Competitors	0.082	(0.054)	−0.076	(0.060)
Consultants	0.016	(0.053)	0.057	(0.059)
Universities	0.079	(0.048)	0.078*	(0.040)
Government/public or private research institutes	0.066	(0.045)	0.111*	(0.059)
Enterprise group	−0.102**	(0.045)	−0.075*	(0.045)
Foreign head office	−0.016	(0.040)	−0.028	(0.051)
Markets				
Local	0.196***	(0.049)	0.153***	(0.034)
National	0.065	(0.065)	0.322***	(0.080)
EU	0.204***	(0.050)	0.035	(0.041)
Other	0.038	(0.039)	−0.064	(0.043)
Country				
Germany	reference		reference	
Spain	−0.156***	(0.056)	−0.211***	(0.043)
France	−0.168***	(0.054)	−0.173***	(0.048)
Italy	−0.035	(0.073)	−0.013	(0.047)
Firm size (number of employees)				
10−19	reference		reference	
20−49	0.018	(0.038)	0.132***	(0.045)
50−99	0.119**	(0.061)	0.206***	(0.065)
100−249	0.132***	(0.045)	0.161***	(0.052)
250−499	0.246***	(0.066)	0.170**	(0.068)
500−999	0.138**	(0.058)	0.120	(0.124)
≥1000	0.209**	(0.091)	0.168*	(0.089)
3−digit NACE	included		included	
Pseudo−R^2	0.159		0.263	
Log−likelihood	−1,219.3		−465.0	
Number of observations	2,111		1,066	

Notes: Standard errors are bootstrapped (b. S. E.). Reported are marginal effects at sample means for the probability of the introduction of a product innovation. Levels of significance are ***1%, **5%, *10%.

Our main interest relates to the output elasticity with respect to innovation for firms in different sectors. Results for the productivity equations are shown in table 5-6.

Table 5-6. Results of the productivity equation by sector

	Food	
	Coef.	b. S. E.
Product innovation	0.423***	(0.100)
Enterprise group	0.302***	(0.041)
Foreign head office	0.100	(0.065)
Markets		
Local	0.058	(0.057)
National	0.348***	(0.054)
EU	0.231***	(0.048)
Other	0.115***	(0.036)
Country		
Germany	reference	
Spain	0.142**	(0.061)
France	0.454***	(0.057)
Italy	0.410***	(0.061)
Firm size (number of employees)		
10−19	reference	
20−49	0.058	(0.041)
50−99	0.189***	(0.044)
100−249	0.185***	(0.064)
250−499	0.093	(0.074)
500−999	0.066	(0.103)
≥1000	0.153	(0.115)
3−digit NACE	included	
Constant	11.138***	(0.079)
R^2	0.496	
Number of observations	3333	

Notes: Standard errors are bootstrapped (b. S. E.). Levels of significance are ***1%, **5%, *10%.

Table 5-6. Results of the productivity equation by sector (continued)

	Chemicals and pharmaceuticals		Computer, electronic and optical products	
	Coef.	b. S. E.	Coef.	b. S. E.
Product innovation	−0.149	(0.122)	−0.024	(0.133)
Enterprise group	0.384***	(0.045)	0.169***	(0.065)
Foreign head office	0.182***	(0.041)	0.181***	(0.056)
Markets				
Local	0.166***	(0.059)	0.044	(0.052)
National	0.223**	(0.098)	0.100	(0.109)
EU	0.016	(0.066)	0.303***	(0.074)
Other	0.114**	(0.053)	0.145*	(0.080)
Country				
Germany	reference		reference	
Spain	−0.037	(0.074)	−0.127*	(0.073)
France	0.091	(0.073)	0.225***	(0.063)
Italy	0.259***	(0.078)	0.045	(0.064)
Firm size (number of employees)				
10−19	reference		reference	
20−49	0.133***	(0.046)	0.070	(0.056)
50−99	0.280***	(0.055)	0.181**	(0.071)
100−249	0.365***	(0.058)	0.206***	(0.076)
250−499	0.357***	(0.073)	0.273***	(0.076)
500−999	0.540***	(0.075)	0.543***	(0.097)
≥1000	0.659***	(0.083)	0.508***	(0.081)
3−digit NACE	included		included	
Constant	11.855***	(0.119)	11.032***	(0.105)
R^2	0.273		0.297	
Number of observations	2111		1066	

Notes: Standard errors are bootstrapped (b. S. E.). Levels of significance are ***1%, **5%, *10%.

For food firms, product innovation shows a positive effect suggesting an increase in labor productivity by approximately 42%. This seems relatively significant but is well within the range of coefficients usually reported in other studies.[11] The most surprising finding is that for both high-tech sectors, no positive effect of innovation output on labor productivity is evident. The coefficients even show a negative sign but are not statistically significant.

5.7. Robustness checks

In the following, we discuss the results of various robustness checks, which show that our conclusions do not change with alternative model specifications or alternative sampling procedures. For brevity, we report only the output elasticity of innovation in table 5-7.

In model 1, we rely on the predicted R&D intensity as the sole instrumental variable for innovation output in the knowledge production function. Then, we can use the cooperation variables as additional instruments in the Heckman model (for examples of studies that use the cooperation variables in the Heckman model, see Acosta, Coronado, and Romero 2015; Griffith et al. 2006; Tevdovski, Tosevska-Trpcevska, and Disoska 2017). Model 2 estimates the knowledge production function and the productivity equation only for the subsample of innovative firms (R&D expenditures greater than zero) and incorporates the Mill's ratio as an explaining variable in these model stages to encounter possible selection bias. In model 3, the smallest (fewer than 20 employees) and the largest (more than 499 employees) firms are omitted from the regressions to account for possible large heterogeneity between firms of different sizes.

[11] Hashi and Stojčić (2013), as well as Tevdovski, Tosevska-Trpcevska, and Disoska (2017) find marginal effects of innovation on labor productivity higher than 100% in some cases.

Table 5-7. Overview of estimated output elasticity of innovation with alternative model specifications

No.	Description	Food	Chemicals and pharmaceuticals	Computer, electronic and optical products
1	Incorporating cooperation variables in both equations of the Heckman model	0.445*** (0.125)	−0.166 (0.117)	−0.122 (0.147)
2	Estimation of the last two stages of the CDM model only for innovative sample, using Mill's ratio	−0.051 (0.254)	−0.046 (0.222)	−0.297 (0.413)
3	Estimation only for medium-sized firms	0.535*** (0.125)	−0.245* (0.128)	−0.026 (0.137)
4	Alternative product innovation indicator: introduced a product new to the market	0.364*** (0.105)	−0.253** (0.113)	−0.023 (0.129)
5	Alternative product innovation indicator: turnover share of new products	0.006*** (0.002)	−0.005** (0.002)	−0.001 (0.002)
6	Without Spain	0.119 (0.143)	−0.257* (0.138)	0.016 (0.124)
7	Without Italy	0.397*** (0.103)	−0.113 (0.133)	−0.086 (0.128)
8	Using country weights	0.252** (0.103)	−0.290** (0.129)	−0.010 (0.124)

In model 4 and model 5, we employ alternative product innovation indicators to address the possible concern that products ‘new to the firm’ do not necessarily quantify ‘true’ innovations or the success of new products. For model 4, this is the binary information whether the firm introduced a product that was new to the market and for model 5, it is the share of turnover attributed to these products new to the market. In model 6 and model 7, we excluded Spain or Italy from the estimation to account for possible technology differences in these countries. The estimation of model 8 accounts for the differences in observation count by applying sampling weights based on the observation count by country.

In summary, the results from our original model are largely confirmed. In most cases, we find a positive and significant output elasticity of innovation for food firms. For the two high-tech sectors, we find in most estimations insignificant coefficients for innovation output and for the chemical and pharmaceutical subsector, even statistically significant negative ones in some estimations.

5.8. Discussion

We can see from the descriptive statistics in the appendix that a larger share of firms in the high-tech sector introduced a product innovation compared to firms in the food sector. Still, a considerable share of high-tech firms (up to 50%) did not introduce any product innovations. One would suspect that consequently, these firms perform worse than their innovative counterparts, especially in their innovation-focused environment. Contrary to our expectations, our results show that the positive effect of innovation output on labor productivity seems to be stronger in the food sector. In the following, we discuss possible reasons for this result.

First, one has to consider the differences in the innovation process already described. The CIS survey covers a time period of three years. If a firm faces long product life cycles, new products introduced during the preceding three years might be still in their growth phase and accordingly contribute less to productivity. In other words, a firm then profits to a greater extent from product innovations in earlier years and might be innovative even without any new product introductions during the past three years. In this case, it would be necessary to consider a longer time lag in the productivity effects of innovation, i.e. resort to a model following closely equation (5-4). While this aspect offers a possible explanation for the insignificant relationship between product innovation and labor productivity in the pharmaceutical and chemical sector, it does not apply to the electronics sector where we expect short product life cycles. Also, it does not offer an explanation for the insignificant productivity effects of process innovation on the chemical and pharmaceutical as well as on the electronics sector that we find.

Another explanation relates to the econometric strategy. Innovation in the productivity equation is prone to a variety of sources of endogeneity, not only based on simultaneity but also omitted variables as the business strategy (e.g. brand focus contrary to a focus on mass products in the food sector) that affect the level of innovation efforts and labor productivity alike. Although possible endogeneity is taken into account in all estimation stages, the CDM methodology relies on the abundance of valid instruments in the CIS dataset. We acknowledge that the exogeneity of the used instruments is debatable. However, with the robustness checks we could show that the results can resist various modifications of the instrumental variable setup. To build up intuition about the relationship between labor productivity and product as well as process innovation output, in table 5-8 we report results from OLS regressions of labor productivity on the product or process innovation dummy and additional control variables.

Table 5-8. OLS results for returns to innovation

	Food		Chemicals and pharmaceuticals		Computer, electronic and optical products	
	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.
Product innovation	0.190***	(0.032)	0.071**	(0.035)	0.178***	(0.046)
Process innovation	0.262***	(0.030)	−0.017	(0.034)	0.008	(0.039)

Note: Reported are the results of two separate estimations for each sector of the regression of the logarithm of labor productivity on the product or process innovation dummy and additional control variables (firm size, NACE 3-digit identifiers, and country dummies). Standard errors (S. E.) are robust.

These coefficients are possibly biased but keeping in mind our insecurity about the quality of our instruments and that we are not sure how strong the correlation of the regressors with the error is, they serve as a useful benchmark for the endogeneity-robust instrumental variable results. The differences between the sectors are not as distinct as in the CDM model. What we also see here, however, is that the coefficients are larger for the food sector than for the high-tech sectors.

5.9. Conclusions

Our study aimed at uncovering differences in the productivity effects of innovation in the food versus the high-tech manufacturing sector, as we suspect that these differences are a major driver for the sectoral differences observed in R&D intensity. The results indeed point to major differences and do not confirm our expectations. While we find strong and significant positive productivity effects for innovation output in the case of the food sector, we find no statistically significant effects for the high-tech sectors. While the CIS dataset offers a unique data coverage, the reason for this result is hardly explored with the cross-sectional structure of the CIS dataset since we believe that for a full picture of the innovativeness of firms, a longer period than three years must be taken into account, especially in the pharmaceutical and chemical sector. More precise analyses might be possible with the upcoming implementation of a panel structure in the CIS surveys.

Given the long-standing classification of manufacturing sectors into low-tech and high-tech subsectors based on observed R&D expenditure ratios, it is surprising that there are not more studies using the CIS dataset and examining the impact of innovation activity on firm performance separately by sector. Even if our study does not provide a clear justification for its results, it shows that between firms of different manufacturing subsectors, there are significant differences in innovation behavior and productivity effects of innovation that need to be explored further

5.10. Appendix

5.10.1. Descriptive statistics

Table 5-9. Descriptive statistics

Sector	Food			
Country	DE	ES	FR	IT
Observations	210	1,641	901	581
	162,232.1	38,387.5	82,996.9	72,180.0
Turnover (thousand euros)	(566,219.6)	(123,956.4)	(243,520.6)	(236,930.4)
Employees	413.3	107.9	178.0	154.7
	(1,273.7)	(258.4)	(339.5)	(477.2)
	209,486.8	312,363.1	329,488.5	370,007.1
Turnover per employee (euros)	(348,269.4)	(685,452.6)	(504,469.5)	(737,262.6)
	2,236.3	2,972.2	9,354.4	3,317.6
R&D expenditures per employee	(6,154.3)	(13,517.9)	(47,469.0)	(9,395.1)
Product innovation	0.371	0.293	0.332	0.363
Public funding				
Local	0.044	0.087	0.137	0.295
National	0.079	0.147	0.102	0.125
EU	0.035	0.038	0.067	0.069
Markets				
Local	0.848	0.966	0.909	0.943
National	0.433	0.801	0.640	0.838
EU	0.295	0.576	0.499	0.670
Other	0.186	0.397	0.334	0.494
Foreign head office	0.057	0.048	0.089	0.040
Enterprise group	0.243	0.285	0.467	0.387
Number of employees				
10-19	0.224	0.252	0.353	0.336
20-49	0.267	0.296	0.228	0.258
50-99	0.167	0.214	0.091	0.134
100-249	0.157	0.147	0.092	0.131
250-499	0.057	0.057	0.141	0.083
500-999	0.048	0.023	0.057	0.033
≥1000	0.081	0.011	0.039	0.026

Table 5-9. Descriptive statistics (continued)

Cooperation partners				
Other enterprise group members	0.024	0.068	0.128	0.021
Suppliers	0.019	0.087	0.127	0.050
Customers	0.019	0.048	0.054	0.017
Competitors	0.010	0.042	0.029	0.021
Consultants	0.010	0.063	0.100	0.059
Universities	0.019	0.079	0.080	0.065
Government/public or private research institutes	0.019	0.102	0.063	0.029

	Chemicals and pharmaceuticals			
	DE	ES	FR	IT
Observations	298	334	218	216
Turnover (thousand euros)	159,859.5 (516,547.5)	9,439.2 (18,261.5)	113,269.3 (317,852.6)	53,884.8 (128,973.1)
Employees	507.0 (1,287.3)	56.7 (77.6)	356.9 (806.4)	233.6 (694.3)
Turnover per employee (euros)	186,246.4 (184,212.8)	141,712.4 (131,675.8)	267,892.8 (560,042.8)	209,048.5 (128,735.2)
R&D expenditures per employee	20,896.9 (39,234.0)	11,038.1 (17,646.7)	27,473.0 (60,624.9)	11,955.5 (15,415.2)
Product innovation	0.836	0.584	0.734	0.764
Public funding				
Local	0.312	0.192	0.276	0.330
National	0.784	0.302	0.465	0.247
EU	0.296	0.123	0.227	0.176
Markets				
Local	0.560	0.919	0.784	0.861
National	0.923	0.949	0.972	0.949
EU	0.862	0.772	0.849	0.907
Other	0.832	0.698	0.812	0.856
Foreign head office	0.131	0.090	0.243	0.153
Enterprise group	0.443	0.311	0.661	0.736

Table 5-9. Descriptive statistics (continued)

Number of employees				
10-19	0.195	0.338	0.216	0.162
20-49	0.309	0.356	0.216	0.185
50-99	0.124	0.162	0.138	0.190
100-249	0.148	0.099	0.092	0.222
250-499	0.047	0.045	0.197	0.139
500-999	0.054	0.000	0.060	0.074
≥1000	0.124	0.000	0.083	0.028
Cooperation partners				
Other enterprise group members	0.087	0.117	0.330	0.176
Suppliers	0.104	0.162	0.317	0.190
Customers	0.195	0.177	0.266	0.088
Competitors	0.060	0.078	0.156	0.125
Consultants	0.097	0.081	0.266	0.259
Universities	0.339	0.159	0.321	0.278
Government/public or private research institutes	0.262	0.168	0.252	0.157

	Computer, electronic and optical products			
	DE	ES	FR	IT
Observations	209	1,049	329	524
Turnover (thousand euros)	614,818.8 (1,770,923.1)	50,579.4 (182,278.7)	233,139.9 (801,394.3)	131,309.9 (288,118.6)
Employees	1373.6 (3,868.7)	109.4 (197.9)	405.4 (805.2)	260.5 (401.3)
Turnover per employee (euros)	431,971.4 (697,088.5)	368,254.6 (1,271,700.3)	423,034.4 (503,981.2)	493,724.3 (1,293,250.9)
R&D expenditures per employee	22,926.9 (30,078.0)	7,651.8 (17,010.7)	14,197.9 (18,569.1)	10,037.6 (18,732.0)
Product innovation	0.727	0.501	0.587	0.586

Table 5-9. Descriptive statistics (continued)

Public funding				
Local	0.220	0.102	0.145	0.170
National	0.575	0.214	0.245	0.160
EU	0.394	0.051	0.096	0.097
Markets				
Local	0.541	0.952	0.748	0.876
National	0.933	0.952	0.915	0.922
EU	0.885	0.850	0.881	0.884
Other	0.775	0.707	0.748	0.754
Foreign head office	0.249	0.201	0.398	0.185
Enterprise group	0.670	0.462	0.793	0.782
Number of employees				
10-19	0.134	0.224	0.155	0.177
20-49	0.172	0.331	0.188	0.116
50-99	0.158	0.195	0.109	0.156
100-249	0.120	0.149	0.100	0.246
250-499	0.096	0.060	0.237	0.158
500-999	0.057	0.029	0.131	0.088
≥1000	0.263	0.012	0.079	0.057
Cooperation partners				
Other enterprise group members	0.139	0.128	0.304	0.155
Suppliers	0.124	0.107	0.240	0.103
Customers	0.129	0.104	0.164	0.078
Competitors	0.067	0.057	0.094	0.057
Consultants	0.077	0.100	0.246	0.164
Universities	0.282	0.142	0.243	0.216
Government/public or private research institutes	0.239	0.162	0.152	0.124

Note: Where standard errors in parentheses are not given, the values are means of dummy variables, i.e. the share of the attribute in the population.

5.10.2. Variable descriptions

Labor productivity: the company's total turnover per employee in 2014.

R&D intensity: the company's total R&D expenditures per employee in 2014.

Public funding: dummy variables indicating whether the company received public funding from government institutions at the local, national, or EU level.

Enterprise group: dummy variable indicating that the company belongs to an enterprise group.

Foreign head office: dummy variable indicating that its head office is located outside the country.

Markets: dummy variables indicating whether the firm sells its products in local, national, EU, or non-EU markets.

Cooperation partners: dummy variables indicating cooperation with various innovation partners. The dummy variables assume the value of one if the company cooperated with any partner of the respective group, irrespective of the partner's nationality.

5.10.3. Results for the pooled manufacturing sector

Table 5-10. Results of the Heckman selection model for the German manufacturing sector

	DE			
	Selection equation		Intensity equation	
	Coef.	S. E.	Coef.	S. E.
Public funding				
Local level	0.251***	(0.051)	0.419***	(0.094)
National level	0.319***	(0.028)	0.463***	(0.068)
EU	0.296***	(0.070)	0.288***	(0.098)
Enterprise group	0.034**	(0.015)	0.234***	(0.075)
Foreign head office	−0.042**	(0.022)	0.212**	(0.094)
Markets				
Local	0.000	(0.012)	−0.126**	(0.058)
National	0.034**	(0.016)	0.188	(0.119)
EU	0.027*	(0.015)	0.165*	(0.087)
Other	0.054***	(0.014)	0.210***	(0.076)
Firm size (number of employees)				
10−19	reference			
20−49	0.018	(0.015)	−0.324***	(0.086)
50−99	0.058***	(0.018)	−0.644***	(0.097)
100−249	0.089***	(0.021)	−0.893***	(0.111)
250−499	0.116***	(0.027)	−0.604***	(0.137)
500−999	0.170***	(0.036)	−0.156	(0.144)
≥1000	0.334***	(0.048)	0.263**	(0.129)
2−digit NACE				
10 (food)	reference			
11	0.095**	(0.043)	0.393	(0.324)
12	−0.021	(0.080)	0.644*	(0.380)
13	0.103***	(0.040)	0.395*	(0.224)
14	−0.035	(0.044)	0.725***	(0.250)
15	0.078	(0.051)	0.275	(0.297)
16	0.056*	(0.033)	0.741***	(0.242)
17	−0.011	(0.036)	0.840***	(0.276)
18	0.035	(0.033)	0.646***	(0.243)
19	0.112*	(0.067)	2.326***	(0.356)
20 (chemicals)	0.136***	(0.040)	1.174***	(0.209)
21 (pharmaceuticals)	0.071	(0.053)	1.965***	(0.259)
22	0.017	(0.030)	0.595***	(0.203)

Table 5-10. Results of the Heckman selection model for the German manufacturing sector (continued)

23	0.023	(0.031)	0.670***	(0.210)
24	−0.043	(0.035)	0.704***	(0.221)
25	0.015	(0.024)	0.455**	(0.194)
26 (electronics)	0.138***	(0.032)	1.509***	(0.189)
27	0.073**	(0.031)	0.949***	(0.199)
28	0.121***	(0.030)	0.855***	(0.184)
29	0.056	(0.036)	1.069***	(0.213)
30	0.095*	(0.055)	1.045***	(0.242)
31	0.052	(0.035)	0.233	(0.256)
32	0.063**	(0.032)	0.748***	(0.212)
33	0.003	(0.029)	0.520**	(0.232)
Rho	−0.059	(0.075)		
Log−likelihood	−4,707.1			
Number of observations	2,950			

Notes: Standard errors (S. E.) are robust. Shown are marginal effects on the probability of positive R&D expenditures (selection equation) and marginal effects on expected R&D intensity conditional on positive R&D (intensity equation). Levels of significance are ***1%, **5%, *10%.

Table 5-11. Results of the Heckman selection model for the Spanish manufacturing sector

	ES			
	Selection equation		Intensity equation	
	Coef.	S. E.	Coef.	S. E.
Public funding				
Local level	0.439***	(0.024)	0.400***	(0.049)
National level	0.561***	(0.025)	0.689***	(0.047)
EU	0.384***	(0.057)	0.444***	(0.076)
Enterprise group	0.102***	(0.015)	0.357***	(0.046)
Foreign head office	−0.038*	(0.022)	0.113*	(0.064)
Markets				
Local	0.065**	(0.026)	−0.115	(0.104)
National	0.147***	(0.022)	0.062	(0.107)
EU	0.096***	(0.016)	0.076	(0.073)
Other	0.137***	(0.014)	0.117**	(0.053)
Firm size (number of employees)				
10−19	reference			
20−49	0.070***	(0.014)	−0.376***	(0.054)
50−99	0.071***	(0.017)	−0.661***	(0.062)
100−249	0.145***	(0.020)	−0.912***	(0.068)
250−499	0.296***	(0.034)	−1.103***	(0.089)
500−999	0.266***	(0.051)	−0.998***	(0.137)
≥1000	0.466***	(0.075)	−0.948***	(0.196)
2−digit NACE				
10 (food)	reference			
11	−0.127***	(0.033)	−0.532***	(0.135)
12	−0.268*	(0.150)	−1.609*	(0.899)
13	−0.036	(0.034)	0.105	(0.118)
14	−0.174***	(0.041)	0.107	(0.204)
15	−0.269***	(0.044)	−0.273	(0.197)
16	−0.178***	(0.039)	−0.164	(0.169)
17	−0.146***	(0.036)	−0.272*	(0.161)
18	−0.130***	(0.036)	0.105	(0.177)
19	2.366***	(0.054)	0.750*	(0.406)
20 (chemicals)	0.223***	(0.025)	0.459***	(0.074)
21 (pharmaceuticals)	0.266***	(0.044)	1.409***	(0.112)
22	−0.023	(0.026)	0.071	(0.086)
23	−0.078***	(0.028)	−0.180*	(0.102)
24	−0.124***	(0.035)	−0.118	(0.121)

Table 5-11. Results of the Heckman selection model for the Spanish manufacturing sector (continued)

25	−0.022	(0.021)	0.091	(0.076)
26 (electronics)	0.237***	(0.036)	0.946***	(0.092)
27	0.096***	(0.031)	0.346***	(0.099)
28	0.058**	(0.023)	0.289***	(0.075)
29	0.027	(0.031)	0.340***	(0.100)
30	0.039	(0.046)	0.277*	(0.162)
31	−0.105***	(0.034)	−0.148	(0.121)
32	−0.009	(0.035)	0.210	(0.138)
33	−0.208***	(0.036)	−0.208	(0.149)
Rho	−0.169	(0.047)		
Log−likelihood	−13,114.4			
Number of observations	11,296			

Notes: Standard errors (S. E.) are robust. Shown are marginal effects on the probability of positive R&D expenditures (selection equation) and marginal effects on expected R&D intensity conditional on positive R&D (intensity equation). Levels of significance are ***1%, **5%, *10%.

Table 5-12. Results of the Heckman selection model for the French manufacturing sector

	FR			
	Selection equation		Intensity equation	
	Coef.	S. E.	Coef.	S. E.
Public funding				
Local level	0.472***	(0.049)	0.419***	(0.092)
National level	0.555***	(0.048)	0.354***	(0.092)
EU	0.150*	(0.080)	0.506***	(0.104)
Enterprise group	0.085***	(0.020)	0.089	(0.075)
Foreign head office	−0.026	(0.025)	0.043	(0.077)
Markets				
Local	0.013	(0.025)	−0.235***	(0.079)
National	0.098***	(0.026)	−0.136	(0.145)
EU	0.119***	(0.023)	0.133	(0.102)
Other	0.107***	(0.021)	0.270***	(0.080)
Firm size (number of employees)				
10−19	reference		reference	
20−49	0.016	(0.022)	−0.122	(0.094)
50−99	0.100***	(0.029)	−0.490***	(0.109)
100−249	0.187***	(0.034)	−0.536***	(0.120)
250−499	0.290***	(0.031)	−0.734***	(0.106)
500−999	0.375***	(0.044)	−0.417***	(0.136)
≥1000	0.437***	(0.066)	−0.535***	(0.147)
2−digit NACE				
10 (food)	reference		reference	
11	0.008	(0.068)	0.774***	(0.243)
12	0.355	(0.265)	1.502*	(0.771)
13	−0.008	(0.060)	0.048	(0.227)
14	−0.045	(0.074)	−0.409	(0.298)
15	0.054	(0.081)	−0.385	(0.270)
16	−0.054	(0.049)	−0.303	(0.208)
17	0.000	(0.051)	0.202	(0.214)
18	−0.016	(0.054)	0.742***	(0.234)
19	−0.024	(0.133)	1.188**	(0.506)
20 (chemicals)	0.083**	(0.042)	0.947***	(0.121)
21 (pharmaceuticals)	0.101	(0.073)	1.410***	(0.184)
22	0.027	(0.036)	0.259*	(0.134)
23	0.034	(0.043)	0.379**	(0.176)
24	−0.023	(0.055)	0.244	(0.173)

Table 5-12. Results of the Heckman selection model for the French manufacturing sector (continued)

25	−0.050*	(0.028)	0.466***	(0.119)
26 (electronics)	0.223***	(0.051)	1.274***	(0.142)
27	0.069	(0.050)	0.875***	(0.160)
28	0.151***	(0.035)	0.633***	(0.115)
29	−0.025	(0.052)	0.627***	(0.169)
30	0.071	(0.083)	0.551**	(0.233)
31	0.085	(0.060)	0.022	(0.225)
32	0.119**	(0.055)	0.447**	(0.184)
33	−0.101***	(0.039)	0.083	(0.172)
Rho	0.033	(0.083)		
Log−likelihood	−6,881.0			
Number of observations	4,873			

Notes: Standard errors (S. E.) are robust. Shown are marginal effects on the probability of positive R&D expenditures (selection equation) and marginal effects on expected R&D intensity conditional on positive R&D (intensity equation). Levels of significance are ***1%, **5%, *10%.

Table 5-13. Results of the Heckman selection model for the Italian manufacturing sector

	IT			
	Selection equation		Intensity equation	
	Coef.	S. E.	Coef.	S. E.
Public funding				
Local level	0.883***	(0.059)	0.341***	(0.072)
National level	0.697***	(0.082)	0.569***	(0.077)
EU	0.587***	(0.128)	0.251***	(0.091)
Enterprise group	0.044***	(0.016)	0.124**	(0.061)
Foreign head office	0.010	(0.027)	−0.106	(0.078)
Markets				
Local	0.041*	(0.021)	−0.114	(0.075)
National	0.120***	(0.022)	−0.227**	(0.105)
EU	0.060***	(0.019)	0.301***	(0.090)
Other	0.094***	(0.017)	0.167**	(0.069)
Firm size (number of employees)				
10−19	reference			
20−49	0.035*	(0.018)	−0.306***	(0.079)
50−99	0.163***	(0.020)	−0.323***	(0.084)
100−249	0.205***	(0.022)	−0.359***	(0.088)
250−499	0.355***	(0.029)	−0.516***	(0.095)
500−999	0.392***	(0.041)	−0.549***	(0.126)
≥1000	0.446***	(0.060)	−0.436***	(0.143)
2−digit NACE				
10 (food)	reference			
11	0.009	(0.051)	0.313*	(0.178)
12	1.660***	(0.067)	0.964**	(0.461)
13	−0.007	(0.033)	0.451***	(0.132)
14	−0.125***	(0.041)	0.373**	(0.185)
15	−0.119***	(0.031)	0.267*	(0.153)
16	−0.048	(0.043)	0.106	(0.189)
17	−0.021	(0.037)	0.604***	(0.153)
18	−0.051	(0.042)	0.091	(0.205)
19	−0.029	(0.054)	1.003***	(0.268)
20 (chemicals)	0.145***	(0.037)	0.698***	(0.134)
21 (pharmaceuticals)	0.132***	(0.044)	1.124***	(0.140)
22	0.016	(0.036)	0.025	(0.148)
23	−0.067**	(0.032)	0.210	(0.135)
24	−0.036	(0.045)	−0.002	(0.160)

Table 5-13. Results of the Heckman selection model for the Italian manufacturing sector (continued)

25	0.009	(0.029)	0.246**	(0.114)
26 (electronics)	0.191***	(0.050)	1.093***	(0.125)
27	0.147***	(0.037)	0.609***	(0.124)
28	0.069**	(0.033)	0.545***	(0.111)
29	0.039	(0.048)	0.587***	(0.143)
30	0.022	(0.059)	0.683***	(0.161)
31	0.033	(0.037)	0.161	(0.131)
32	0.090**	(0.039)	0.265*	(0.138)
33	−0.012	(0.034)	0.166	(0.129)
Rho	−0.031	(0.048)		
Log−likelihood	−9,570.6			
Number of observations	6,656			

Notes: Standard errors (S. E.) are robust. Shown are marginal effects on the probability of positive R&D expenditures (selection equation) and marginal effects on expected R&D intensity conditional on positive R&D (intensity equation). Levels of significance are ***1%, **5%, *10%.

Table 5-14. Results of the knowledge production function (product innovation) for the manufacturing sector

	DE		ES	
	Coef.	b. S. E.	Coef.	b. S. E.
R&D intensity	0.552***	(0.065)	0.312***	(0.027)
Cooperation partners				
Other enterprise group members	0.093	(0.065)	0.177***	(0.022)
Suppliers	0.136**	(0.054)	0.161***	(0.025)
Customers	0.028	(0.050)	0.071***	(0.026)
Competitors	−0.047	(0.085)	−0.021	(0.032)
Consultants	0.098	(0.066)	0.065***	(0.022)
Universities	−0.012	(0.047)	0.010	(0.020)
Government/public or private research institutes	0.017	(0.047)	0.085***	(0.020)
Enterprise group	−0.115***	(0.032)	−0.065***	(0.018)
Foreign head office	−0.144***	(0.032)	−0.059***	(0.016)
Markets				
Local	0.080***	(0.025)	0.099***	(0.022)
National	−0.061*	(0.033)	0.084***	(0.022)
EU	−0.034	(0.029)	0.092***	(0.015)
Other	0.008	(0.024)	0.096***	(0.014)
Firm size (number of employees)				
10−19	reference		reference	
20−49	0.222***	(0.032)	0.156***	(0.016)
50−99	0.426***	(0.053)	0.261***	(0.024)
100−249	0.564***	(0.066)	0.364***	(0.031)
250−499	0.471***	(0.060)	0.516***	(0.053)
500−999	0.350***	(0.059)	0.486***	(0.049)
≥1000	0.346***	(0.065)	0.432***	(0.066)
2−digit NACE				
10 (food)	reference		reference	
11	0.028	(0.095)	−0.033	(0.038)
12	−0.595***	(0.179)	0.249**	(0.115)
13	−0.040	(0.072)	−0.048	(0.032)
14	−0.423***	(0.105)	−0.208***	(0.052)
15	−0.049	(0.081)	−0.095**	(0.045)
16	−0.342***	(0.071)	−0.138***	(0.040)
17	−0.595***	(0.089)	−0.057*	(0.029)
18	−0.372***	(0.071)	−0.156***	(0.031)
19	−1.107***	(0.240)	0.123	(0.166)
20 (chemicals)	−0.542***	(0.113)	0.013	(0.028)

Table 5-14. Results of the knowledge production function (product innovation) for the manufacturing sector (continued)

21 (pharmaceuticals)	−1.043***	(0.166)	−0.426***	(0.051)
22	−0.365***	(0.090)	−0.035	(0.022)
23	−0.328***	(0.077)	−0.005	(0.023)
24	−0.563***	(0.084)	−0.093***	(0.027)
25	−0.278***	(0.061)	−0.072***	(0.018)
26 (electronics)	−0.571***	(0.114)	−0.082***	(0.032)
27	−0.385***	(0.092)	−0.024	(0.025)
28	−0.275***	(0.072)	0.016	(0.023)
29	−0.480***	(0.098)	−0.116***	(0.028)
30	−0.464***	(0.107)	−0.131**	(0.054)
31	−0.009	(0.068)	0.023	(0.034)
32	−0.290***	(0.076)	−0.068**	(0.030)
33	−0.312***	(0.077)	−0.108***	(0.035)
Pseudo−R^2	0.226		0.216	
Log−likelihood	−1549.6		−5471.2	
Number of observations	2,950		11,296	

	FR		IT	
	Coef.	b. S. E.	Coef.	b. S. E.
R&D intensity	0.361***	(0.044)	0.578***	(0.054)
Cooperation partners				
Other enterprise group members	0.275***	(0.039)	0.126**	(0.052)
Suppliers	0.158***	(0.033)	0.200***	(0.034)
Customers	0.255***	(0.041)	0.134**	(0.061)
Competitors	−0.009	(0.057)	−0.067	(0.055)
Consultants	0.126***	(0.041)	0.020	(0.037)
Universities	0.106**	(0.045)	0.140***	(0.032)
Government/public or private research institutes	0.036	(0.055)	0.033	(0.068)
Enterprise group	0.008	(0.023)	−0.007	(0.017)
Foreign head office	−0.025	(0.022)	0.040	(0.032)
Markets				
Local	0.103***	(0.025)	0.121***	(0.031)
National	0.178***	(0.026)	0.265***	(0.027)
EU	0.049*	(0.027)	−0.058**	(0.026)
Other	0.006	(0.028)	0.005	(0.023)

Table 5-14. Results of the knowledge production function (product innovation) for the manufacturing sector (continued)

Firm size (number of employees)				
10−19	reference		reference	
20−49	0.021	(0.015)	0.201***	(0.022)
50−99	0.183***	(0.036)	0.345***	(0.029)
100−249	0.291***	(0.04)	0.338***	(0.028)
250−499	0.390***	(0.046)	0.559***	(0.045)
500−999	0.288***	(0.051)	0.535***	(0.048)
≥1000	0.417***	(0.067)	0.503***	(0.069)
2−digit NACE				
10 (food)	reference		reference	
11	−0.275***	(0.067)	−0.297***	(0.056)
12	−0.707***	(0.135)	−0.433**	(0.203)
13	−0.009	(0.070)	−0.296***	(0.039)
14	0.058	(0.093)	−0.367***	(0.043)
15	0.210**	(0.083)	−0.327***	(0.040)
16	0.014	(0.063)	−0.074	(0.046)
17	−0.120**	(0.057)	−0.403***	(0.055)
18	−0.252***	(0.063)	−0.161***	(0.044)
19	−0.626***	(0.125)	−0.706***	(0.095)
20 (chemicals)	−0.287***	(0.061)	−0.225***	(0.041)
21 (pharmaceuticals)	−0.547***	(0.094)	−0.710***	(0.063)
22	−0.031	(0.035)	−0.011	(0.033)
23	−0.136***	(0.039)	−0.185***	(0.033)
24	−0.124**	(0.053)	−0.130***	(0.043)
25	−0.227***	(0.035)	−0.202***	(0.034)
26 (electronics)	−0.288***	(0.084)	−0.365***	(0.075)
27	−0.162***	(0.059)	−0.181***	(0.050)
28	−0.036	(0.047)	−0.174***	(0.043)
29	−0.160***	(0.062)	−0.346***	(0.061)
30	−0.104	(0.090)	−0.371***	(0.071)
31	0.063	(0.056)	−0.037	(0.043)
32	−0.055	(0.066)	−0.047	(0.040)
33	−0.126***	(0.038)	−0.215***	(0.038)
Pseudo−R^2	0.320		0.244	
Log−likelihood	−2259.0		−3409.8	
Number of observations	4,873		6,656	

Notes: Standard errors are bootstrapped (b. S. E.). Shown are marginal effects at sample means on the probability of the introduction of a product innovation. Levels of significance are ***1%, **5%, *10%.

Table 5-15. Results of the productivity equation for the manufacturing sector

	DE		ES	
	Coef.	b. S. E.	Coef.	b. S. E.
Product innovation	−0.051	(0.122)	0.217***	(0.048)
Enterprise group	0.207***	(0.029)	0.370***	(0.024)
Foreign head office	0.356***	(0.055)	0.199***	(0.034)
Markets				
Local	−0.057**	(0.023)	0.090***	(0.034)
National	0.208***	(0.036)	0.376***	(0.030)
EU	0.214***	(0.043)	0.275***	(0.025)
Other	0.078*	(0.040)	0.147***	(0.020)
Firm size (number of employees)				
10−19	reference		reference	
20−49	−0.023	(0.037)	0.097***	(0.018)
50−99	0.059	(0.041)	0.171***	(0.025)
100−249	0.130***	(0.041)	0.139***	(0.028)
250−499	0.279***	(0.070)	0.141***	(0.041)
500−999	0.364***	(0.095)	0.280***	(0.058)
≥1000	0.492***	(0.074)	0.273***	(0.088)
2−digit NACE				
10 (food)	reference		reference	
11	0.504***	(0.105)	0.162***	(0.041)
12	1.329***	(0.472)	−0.255	(0.256)
13	−0.123	(0.115)	−0.405***	(0.048)
14	0.024	(0.138)	−0.796***	(0.070)
15	0.026	(0.117)	−0.462***	(0.052)
16	0.191**	(0.096)	−0.278***	(0.046)
17	0.336***	(0.103)	0.011	(0.046)
18	0.103	(0.088)	−0.450***	(0.044)
19	2.602***	(0.298)	0.888	(1.166)
20 (chemicals)	0.573***	(0.105)	0.033	(0.036)
21 (pharmaceuticals)	0.176	(0.116)	−0.165***	(0.047)
22	0.025	(0.083)	−0.262***	(0.036)
23	0.091	(0.085)	−0.209***	(0.038)
24	0.321***	(0.112)	0.148**	(0.060)
25	−0.017	(0.077)	−0.366***	(0.027)
26 (electronics)	0.042	(0.086)	−0.582***	(0.044)
27	0.019	(0.086)	−0.381***	(0.041)
28	0.150*	(0.087)	−0.399***	(0.029)
29	0.192**	(0.096)	−0.276***	(0.052)

Table 5-15. Results of the productivity equation for the manufacturing sector (continued)

30	0.173*	(0.100)	−0.426***	(0.082)
31	0.054	(0.093)	−0.627***	(0.031)
32	−0.130	(0.080)	−0.587***	(0.046)
33	0.092	(0.087)	−0.573***	(0.035)
Constant	11.234***	(0.070)	11.104***	(0.046)
R^2	0.415		0.319	
Number of observations	2,950		11,296	

	FR		IT	
	Coef.	b. S. E.	Coef.	b. S. E.
Product innovation	0.098*	(0.056)	0.123**	(0.062)
Enterprise group	0.227***	(0.028)	0.305***	(0.023)
Foreign head office	0.122***	(0.025)	0.103***	(0.033)
Markets				
Local	−0.012	(0.037)	0.012	(0.032)
National	0.244***	(0.036)	0.221***	(0.027)
EU	0.074**	(0.031)	0.272***	(0.028)
Other	0.111***	(0.031)	0.176***	(0.028)
Firm size (number of employees)				
10−19	reference		reference	
20−49	0.055**	(0.025)	0.143***	(0.028)
50−99	0.069**	(0.030)	0.183***	(0.031)
100−249	0.094**	(0.041)	0.209***	(0.034)
250−499	0.118***	(0.040)	0.251***	(0.036)
500−999	0.205***	(0.054)	0.313***	(0.048)
≥1000	0.347***	(0.060)	0.484***	(0.059)
2−digit NACE				
10 (food)	reference		reference	
11	0.655***	(0.080)	0.348***	(0.069)
12	0.857	(0.571)	−0.875***	(0.242)
13	−0.303***	(0.113)	−0.565***	(0.053)
14	−0.488***	(0.099)	−0.754***	(0.062)
15	−0.654***	(0.113)	−0.457***	(0.047)
16	−0.065	(0.052)	−0.403***	(0.064)
17	−0.092*	(0.051)	−0.095**	(0.047)
18	−0.322***	(0.051)	−0.508***	(0.057)
19	0.879***	(0.259)	0.920***	(0.120)

Table 5-15. Results of the productivity equation for the manufacturing sector (continued)

20 (chemicals)	0.178***	(0.055)	0.102*	(0.055)
21 (pharmaceuticals)	−0.056	(0.068)	−0.080	(0.058)
22	−0.218***	(0.037)	−0.380***	(0.047)
23	−0.138**	(0.066)	−0.323***	(0.047)
24	−0.062	(0.056)	0.095	(0.065)
25	−0.298***	(0.035)	−0.437***	(0.041)
26 (electronics)	−0.317***	(0.050)	−0.649***	(0.053)
27	−0.218***	(0.057)	−0.511***	(0.057)
28	−0.166***	(0.044)	−0.441***	(0.043)
29	−0.245***	(0.067)	−0.512***	(0.076)
30	−0.253***	(0.069)	−0.641***	(0.097)
31	−0.367***	(0.068)	−0.513***	(0.053)
32	−0.406***	(0.052)	−0.536***	(0.059)
33	−0.202***	(0.041)	−0.548***	(0.051)
Constant	11.762***	(0.056)	11.558***	(0.055)
R^2	0.262		0.382	
Number of observations	4,872		6,656	

Notes: Standard errors are bootstrapped (b. S. E.). Levels of significance are ***1%, **5%, *10%.

6. Innovation and Efficiency at Firm Level: Insights from a Literature-Based Innovation Output Indicator

This manuscript is coauthored with Corina Jantke and Johannes Sauer and currently under review at Research Policy.

Authors' contributions: All authors contributed jointly to development of the research question. Data collection was supervised by Corina Jantke and further data was collected by Fabian Frick. Fabian Frick conducted the analysis and wrote the manuscript. Corina Jantke contributed to reviewing and editing the manuscript. Johannes Sauer contributed to refinements of the models and estimation strategies, as well as reviewing and editing the manuscript.

6.1. Abstract

This study explores contemporaneous and lagged effects of product and process innovation on production efficiency of dairy processors in the German market. We rely on a literature-based innovation output indicator that is based on new product introductions published in a trade journal. As an indicator for process innovation, we use the number of patent applications issued by the dairy. These indicators are merged on a panel dataset comprising publicly available financial data to estimate a production function incorporating the innovation indicators as efficiency-explaining variables. Endogeneity of innovation variables and production inputs is accounted for by instrumentation using a system GMM approach. While we find no positive effect of patents or the number of new product launches on efficiency, we find a consistent positive effect of successful new products on the dairy processors' technical efficiency. On the methodological side, our results confirm the relevance of the literature-based innovation output indicator as a differentiated measure of product innovation suitable for measuring the innovation effect on firm performance. Regarding innovation management in the food sector,

the results highlight the challenge related to high failure rates of new products in the food sector and emphasize the importance of new product quality for business performance of dairy processors.

6.2. Introduction

Justification of policy support for private-sector innovation projects builds on the positive effect of innovation activity on firm performance and consequently, economic welfare. A large body of literature aims at investigating this relationship. Besides efficiency or productivity, studies hereby focus, for example, on the effect of innovation on firm or sales growth (Coad, Segarra, and Teruel 2016; Ernst 2001; Artz et al. 2010), competitiveness (Banterle et al. 2014), or internationalization (Cassiman, Golovko, and Martínez-Ros 2010; Tavassoli 2018; Monreal-Pérez, Aragón-Sánchez, and Sánchez-Marín 2012). When evaluating the innovation-firm performance nexus, researchers face a number of empirical challenges. One crucial task is the valid measurement of innovation activity. In the past, a wide variety of quantitative and qualitative indicators for innovation activity has been developed. In general, a main difference between these indicators lies in their orientation towards inputs, outputs, or intermediates in the innovation process. Specifically, Becheikh, Landry, and Amara (2006) and Dziallas and Blind (2019) show how the indicators can be categorized along firm-specific (e.g., the firm's innovation culture or strategy) and external (e.g., market or environment) dimensions, which reflect the innovation input side and influence both the innovation process and the innovation outcome. On the other hand, there are indicators reflecting the innovation output side and are related to the innovation process (e.g., time-to-market) or the innovative product itself (e.g., intellectual property rights or new product counts). Early prominent studies predominantly built on research and development expenditures as an innovation indicator (see, for example, studies in Griliches 1984). A consensus emerging in recent years, however, is that research and development expenditures represent an input to the innovation process and only indirectly affect firm performance via the innovation outputs the firm generates, in the form of new products, as well as improved processes and techniques introduced into the production process (Becheikh, Landry, and Amara 2006). Therefore, a recommendation by OECD and Eurostat (2005) for innovation surveys is to directly inquire firms about the number of new products and processes introduced. For European countries, the Community Innovation Survey has gathered these data since the 1990s. In recent years, a considerable number of studies have employed this dataset, and the model proposed by Crépon, Duguet, and Mairesse (1998), for examining the productivity or efficiency implications of innovation (Lööf and Heshmati 2002; Janz, Lööf, and Peters 2003; Griffith et al. 2006; Raffo, Lhuillery, and Miotti 2008; Castellacci 2011; Hashi and Stojčić 2013; Siedschlag and Zhang 2014; Sauer and Vrolijk 2019).

Moreover, a requirement for datasets suitable for analysis of the innovation-efficiency relationship is not only the inclusion of viable innovation indicators, but also the availability of measures of relevant production inputs. The European Community Innovation Survey, for example, offers a wide scope regarding coverage of sectors and the number of observations. However, the dataset does not include proxies for capital and intermediates inputs, impairing its use in the production function framework.

Besides measurement of innovation and production inputs and outputs, another econometric challenge is endogeneity of innovation in the production function. On one hand, simultaneity must be expected when innovation affects efficiency and at the same time greater efficiency causes greater innovation output, for example, by additional resources that can be dedicated to innovation activities. On the other hand, unobserved factors—the business model, for example—must be considered, which can affect productivity and innovation activity alike. Regarding food companies, which are examined in this article, Hirsch et al. (2014) show that individual firm effects are important drivers of profitability. Simultaneously, individual firm effects—like the food firm's orientation toward product, process, and market—are an important determinant of its innovation behavior (Traill and Meulenberg 2002).

For specific industry subsectors where panel datasets including both production and innovation variables are not available, publicly available innovation indicators that can be merged with production data can offer a solution. One of these is what has been termed the literature-based innovation indicator (Kleinknecht 1993; Coombs, Narandren, and Richards 1996). Instead of survey-based self-reported product innovation measures, this indicator builds on the number of new product introductions published in trade journals. Collecting these data and the construction of panel datasets enables a more powerful treatment of firm heterogeneity and endogeneity by expunging firm fixed effects and using lagged variables as instruments, possibly leading to more robust model results.

The indicator has been used to examine the effect of innovation on firm growth (Cucculelli and Ermini 2012), differences in innovation output by nationality and firm size (Coombs, Narandren, and Richards 1996), association of product innovation capacity with trade competitiveness (Santarelli and Piergiovanni 1996), or the problem-solving behavior of firms in the innovation process (Katila and Ahuja 2002).

To the best of our knowledge, however, there are few—if any—studies employing the literature-based innovation indicator to analyze the effect of innovation on firm efficiency or productivity. This could be because the indicator is time-consuming to collect (Acs, Anselin, and Varga 2002) and, therefore, is only suitable for selected subsectors. In this article, we focus on such a specific subsector—namely, the dairy processing sector. As an extension to the conventional literature-based indicator, we exploit information on "best new products" awarded by a leading trade journal based on individual votes by journal readers. By this, we include an additional indicator, which accounts for the innovative content of the new product introductions based on expert opinion. With these two product innovation indicators differentiating between the pure number of new product introductions and the number of successful new product introductions, we contribute to the previous literature that often shows ambiguous results concerning the efficiency effect of innovation in the food sector. To further clarify the innovation activity of dairy firms and relate the results of the literature-based indicator to a more conventional innovation indicator, we additionally take into account process innovation with the help of patent counts.

6.3. Background

The food sector is one of the most important subsectors of the European Union's manufacturing sector (Menrad 2004; Eurostat 2017b), and within the food sector, a significant share of output is generated by the manufacture of dairy products.[12] The dairy processing sector is often of special interest for agricultural policy because of its close link to agricultural production, due to long-term delivery contracts between dairy processors and dairy farmers. Via the milk payout price, the economic situation of the dairy processor directly influences the economic situation of the dairy farmers. Therefore, the mechanics of profitability of dairy companies are also of policy interest—especially in light of recent events in the dairy market: With the abolition of the European Union milk quota and recurrent milk price lows, policy makers are looking for appropriate measures for the stabilization of income of milk producers. Prerequisites are, therefore, the competitiveness and financial stability of dairy processors, since greater profitability makes way for passing on profits to dairy farmers in the form of higher milk payout prices.

In recent decades, the European dairy sector underwent significant and continuing structural change due to (partially international) mergers and acquisitions, resulting in increasing market concentration.[13] Simultaneously, in downstream markets, the dairy sector in many countries faces an ongoing concentration in the food retail sector (Hendrickson et al. 2001; Dobson, Waterson, and Davies 2003). Ger-

[12] In 2017, the production value of the dairy processing sector amounted to approximately 17% of the food sector of the EU 28 (Eurostat 2019).

[13] For example, the German Federal Office for Agriculture and Food indicates that the number of dairy companies in Germany has decreased from 194 in 2009 to 124 dairies in 2015 (BLE 2017).

many, for example, has one of the most competitive food retail sectors characterized by dominant market power of the largest five grocers accounting for 70 percent of the retail market (USDA 2017). Possibly as a consequence, competition among European dairy processors was found to be high, leading to low profit persistency (Hirsch and Hartmann 2014).

In such an environment, innovation activity can open some leeway for food processors, since innovation is generally, and in the food sector, regarded as an important factor for competitiveness (Grunert et al. 1997). On one hand, product innovation brings a competitive edge and satisfies consumer expectations (Bigliardi and Galati 2013), which can strengthen bargaining power in price negotiations with food retailers. For example, product innovation can be a way to counter competition between manufacturers' and private labels (Venturini 2006). Process innovation, on the other hand, can help decrease costs or provides techniques for new product developments.

Studies specifically focusing on the food sector are scarce, and the results across studies are ambiguous. Geroski, Machin, and van Reenen (1993) find a negative effect of the number of innovations on profitability of firms in the food, drinks, and tobacco sector. Cahill, Rich, and Cozzarin (2015) find significant positive correlation of innovation with profit levels but not profit margins in Canadian food companies. Acosta, Coronado, and Romero (2015) focus on the Spanish food industry and uncover a significant positive effect of product innovation on labor productivity, while the effect of process innovation is also found positive but insignificant. For a sample of Spanish agri-food firms, Alarcón and Sánchez (2013) find ambiguous lagged effects of external R&D spending on profitability (return on total assets). For internal R&D, they find no significant effects. Frick, Jantke, and Sauer (2019) focus on the food industry in France, Germany, Italy, and Spain, finding positive effects of innovation outputs on labor productivity. While the aforementioned studies focus on the food sector in general, we are not aware of any studies focusing on innovation effects specifically in the dairy sector.

Experience on success rates of new (consumer) product introductions in the food sector shows that a positive effect of new product developments on firm performance is far from guaranteed. It is common practice for food manufacturers to launch a plethora of new consumer products, with only a fraction of these representing "real" innovations and the majority consisting of "me too" or seasonal products (Ernst and Young and Nielsen 2000 cited in Juriaanse 2006). Connected to this is a high failure rate of new product introductions (McNamara, Weiss, and Wittkopp 2003; Winger and Wall 2006; Stoneman, Bartoloni, and Baussola 2018, 47). That is, many newly launched products are not successful in the market and are likely unable to earn back the costs of their development. The two product innovation indicators of our study consider this by separating the number of successful new product introductions from the total number of new product introductions.

Before we discuss the data employed in Section 6.5, we present the modelling framework of our study in the next section.

6.4. Theoretical and empirical model

We follow a production function framework where dairy i in year t produces output Q with a given set of inputs in the vector X, conditional on (technical) efficiency A:

$$Q_{it} = f(X_{it}, A_{it}, t). \tag{6-1}$$

A_{it} quantifies differences in production across firms not attributable to production inputs or the technology level common to all firms (t). These can arise, for example, due to technological differences in machinery and production processes. If output is measured by revenue and inputs are measured by costs, which are not exactly adjusted for yearly differences in prices between firms, then A_{it} additionally picks up profitability differences. Measurement of productivity based on revenue has been termed "revenue productivity" rather than "physical productivity"

(Foster, Haltiwanger, and Syverson 2008). In our article, we prefer the term "efficiency" to "productivity" to emphasize that this measure does not incorporate possible scale effects.

We further assume that a dairy's efficiency can be expressed as

$$A_{it} = g(product\ innovation, process\ innovation, v_i, u_{it}), \qquad (6\text{-}2)$$

u_{it}, and the firm-specific, time-invariant efficiency level, v_i.It is to be assumed that dairies operate at an individual efficiency level, v_i, depending on environmental conditions or the dairy's type of business model. This can relate to available infrastructure and characteristics of raw milk suppliers determining efficiency of milk collection, the customer focus of the dairy, or share of consumer vs. bulk products. The product range of dairies seems to be of major importance here, since considerably higher value added can be expected for consumer products such as cheese, yogurt, or dessert products compared to bulk products, such as milk or powdered milk sold on the spot market. Time-varying efficiency, u_{it}, might be influenced by changing unobserved factors such as the managerial effort, qualification of employees, or the quality of factory equipment and raw milk input.To paint a more complete picture of the innovation activity of firms, in addition to product innovation, we include process innovation in the analysis. For product innovation, we assume a positive effect on firm efficiency for the following reasons. On one hand, product innovation activity is a sign of adaptiveness and the ability to satisfy consumer needs by product differentiation. Therefore, we expect that dairy processors can use product innovation to gain competitive advantage over rivalling firms and strengthen their position in food retail stores, thereby securing utilization of plant capacities. On the other hand, we expect that with newly introduced products, dairy processors can achieve higher product-level value added, since prices can possibly be set higher than for existing products, as found in the case of "Functional Foods" (Menrad 2003). Both effects would positively influence the overall profit margin of the dairy processor and, thus, our revenue-based efficiency measure. Similarly, we expect a positive effect of process innovation. Process innovations, by nature, aim to implement new equipment or processes that enable input savings or improvements in product quality. Additionally, process innovations are frequently jointly implemented with product innovations, for example, when specific equipment is needed for the manufacture of products with new functions or higher quality.

Assuming a Cobb-Douglas production function, we arrive at our empirical model

$$\ln \mathrm{Q}_{\mathrm{it}} = \gamma_0 + \sum_{k=1}^{3} \beta_k \ln X_{ikt} + \sum_{n=1}^{N} \alpha_n innovation_{int} + \sum_{t=1}^{T} \gamma_t year_t + v_i + u_{it} + \mathrm{e}_{\mathrm{it}}, \quad (6\text{-}3)$$

in three production inputs: labor, capital, and materials.[14] We include various innovation variables in the model, which we discuss in the next section. Since u_{it} is unobserved, it forms along with idiosyncratic errors in e_{it} a compound error term in the regression equation. For a flexible representation of yearly shocks on supply and demand markets, we prefer a set of year dummies γ_t to a time trend.

Several variables in this model must be considered as possibly endogenous. First, we expect innovation to be correlated with (unobserved) v_i for the aforementioned reasons. For example, dairy processors with a focus on consumer products are likely to introduce a larger number of product innovations and, simultaneously, show larger profitability. Furthermore, we consider that innovation and output might be simultaneously determined, for example, when product innovation leads to greater profitability and successful new products lead firms to decide

[14] Although a more flexible functional form is in general regarded as advantageous, we prefer a Cobb-Douglas form for its parsimony in parameters and consequently the number of required instruments. Translog specifications of the models did not yield different or clearer results.

We opted for a production function specification instead of a production frontier because the distribution of predicted residuals from an OLS regression did not show negative skew.

on greater innovation budgets. Similar effects can be expected for process innovation.

Secondly, we consider possible endogeneity of the production inputs. Dairy processors base their production on a relatively stable raw milk supply since supplying farmers usually do not switch between dairies on a regular basis. However, dairy processors can trade raw milk on the spot market, adjusting the milk quantity according to the current business situation. It must also be considered that some dairies incorporate profit or turnover participation schemes into the milk payout price. This suggests that the raw milk input is correlated with u_{it}, especially when it is measured as costs of intermediates, as in our case. Lastly, the intermediates input can also correlate with v_i, for example, if dairies with a focus on organic products show higher profit margins and higher milk payout prices. We also consider possible correlation of labor with u_{it}, since labor can be adjusted to the current business situation by hiring or dismissal of staff. Capital, in contrast, is subject to greater adjustment cost. Therefore, we consider that capital might be a predetermined regressor; that is, it might be determined by past but not contemporaneous u_{it}.

To tackle the endogeneity of regressors, one has to consider possible instrumental variables. For the innovation variables, this task is complicated by the fact that many variables associated with innovation must also be expected to be associated with efficiency. Many of the studies employing the model of Crépon, Duguet, and Mairesse (1998) and the Community Innovation Survey dataset rely on instruments such as the use of public funding, collaborative innovation, or the type of information sources used for innovation activity. However, the exogeneity of such instruments is debatable, since firms only apply for public funding or initiate collaborations if they intend to conduct innovation projects.

For our dataset, we cannot provide suitable additional instruments outside the dataset for innovation and endogenous production inputs. We tackle the possible endogeneity of regressors in a stepwise procedure by applying several regression models, gradually increasing in robustness to the sources of endogeneity. The first model is an OLS model, neglecting correlation of regressors with u_{it} as well as v_i. In the second model, we build a two-stage-least-squares model, instrumenting contemporaneous levels of intermediates input, labor, and innovation by one-period lags. Thus, this approach tackles correlation of these regressors with u_{it} but not v_i. The third model consists of a fixed effects approach which is robust to influences of v_i but not to correlation with u_{it}. The fourth and final model eventually takes into account all mentioned sources of endogeneity by applying a system GMM model, following Blundell and Bond (1998). This approach has the advantage that valid instruments are formed by lags of the endogenous variables and, therefore, additional variables outside of the dataset are not required. The general setup of the approach consists of two equations. In the first equation, the time invariant effects (v_i) are removed by first differencing or by a "forward orthogonal transform," and the transformed endogenous variables are then instrumented by their lagged levels. In the second equation, the level of the dependent variable is regressed on the levels of the independent variables, and therefore, v_i is not removed. Instead, endogenous regressors are instrumented by their differences, which are assumed exogenous to the time invariant effects. For the first equation in this model, we choose the "forward orthogonal transform," which removes v_i by subtracting all available future observations of the variable and has the advantage of maximizing sample size when there are gaps in the data. For further details of the procedure, we refer to Roodman (2009b). One critical point of the system GMM approach concerns the number of instruments. For endogenous regressors, all available lags that are uncorrelated with the error term can be incorporated into the instrument matrix. This bears the risk that an excessive number of instruments are included in the estimation, and endogenous regressors are overfit. Therefore, the approach is said to be best suited for datasets of small T and large N, since an increasing number of individuals increases the number of observations relative to the number of instruments. For a discussion on this topic see Roodman (2009a). This issue is relevant for us, as our dataset contains a limited number of individuals. We tackle this problem with an as far as possibly reduced instrument set, along with a sensitivity test on a further reduced instrument count.[15]

Apart from contemporaneous effects of innovation on productivity, we also consider lagged effects in a second set of regression analyses.[16] It may be that new product introductions undergo the typical product life cycle stages with small and growing revenues immediately after their introduction and a larger impact on revenues at later stages. Concerning process innovation, firms might require some time to adjust to newly introduced production techniques. Therefore, lagged effects of product and process innovations on firm efficiency are plausible. This empirical model is described as

$$\ln \mathrm{Q_{it}} = \gamma_0 + \sum_{k=1}^{3} \beta_k \ln X_{ikt} + \sum_{n=1}^{N} \sum\nolimits_{t-3}^{t-1} \alpha_{nt} innovation_{int} + \sum_{t=1}^{T} \gamma_t year_t + v_i + u_{it} + \mathrm{e_{it}}, \tag{6-4}$$

where we consider up to three-period lagged effects of innovation. Although we do not expect past innovation activity to be influenced by contemporaneous time-varying efficiency u_{it}, we still must consider correlation of innovation activity with time-invariant efficiency v_i. As before, intermediates and labor inputs are also likely to be correlated with both u_{it} and v_i. Therefore, we show the results of two endogeneity-robust models. The first applies an instrumental variable fixed effects approach, which eliminates v_i by the within transformation. To mitigate endogeneity by correlation with u_{it}, we instrument materials and labor input by their one-period lags. These instruments might not be fully exogenous, since

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[15] We reduce the instrument count by restricting lag lengths of “GMM style” instruments, as well as “collapsed” instrument matrices, both options that can be implemented with the user-written command “xtabond2” (Roodman 2009b) in STATA.

[16] We decide on a separate examination of contemporaneous and lagged effects for the greater flexibility in the choice of instrumental variables.

transformation of the instruments and the error can introduce correlation between the two, similar to dynamic panel bias. However, we assume this to be of minor importance given a fairly long study period. As a second set of models, we estimate three separate system GMM models with differing lag lengths of the innovation variables.

Figure 6-1 provides a graphical depiction of all interrelations considered in our study.

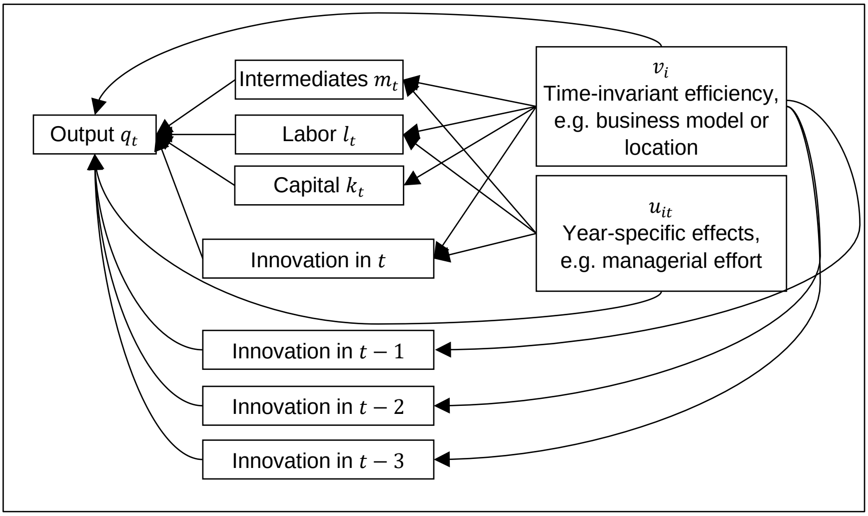

Figure 6-1. Depiction of considered interrelations

In all models, we include additional control variables. We control for a cooperative background of the dairy, since cooperatively owned firms can be expected to show different efficiency due to differing business objectives (Soboh, Oude Lansink, and van Dijk 2012; Hirsch and Hartmann 2014). We further control for product focus, as well as for the case where financial data are published as consolidated statements. We consider all these variables as exogenous. Regarding the product range of dairies, this can be justified by considering that changes in the product portfolio are subject to adjustment costs in the form of investments in new equipment and expertise. The cooperative background is not determined by current business decisions but is, rather, a result of the historic development of the dairy. The reporting of consolidated financial statements is connected to firm size, which can be expected to influence the innovation activity and, possibly, efficiency of the dairy. Therefore, incorporating information on whether consolidated statements are reported should reduce rather than introduce endogeneity into the estimation.

6.5. Data

The data we employ stem from several sources. The two literature-based product innovation indicators stem from reviews on newly listed dairy products conducted by a German dairy trade journal ("Milch-Marketing").[17] At the beginning of every year, the journal lists new dairy products launched on the German market during the preceding year and awards the "best" new products, which are determined by journal readers' votes. Because readers of the journal are typically retail professionals, the election of a product reflects an expert-based evaluation of its innovativity and sales volume. We construct the first product innovation indicator by summing up the number of listed new products for each dairy, that is, the product nominations of a dairy per year ($productnom$). The second product innovations indicator is formed by the sum of product winners of a dairy per year ($productwin$). Using these two variables as product innovation indicators is motivated by the idea that—considering the high failure rates of new product innovations in the retail stage—it might not be enough for dairies to only introduce a great number of new products; but they must introduce the "right" new products. This quality of new product introductions is reflected in the variable $productwin$.

[17] According to information from the journals' editorial office, dairies generally notify the journal about new product introductions. Because dairies have an interest in making new product introductions public, it is to be expected that almost all new products in the market are covered by the journal's review. Some new product introductions that are not reported to the journal are additionally researched by the journal itself. Therefore, especially for German dairies, which constitute the majority of our sample, we can expect almost complete coverage of all new products introduced into the market.

While the advantages of the literature-based indicator have been already discussed, we acknowledge that this indicator also has some shortcomings.[18] First, only consumer products are listed and, thus, innovation activity in industry products is neglected. Second, the product listings are restricted to the German market and, therefore, product innovation activity of firms on markets outside Germany is neglected, while its effect might be mirrored in the financial data that we use. Still, we are confident that the indicator we construct serves well as an indicator for the product innovation activity of the dairy processor. Regarding the first point, we consider this less of a problem, since most of the dairy companies included in our dataset have a clear focus on consumer products. Regarding the second point, we consider it likely that internationally operating dairies use new product developments for several countries in which they are active.

As an indicator for process innovation, we use information on patent applications. Some controversy concerns the suitability of patents as a measure of process innovation. On one hand, patents represent the act of invention, which is only an intermediate step in the innovation process, and, thus, does not guarantee successful implementation of the new technique (Coombs, Narandren, and Richards 1996; Mairesse and Mohnen 2010). Additionally, the number of patents held by a firm might not quantify its full innovation activity, since not all inventions are patentable and firms might refrain from patent applications to avoid costs for application and defending the patent, or for the sake of secrecy (Griliches 1990; Cohen, Nelson, and Walsh 2000). On the other hand, patents can be regarded as a more objective measure compared to self-reported process innovations from innovation surveys (Mairesse and Mohnen 2005). Therefore, we still consider patenting a valid indicator for process innovation activity—a view that is supported by usually high correlations between patent and research and development activity (Griliches 1990) and by existing works that establish a positive link between

[18] On general strengths and weaknesses of the indicator see also Coombs, Narandren, and Richards (1996).

patents and firm performance (Crépon, Duguet, and Mairesse 1998; Balasubramanian and Sivadasan 2011; Cefis and Ciccarelli 2005; Ernst 2001). We obtain patent data from the Google patents index that contains information from national and international offices. For the companies in our dataset, we conduct search queries with the dairy itself or firms within the dairy's enterprise group as assignee of the patent. We assign a patent to a specific year based on the priority date that refers to a possible earlier application for the same invention. We do not consider whether the patent application was granted or denied, as also denied patent applications are a sign of innovation activity.

For production output and inputs, we use data of financial statements. The data stem mainly from publicly available annual reports while some data was obtained from the "Amadeus" database by Bureau van Dijk. As the single production output, we use revenues that we deflate by a consumer price index for dairy products and eggs. The number of employees constitutes the labor input. As capital input, we use the capital stock in fixed assets deflated by a price index for machinery in food production. We measure the intermediates input by the cost of materials. As a deflator, we use a price index for farm-level milk prices, as we expect that the major share of materials cost is comprised by the raw milk input. All price indices were obtained from the German statistical office Destatis (2019).

To proxy for the business model of the dairy, we use additional information on the product range of the company extracted from sector reviews regularly published as special issue of an industry journal (Soßna 2007; Soßna 2014 and earlier editions). From these data, we generate dummy variables indicating whether the company produces fresh products (fresh milk, cream, yogurt, dessert products), butter, powders (milk or whey powder), or cheese.

After merging the data sources, our dataset spans the period 2001 to 2017 and includes 600 complete observations from 53 firms. Descriptive statistics are given in table 6-1.

Table 6-1. Descriptive statistics of variables used in regressions

Variable	Mean	SD	Min	Max
Revenue (million EUR)	567.3	780.1	23.9	6,138.0
Costs of materials (million EUR)	416.7	566.4	17.0	4,033.5
Number of employees	1,006.4	2,074.0	35.0	26,624.0
Fixed assets (million EUR)	84.1	158.6	2.2	1,402.4
Number of product nominations per year	3.3	3.9	0.0	25.0
Number of product winners per year	0.7	1.0	0.0	6.0
Number of patent applications per year	0.4	1.7	0.0	22.0
Cost share of materials	0.867	0.064	0.569	0.965
Cost share of labor	0.103	0.049	0.030	0.282
Cost share of capital	0.030	0.023	0.004	0.297
Number of observations		600		

Note: Monetary values are given in nominal values. Cost shares are calculated with financial data on costs of materials, costs of employees, and depreciation.

6.6. Results and discussion

Table 6-2 lists the results for the contemporaneous innovation effects. The second column shows the results for the OLS regression, which ignores correlation of regressors with contemporaneous efficiency and unobserved time-invariant factors. Compared to table 6-1, the coefficients of production inputs are quite similar to the calculated cost shares, offering no clear evidence for serious bias of these coefficients. The product focus of the dairies seems to be of some importance for the dairy’s output. A cooperative background is attributed a weakly significant negative effect of approximately five percent, which is consistent with results of other studies (Hirsch and Hartmann 2014). The product innovation variables show a statistically significant positive association with output and, thus, efficiency. The number of product nominations only reveals a small and weakly significant coefficient, whereas the number of product winners shows a stronger association of 1.5% per product. In contrast, process innovation shows a negative but not statistically significant coefficient. However, as discussed, we cannot rule out that the coefficients of this model are biased, for which we turn our attention to results of the more robust models.

The third column lists the results for the two-stage least squares model, which tackles correlation of regressors with time-variant but not with time-invariant unobserved factors. Overall, the coefficients are similar to the OLS results. Interestingly, the coefficient of product winners increases more than threefold, but loses its statistical significance.

The fourth column of table 6-2 gives the results of the fixed effects model, robust to influences of v_i but not u_{it}. Some differences to the first two models become apparent here. The materials coefficient increases, while the coefficients of labor and capital shrink considerably. This result is not too surprising, since the poor performance of the fixed effects estimator for production functions—and, especially, the low capital coefficient—is commonly observed (van Beveren 2012). The coefficient for $Productnom$ deteriorates to zero, suggesting that dairies did not achieve higher efficiency in years with extraordinarily many product launches. $Productwin$ keeps its positive sign and is highly statistically significant. This hints on an average positive association of successful product innovations with firm output, with the output increase estimated as one percent per product winner in this model. Remarkably, the process innovation indicator keeps its negative sign and even shows statistical significance.

Table 6-2. Regression results for contemporaneous innovation effects

Variable	OLS		2SLS		FE		SYS-GMM	
Materials	0.816***	(0.017)	0.817***	(0.018)	0.928***	(0.022)	0.956***	(0.041)
Labor	0.143***	(0.019)	0.138***	(0.027)	0.056***	(0.017)	0.034	(0.041)
Capital	0.052***	(0.012)	0.043***	(0.015)	0.006	(0.011)	−0.024	(0.053)
Productnom	0.004*	(0.002)	0.003	(0.010)	0.000	(0.001)	0.011	(0.008)
Productwin	0.015***	(0.006)	0.052	(0.040)	0.010***	(0.003)	0.028*	(0.016)
Patents	−0.004	(0.003)	−0.007	(0.006)	−0.005**	(0.002)	0.004	(0.006)
Fresh products	0.024	(0.021)	0.040	(0.026)	−0.006	(0.010)	0.019	(0.025)
Butter	−0.038*	(0.022)	−0.043*	(0.022)	0.005	(0.012)	−0.043	(0.036)
Powder	0.009	(0.010)	0.015	(0.012)	0.017	(0.010)	−0.016	(0.027)
Cheese	−0.038*	(0.021)	−0.037**	(0.018)	−0.010	(0.013)	0.016	(0.033)
Cooperative	−0.047*	(0.024)	−0.036	(0.025)	time invariant		−0.045	(0.046)
Consoli-dated	−0.048*	(0.026)	−0.053**	(0.025)	−0.015	(0.019)	0.012	(0.057)
Constant	2.071***	(0.298)	2.198***	(0.340)	1.233***	(0.346)	1.675**	(0.770)
Year dummies	(0.000)		(0.000)		(0.000)		(0.000)	
R^2	0.995		0.994		0.971		0.995	
Regressors treated as endogenous	*None*		*Materials, Labor, Productnom, Productwin, Patents*		*None*		*Materials, Labor, Productnom, Productwin, Patents, Capital as predetermined*	
Number of instruments	*29*		*28*		*29*		*53*	
Number of observations	*600*		*537*		*600*		*600*	

Note: Significance levels are ***1%, **5%, *10%. Year dummies are included in all regressions and the values shown are p-values for tests on joint significance. R^2 is the Within-R^2 for the FE model and the correlation coefficient of observed and predicted output for the system GMM model. Standard errors in parentheses are clustered for OLS, 2SLS, FE, and Windmeijer-corrected for the SYS-GMM model. Number of instruments reports the total instrument count (included and excluded instruments).

Lastly, we shift our attention to the system GMM approach, which takes into account all of the considered sources of endogeneity and hence aims at uncovering true causal effects. The coefficient of the materials input lies higher than the fixed effects result. The coefficients of labor and capital are statistically insignificant, which could be explained by weak instrument performance and the time-invariant nature of capital input that might affect estimation in the transformed equation of the model. The effect of product nominations is estimated to be close to zero. The coefficient for patents changes its sign compared to the other models but again without statistical significance. The effect of $Productwin$ seems to be once more the most significant one, with the effect estimated to almost three percent per successful product introduction.

These results are based on the incorporation of 53 instruments, or as many instruments as firms in the dataset. To provide insight into the sensitivity of the results to a changing instrument count, table 6-3 demonstrates the results of a robustness check on the system GMM outcomes. The reduced instrument counts are implemented by further restricting the length of the lags used for “GMM-style” instruments. The second column repeats the results of the system GMM model in table 6-2, which restricted the lag length to $t - 4$. Compared to this baseline model, the instrument count is gradually reduced in column three and four. The fifth column shows the results of a model with considerably increased instrument count and that increasing the instrument count does not provide different results. Overall, in all models, we find a consistent positive effect of the number of product winners. Apart from $Productnom$ in two models, the effects of the two other innovation proxies remain close to zero and statistically insignificant.

Table 6-3. Sensitivity of system GMM results to reduced instrument count

	Lag limit			
Variable	t−4	t−3	t−1	t−8
Materials	0.956***	0.948***	0.947***	0.876***
	(0.041)	(0.041)	(0.077)	(0.059)
Labor	0.034	0.045	0.077	0.083
	(0.041)	(0.048)	(0.077)	(0.054)
Capital	−0.024	−0.015	−0.060	0.021
	(0.053)	(0.051)	(0.059)	(0.030)
Productnom	0.011	0.007	0.018**	0.007*
	(0.008)	(0.007)	(0.009)	(0.004)
Productwin	0.028*	0.034**	0.065*	0.016**
	(0.016)	(0.017)	(0.036)	(0.007)
Patents	0.004	0.005	0.006	0.000
	(0.006)	(0.005)	(0.006)	(0.005)
Number of instruments	53	47	35	77

Note: Significance levels are ***1%, **5%, *10%. Standard errors in parentheses are Windmeijer-corrected. Results of control variables are not shown.

Our last set of results concerns possible lagged effects of innovation (table 6-4). The instrumental variable fixed effects approach surprisingly shows many negative signs for product nominations and patents, which are even partly statistically significant. Consistent with the earlier results are the positive signs of lagged $Productwin$, with the two-period lag showing weak statistical significance. The system GMM results show no statistical significance overall for the innovation variables. The effects of patents and product nominations are estimated close to zero. Once again, $Productwin$ shows a tendency for positive effects, however, without statistical significance and smaller than the contemporaneous effect estimated earlier.

Overall, the results partly align with our expectations. For product innovations, we find the number of new product introductions ($productnom$) only weakly associated with efficiency across all models. For lagged effects of this variable, we even find statistically significant negative coefficients. Perhaps, this reflects costs associated with unsuccessful product introductions that arise from discontinuation of the product or cannibalization effects within the product program of the dairy. In contrast, we find a consistent positive relationship between efficiency and the number of successful new product introductions ($productwin$). These results mirror the challenge concerning high failure rates of new food products: Simply introducing many products seems to be (on average) not a promising business strategy; only successful new products, on average, have a positive effect on the business performance. Our results confirm this for the special case of the dairy sector, stressing the importance of a dairy processors' ability to meet customer needs and find the appropriate marketing strategy for new product introductions.

Table 6-4. Results for lagged effects of innovation

Variable	FE−IV	SYS−GMM		
Materials	0.918***	0.910***	0.965***	0.972***
	(0.030)	(0.073)	(0.060)	(0.079)
Labor	0.085***	0.050	0.020	0.007
	(0.019)	(0.100)	(0.051)	(0.082)
Capital	−0.008	0.013	0.012	0.015
	(0.013)	(0.037)	(0.038)	(0.040)
Productnom				
t−1	0.001	0.003		
	(0.002)	(0.005)		
t−2	−0.002**		0.000	
	(0.001)		(0.002)	
t−3	−0.002*			−0.001
	(0.001)			(0.001)
Productwin				
t−1	0.003	0.004		
	(0.005)	(0.006)		
t−2	0.007*		0.005	
	(0.004)		(0.003)	
t−3	0.004			0.003
	(0.003)			(0.003)
Patents				
t−1	−0.002	0.002		
	(0.002)	(0.004)		
t−2	−0.002*		0.002	
	(0.001)		(0.003)	
t−3	−0.004			−0.001
	(0.002)			(0.003)
R^2	0.971	0.993	0.994	0.995
Number of instruments	31	46	51	50
Number of observations	420	537	484	434

Note: Significance levels are ***1%, **5%, *10%. Control variables on product range, cooperative organization, consolidated statements, and year dummies are included in all regressions. R^2 is the Within-R^2 for the FE-IV model and the correlation coefficient of observed and predicted output for the system GMM model. Standard errors in parentheses are clustered for FE-IV and Windmeijer-corrected for the SYS-GMM model. Number of instruments reports the total instrument count (included and excluded instruments). The first SYS-GMM model employs a forward transform and the last two a difference transform, since two-period and earlier lags of the innovation variables are exogenous in the difference equation.

Regarding process innovation, we surprisingly find effects close to zero with a tendency of statistically significantly negative associations. This suggests that process innovation activity in the form of patenting is not a promising strategy for the average dairy processor. On one hand, this can be explained by recalling results in other manufacturing sectors. The effectiveness of patents to prevent imitation has generally been questioned in manufacturing industries, for instance, because competitors are able to "invent around" the patent in many cases; therefore, firms might choose not to patent a process innovation, including for secrecy (Cohen 2010). Instead of securing the invention returns, the major motives of patenting are often of strategic considerations (Cohen, Nelson, and Walsh 2000). Thus, a negative relationship between patents and firm performance could be provoked by low returns from patenting and high costs for creating and defending patents (Artz et al. 2010). On the other hand, and specifically for the food sector, it must be considered that food processors source a large share of improvements in production machinery from equipment manufacturers and other suppliers and not from own research and development activities (Traill and Meulenberg 2002). Moreover, it is likely that many process innovations are developed in cooperation with equipment suppliers and not patented. New product development also partly involves process innovation activity, for example, when new product designs require new production techniques. For all of these reasons, patent data might not adequately capture the introduction of innovations into the production process, and a dairy without any patents might be just as innovative. This offers an explanation for the statistically insignificant results.

6.7. Conclusions

Studies focusing on the efficiency effect of innovation in the food sector—and even more in specific sub-sectors, such as the dairy sector—are scarce, and the results are often ambiguous. For product innovation, a source of this ambiguity could stem from heterogeneity in the quality of new product launches. The literature-based product innovation indicator allowed us to examine the link between innovation activity and efficiency in a differentiated manner by including both the total number of new products and an expert-based evaluation of new product quality. The results of our study are consistent across several model specifications and largely conform to expectations from the existing literature, confirming the relevance of the literature-based indicator for meaningful results when studying the performance effects of innovation activity. Therefore, the indicator can be a solution for studies in specific subsectors or in other cases when data on new product introductions is not readily available.

For product innovation activity, the results suggest a positive effect of successful new product introductions on firm performance but no positive effect of the mere number of new product introductions. This reflects the expectation due to high failure rates of new product introductions in the food sector and emphasizes the importance of new product quality. Concerning process innovation, we found no positive association or effect of patenting activity on firm efficiency, suggesting low returns to patenting, on average, and might be explained by relying on suppliers for improvements in production techniques.

Besides choosing a suitable innovation output indicator, the econometric investigation on the topic is generally and in our case complicated by several sources of endogeneity and a lack of suitable instrumental variables. By forming valid instruments from variables of the original dataset, the system GMM approach offers a solution to this challenge but is constrained by small samples as ours. Nevertheless, reliability of our results is confirmed by the magnitude of the coefficients of the innovation variables appearing relatively stable across all applied approaches. Our methodological approach suggests some considerations for future studies. In the absence of truly exogenous effects that can serve as instruments for innovation activity, for example by policy measures, researches must rely on instruments created within the dataset. Therefore, for studies in specific subsectors as ours, emphasis should be placed on sample size.

Part III. Discussion and Conclusions

7. Summaries of the Empirical Studies

7.1. Deregulation and productivity: empirical evidence on dairy production

In the European Union, production quotas were introduced in 1984 to counter the costs caused by large raw milk production surpluses due to guaranteed milk prices. Each dairy farm in the European Union was allocated a production allowance based on its past production volumes. Typically, quota transfers between farms were restricted, for example, by being tied to the land a farmer cultivates. After a recovery of producer prices and demand in the first decade of the 2000's, it was decided that the quota system was to be abolished in 2015. To this end, a soft landing was intended by phasing-out the milk quota system and gradually increasing quota volumes. In parallel, quota transfers between farmers were facilitated, for example, in Germany by the installation of quota exchanges in 2000.

For the resource-efficient production of a good, it is in general desirable that production is centered in production units with the highest productivity, ceteris paribus. Therefore, efficient resource allocation is achieved when production factors flow from less productive to more productive farms (Restuccia 2016). It must be considered whether the efficient reallocation of production resources was impeded in the European Union during the milk quota regulation.

The study in chapter 3 examines whether resource reallocation improved during the phase-out of the milk quota system. For this purpose, a production function framework is applied on a dataset on Bavarian dairy farms. Farm-level productivity is estimated using an endogeneity-robust approach following Wooldridge (2009) and several other techniques. Aggregate productivity and reallocation effects are calculated by applying the approach of Olley and Pakes (1996).

The results of the study show an increase in the covariance between farm-level productivity and farm size coinciding with a period of deregulation efforts. This lends support to the hypothesis of a positive effect of the deregulation efforts on aggregate productivity. Additionally, a second stage regression analysis seeks to clarify the role of the quota phase-out and the increased volatility of farm-gate milk prices during this period. This analysis shows a significant influence of deregulation variables but only a minor effect of the output price variability.

The study shows that efficient resource allocation among dairy farms increased during the study period, likely by an interplay of deregulation efforts and price volatility. Whether this is desirable from a policy perspective is another question since resource reallocation is likely linked to structural change. On the other hand, the results also showed that considerable productivity gains can be achieved by productivity growth within farms and not only between farms.

7.2. Technological change in dairy farming during the milk crisis

The European dairy sector has faced substantial changes over the last few decades. Most prominently, the European Union has strived for deregulation of the sector by lowering intervention price levels, eliminating export subsidies, liberalizing milk quota transfers, gradually increasing quota volumes, and abolishing the milk quota in 2015. These measures have been accompanied by increased raw milk price volatility especially after 2007, which brought many dairy farmers into financial distress. Technical progress within a sector is dependent upon producers' willingness to invest in technological innovation. It must be considered whether the increased output price risk had implications for innovation behavior and hence technological advancement in the European dairy sector due to risk-averse farmers reducing or abstaining from investment into new and therefore risky technology. The study in chapter 4 aims to shed light on this research question. It employs a dataset on West-German dairy farms and estimates technical change as well as technical efficiency for a period before and during increased milk price volatility. Additionally, the study compares the results for specialized dairy farms to results for dairy production in mixed farming. This comparison is motivated by the general risk-spreading advantage of mixed farming. That is, by spreading output price risk across several outputs, mixed dairy farms were possibly less affected by milk price volatility and showed different innovation behavior.

For estimation of the production technology, the study employs a distance function framework that is capable of accounting for multiple outputs and inputs. Technical change is estimated with a conventional time trend as well as a time dummy formulation for specialized dairy farms and a modified time trend formulation for mixed dairy farms.

The results indicate that specialized and mixed dairy farms showed considerable willingness to invest in capital goods during the period of volatile milk prices, which is reflected in high levels of average net investment during these years. This contradicts the original expectation of a direct negative effect of increased output price risk on technical change. Nevertheless, the findings show stagnation in technical change in specialized dairy farming coinciding with the period of volatile milk prices. Additionally, the increased net investments during that time apparently did not translate into increased technical efficiency or scale efficiency. Moreover, a similar pattern of stagnating technical change is found for the case of mixed dairy farming; that is, mixed dairy farms did not show advantageous innovation behavior. Overall, the results suggest that most of the investments were aimed at an expansion of business activities as dairy farmers intended to position themselves for a market after the dairy quota.

7.3. Innovation and productivity in the food vs. the high-tech manufacturing sector

The food manufacturing sector is commonly classified as a low-technology sector, based on the intensity of formal research and development conducted within firms. Yet, food processors face numerous challenges be it by legal requirements, changing consumer needs, the high market power of food retailers, or competition. Therefore, innovation activity can be expected to be vital for the competitiveness of food companies. Numerous empirical studies examine the effect of innovation on firm performance. However, few of these specifically focus on the food sector. The study in chapter 5 explores this relationship in particular for the food sector and additionally compares it to results from two high-tech sectors: chemicals and pharmaceuticals as well as computer, electronic, and optical products. The primary motivation of this approach is that observed differences in research and development intensity should be mirrored in differing returns to innovation across subsectors of the manufacturing sector. Contrary to many other empirical studies, the model is estimated separately by subsectors, which allows uncovering these expected differences in the innovation effects on firm performance.

The analysis employs a dataset from the European Union's "Community Innovation Survey," which conducts periodic surveys on manufacturing firms and their innovation activity in the member states. As a firm performance indicator, labor productivity is used. The study builds on the model by Crépon, Duguet, and Mairesse (1998), which tackles endogeneity by a multi-stage regression approach that employs suitable instrumental variables in each estimation step. The first step estimates the influences on the firm's probability of conducting research and development (that is, innovation inputs) and the intensity thereof. The second step is formed by the knowledge production function that uses the predicted research and development intensity from the first step as a determinant of the firm's propensity to introduce new products or processes into production. Finally, in the last step of the model, labor productivity is regressed on the propensity to innovate and other control variables, hereby estimating the returns to innovation. By using predictions from the previous estimation steps, the model takes into account the simultaneity between firm performance and innovation activity, as well as unobserved factors influencing both variables.

The results of the study point to major differences in the returns to innovation between the subsectors. Contrary to expectations based on observed research and development intensities, we find strong and significant positive productivity effects for innovation output in the case of the food sector, and no statistically significant effects for the high-tech sectors. The results highlight the importance of separate examination of manufacturing subsectors regarding this research question and the need to explore these differences further.

7.4. Innovation and efficiency at firm level: Insights from a literature-based innovation output indicator

In the last decades, the European dairy processing sector has shown considerable structural change characterized by a decrease in the number of independent enterprises due to numerous mergers and acquisitions. Also, the level of internationalization of markets and company structures increased, for example by the emergence of large, multinational and cooperatively organized dairies, or by the expansion of business activities into foreign countries. The dairy processing sector is often of special interest due to its close connections to milk production in the form of long-term delivery contracts and regionally oligopsonistic structures. By this and via the milk payout price, the economic situation of a dairy processor directly impacts the economic situation of dairy farms. Therefore, the mechanics of dairy processors' profitability are also of policy interest.

One important factor for competitiveness is universally seen in a firm's innovation activity. However, the results of empirical studies on the effects of innovation on firm performance in the food sector are often ambiguous, and studies in specific subsectors like the dairy processing sector are scarce. The study in chapter 6 sheds light on this research question by examining the contemporaneous and lagged effects of product and process innovation activity on the technical efficiency of dairy processors. It employs a unique panel dataset comprising financial data from publicly available financial statements and information on business activities of dairy processors active in the German market. As a product innovation indicator, we use the number of newly introduced products compiled by an industry journal. As a second product innovation indicator we use the number of new products that were awarded the best new products of the year by readers of the journal. In this way, the indicator is a measure of the quality of new product introductions by the dairy. As an indicator of process innovation, we use the number of patent applications by the dairy or associated firms. We estimate a production function incorporating innovation activity as efficiency-explaining variables. The endogeneity of innovation activity, as well as of variable production inputs, is tackled by employing a system GMM approach following Blundell and Bond (1998).

The results show a consistent and positive effect of high-quality new product introductions on average dairy processors' efficiency, as well as indications for the positive lagged effects of these. For the mere number of new product introductions and the number of patent applications, however, we find effects close to zero. For process innovation, this can be explained by the reliance on equipment suppliers for implementing improvements in production machinery and possible costs associated with patenting. For the case of product innovation, the results empirically confirm the challenge of high failure rates of new product introductions in the food sector and emphasize the importance of the ability of dairy processors to meet consumer needs and to find the right marketing strategy for new products.

8. Discussion and Conclusions

This chapter synthesizes the results and conclusions of the empirical studies and highlights the scope for further research that can build on the findings of this thesis.

The first study in chapter 3 focuses on aggregate productivity in the dairy farming sector during the phase-out of the EU milk quota system. Employing a dataset of specialized dairy farms in southeast Germany, the study presents empirical evidence of a gradual increase in the reallocation of resources toward more productive farms. This result confirms the general suspicion of a predominantly negative effect of regulatory efforts on efficiency within industry sectors. For manufacturing industries this is, among others, examined by Olley and Pakes (1996), Eslava et al. (2004), Restuccia and Rogerson (2008), Hsieh and Klenow (2009).

Although the results of these studies are not uniform, they predominantly attest the policies under consideration a negative effect on productivity. Therefore, a general consensus is that reforms aimed at removing barriers to competition tend to increase the productivity of industry sectors (Nicoletti and Scarpetta 2005). For the agricultural sector, positive effects of reforms on productivity are, for example, shown by Kirwan, Uchida, and White (2012) in the case of US tobacco production and by Gray, Oss-Emer, and Sheng (2014) in the case of Australian dairy and broadacre agriculture.

The results of chapter 3 further add to the general discussion on the effects of the EU's Common Agricultural Policy on productivity in the farm sector. In this context, concerns have been raised regarding the effect of direct payments on farm performance. Empirical results tend to point to a negative association. However, this relationship might be country-specific, which is shown by Latruffe et al. (2017) on a sample of dairy farms. Also, the negative effect of direct payments is estimated to be reduced by the decoupling of direct payments administered with reforms in 2003. Besides Latruffe et al. (2017) this is confirmed, for example, by

Kazukauskas, Newman, and Thorne (2010) for a sample of Irish dairy farms, and by Rizov, Pokrivcak, and Ciaian (2013) on farms in the EU-15. For the specific case of the milk quota, empirical results, in general, suggest a negative effect on sector and dairy farm performance, which can be amended, however, by liberalizing quota transfers between farms. For example, Gillespie et al. (2015) estimate high productivity growth rates before the quota implementation, low growth rates in the first years of the quota regime, and increasing growth rates following policy reforms. In a similar vein, results by Colman (2000) suggest that tradability of quota rights improves dairy sector efficiency in the United Kingdom.

Expecting deregulation to be the only driver of productivity dynamics in the context of dairy farming is too short-sighted. Alongside the deregulation efforts of the EU came an increase in the output price risk for European dairy farmers. In recent years, many dairy farms were brought into financial distress due to plunging milk prices, which can be also seen by financial aid granted by the European Commission. Therefore, it must be expected that increased price risk also played a role as a determinant of resource reallocation. This expectation is plausible also judging from earlier empirical results on the influence of output price volatility on the investment decisions of farmers. By various authors, milk price volatility is found positively related to dairy farm exits and negatively related to farm growth (Foltz 2004; Stokes 2006; Zimmermann and Heckelei 2012).

On the other hand, a negative effect of price volatility on the exit probability is possible since volatility increases the value of waiting from a real options perspective (Pieralli, Hüttel, and Odening 2017). The results from chapter 3 do not confirm any significant effect of milk price volatility on efficient resource reallocation. Nevertheless, it is likely that it was a combined effect of deregulation and output price volatility that led to an increase in efficient resource allocation. However, whether sector productivity gains by reallocation are desirable remains a political question. An objective of regional agricultural policy in Bavaria is the preservation of traditional farming structures characterized by small-scale family farming. The reallocation of resources within the farming sector is likely connected to greater attrition and the continuing trend of growing average farm sizes. A solution to this trade-off might be also found in the results of the study in chapter 3: The findings show that sector productivity was to a large part determined by productivity growth within incumbent dairy farms. That is, productivity gains do not necessarily require attrition in the sector.

The second study in chapter 4 focusses on the same period of deregulation and volatile milk prices. Unlike the first study, it focusses on technical change during this phase and employs a dataset on dairy farms located across Germany. The investigation considers whether increased output price risk had implications for the innovation behavior and subsequently for technological advancement in the sector. In general, farmers are expected to be risk-averse and therefore postpone investments to collect more information before adopting new and risky new technology (Jensen 1982; Just and Zilberman 1983). It can be also argued from a real options view that increasing market risk increases the value of waiting in an investment decision, even for risk-neutral decision makers (Floridi et al. 2013). Empirical evidence of this relationship in dairy farming can be found in the already mentioned results by Stokes (2006) as well as Zimmermann and Heckelei (2012). Sauer and Zilberman (2012) study the determinant of the decision to adopt automated milking systems and find a negative influence of profit variability. On the other hand, it might also be possible that during uncertain market phases, farmers invest in innovative technology to counter the output price risk. A risk-reducing effect of technical change is shown by Kim and Chavas (2003) as well as Rahelizatovo and Gillespie (2004). Another reason for a negative effect of the price turbulences on investment behavior might be found in possible credit constraints during phases of low milk prices. Several authors confirm a relevant relationship between credit accessibility and innovation behavior in the farming sector (El-Osta and Morehart 1999; Hüttel, Mußhoff, and Odening 2010; Läpple, Renwick, and Thorne 2015).

The results of chapter 4 suggest average annual rates of technical change of 1.0% (mixed dairy farming) to 1.3% (specialized dairy farming). These results are well in line with other studies on mean technical change in dairy farming (Cechura et al. 2017; Newman and Matthews 2006; Kellermann and Salhofer 2014). Nonetheless, the model estimations indicate a distinct slowdown in the rates of technical change in dairy production in recent years during the period of volatile milk prices. Furthermore, the results showed that mixed dairy farms were equally subject to this development. By this, the results conform to expectations. However, the results indicate that this happened despite considerable increases in the willingness to invest in capital goods in both specialized and mixed dairy farming. Scrutinizing growth rates of inputs and outputs further reveals that a large share of investments was likely aimed at an increase in the scale of production, which did not translate into technical progress in the sector during this time. Nonetheless, it is to be considered whether dairy farms achieved technological progress not observed in the data, for example, with respect to the status of animal welfare.

The results of the first two studies are congruent as they both uncover turbulences in the dynamics of productivity during the phase-out of the EU milk quota system that was accompanied by high milk price volatility. The studies, therefore, contribute to the research concerning the dynamics of the European dairy market in light of the elimination of the milk quota system. While a common assumption is that the dynamics in the milk sector will increase following the removal of restrictions by the quota system, the results of empirical studies are not always clear-cut. Comparing the situation before and after the introduction of the quota regime, Huettel and Jongeneel (2011) estimate transition probabilities between farm size classes for Dutch and German dairy farms. Their results regarding the mobility of resources due to the quota implementation are ambiguous. They find overall mobility in both countries to be higher during than before the quota regime, which can be explained by greater interconnectedness of farms under quotas. On the other hand, they find exit mobility decreased under the quota regime. Zimmermann and Heckelei (2012) examine, among other factors, the effect of different quota transfer mechanisms on farm growth dynamics. Their study employs an extensive dataset on dairy farms in the EU-15. Similarly to Huettel and Jongeneel (2011), they find ambiguous results. While liberal quota transfer mechanisms seemed to enhance structural change, they find farm growth facilitated by restrictive quota transfer mechanisms. Boere et al. (2015) examine intervals of land use changes for Dutch dairy farms. Their results show faster land use changes toward the quota abolition, therefore, indicating an increase in the dynamics in the dairy sector due to the quota abolition. Similar conclusions can be drawn from the study by Groeneveld et al. (2016), who examine the tendencies for intensification after the quota abolishment for Dutch dairy farms with a mathematical programming model. They predict intensification tendencies for all but the smallest farm types after the quota abolition. More specifically, Dervillé et al. (2017) focus on the implications of the milk quota elimination for dairy production in less-favored areas of France. They predict a shift away from areas with low milk density without the protective effect of the quota system.

The third and fourth studies of this thesis shift the attention to the stage of dairy and food processing. Both studies examine the effects of innovation activity on firm performance, which can be considered a crucial link for the competitiveness of the dairy sector in light of the restructuring in recent years. The results of both studies show that it is crucial to account for sector-specific heterogeneity when analyzing innovation effects. For the manufacturing sector, this is already suggested by observed differences in the intensity of research and development expenditures, which govern the common classification of subsectors into high, medium, and low-tech industries. Despite this long-standing classification, many studies model innovation effects for pooled samples on manufacturing firms (Griffith et al. 2006; Castellacci 2011; Hashi and Stojčić 2013; Lööf and Heshmati 2002; Raffo, Lhuillery, and Miotti 2008; Siedschlag and Zhang 2014; Tevdovski, Tosevska-Trpcevska, and Disoska 2017). For the food sector, special characteristics that have been highlighted by empirical studies include the reliance on suppliers of equipment for the implementation of process innovations

(Schiefer et al. 2009) and the high failure rate of new product introductions (Juriaanse 2006). Nevertheless, only a few studies specifically focus on the productivity effects of innovation in the food sector (for example, Acosta, Coronado, and Romero 2015).

By comparing the food sector with two high-tech sectors, the study in chapter 5 estimates strong positive productivity effects of innovation for food firms and only statistically insignificant effects for firms in the high-tech sectors. This result does not correspond to expectations from observed research and development intensity, since it should be expected that firms choose research and development expenditures according to the expected return from these investments (Pakes and Schankerman 1984). The results confirm that there are relevant differences in the innovation environments within manufacturing subsectors that need to be taken into account. Heterogeneity between sectors can be explained by differences with respect to product market demand, technological opportunities, or appropriability conditions (Pakes and Schankerman 1984), as well as different product life cycle lengths (Broda and Weinstein 2010).

The fourth study in chapter 6 takes account of sector-specific effects by performing the analysis specifically on dairy processors. By this, it contributes to the literature on performance mechanics in dairy processing. Only a few studies focus on this specific subsector. Geylani and Stefanou (2011) study total factor productivity growth in US American dairy processors. They find that during their study period from 1972 to 1995, productivity was largely driven by the exploitation of scale effects. Hirsch and Hartmann (2014) examine profit persistency in a sample of European dairy processors. They find the level of profit persistency to be low and conclude that competition is high among dairy processors in Europe. Soboh, Oude Lansink, and van Dijk (2012) focus on performance measurement in dairy cooperatives versus investor-owned dairies. They argue that different performance measures must be applied for each business form due to the differing business objectives. In another study, Soboh, Oude Lansink, and van Dijk (2014) show that in a sample of European dairies, cooperatives have more productive technology that shows a higher catch-up rate but are less efficient than investor-owned dairies.

Against this background and in light of the new challenges, innovation activity can be suspected to be one important factor for dairy processors' well-being in the near future, since innovation is in general considered important for competitiveness (Grunert et al. 1997). Apart from more cost-effective production due to process and organizational innovations, product innovation can provide higher valued products and strengthen international competitiveness and export performance (Bojnec and Fertő 2014). The findings of chapter 6 contribute to this line of research by examining the link between business performance and product innovation as well as process innovation. By incorporating two product innovation indicators, the study takes into account the high failure rates in new product introductions. The results suggest no positive link between efficiency and process innovation when measured with patent applications. This can be explained on the one hand by the possible poor performance of patent data as a process innovation indicator, and also by the reliance of dairy processors on equipment suppliers for the implementation of process innovations. For product innovation, no positive effect is found for the total number of new product introductions. However, a significant positive effect is found for the number of successful new products on efficiency. This result emphasizes the significance of new product quality and the importance of dairy processors' ability to find the right marketing strategy for their new products.

Apart from the empirical results, the studies in this thesis also make several methodological contributions. The first study in chapter 3 deals with the endogeneity-robust estimation of the production technology of dairy farms. Hereby, it shows an application of the recently proposed production function estimation routine by Wooldridge (2009). Additionally, it compares the results from this estimation method to more established productivity estimation methods. It shows that the results are robust across several approaches, including stochastic frontier analysis, an ordinary-least-squares fixed-effects approach, and a non-parametric productivity index approach. This suggests no serious bias of production function estimates due to endogenous input choice. Nevertheless, the study illustrates the usefulness of the estimation routine by Wooldridge (2009) for robust productivity estimates in studies of similar contexts.

The second study in chapter 4 aims to model possible shifts in the innovation efforts of mixed dairy farms with respect to different outputs due to milk price volatility. For this purpose, it applies a modified time trend formulation following Stevenson (1980). The third study's (chapter 5) major methodological plea is for properly accounting for heterogeneity (especially industry effects) when evaluating the implications of innovation activity on firm performance.

The fourth study in chapter 6 tackles the endogeneity of innovation as well as production inputs in the production function using the system GMM approach by Blundell and Bond (1998). It shows the importance of differentiated indicators for innovation activity for an elaborate view on the effects of innovation. The results of the study illustrate that the so-called literature-based indicator can serve as a viable innovation output indicator for this type of analysis.

The results of the studies presented suggest significant scope for further research. With respect to the research topics of all studies, additional insights could be achieved with newer and ideally more informative datasets. In the context of the first study, it is of special relevance how resource reallocation has developed after the final abolition of the milk quota system in early 2015. Aggregate data for Germany suggests that farm exits and average herd size growth in dairy farming continued at a similar rate as during the milk quota years (figure 8-1).[19] This might also suggest that the "soft landing" approach intended by gradual quota increases did not miss its target of preventing a shock to dairy production in the year of

[19] As of today (January 2020), no newer data as presented in the introduction are available for other countries on Eurostat's online database.

quota abolition. Nevertheless, reliable estimates of reallocation effects could be attained with more recent farm-level data. With respect to output price risk, it is likely that price developments influenced dairy farmers' behavior also beyond the thesis's study periods, since milk prices in the EU continued to be volatile post 2014. New milk price lows were reached during 2016, resulting in a similar price pattern as in 2009 (see figure 8-1).

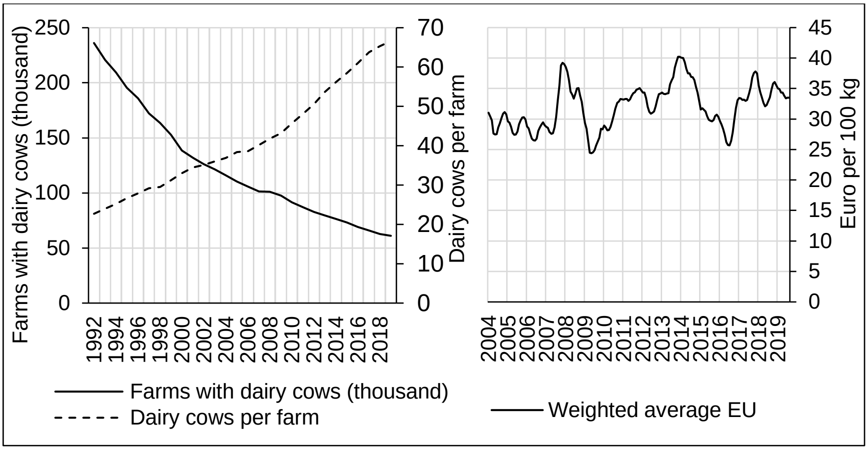

Figure 8-1. Number of farms with dairy cows and the average number of dairy cows per farm in Germany (left) and weighted average EU raw milk price (right)

Source of data: Destatis (2019), EU Milk Market Observatory (2019)

Following up on the results of chapter 4, further monitoring of the rates of technical change in dairy farming seems crucial. For Germany, new data could show whether rates of technical change have recovered and how the continuing price volatility has impacted rates of technical change. Also, the exact causes for the technical change stagnation observed in chapter 4 need to be verified to explore possible remedies and ways to foster technical progress. Additionally, data on dairy farms in other European countries could be used to uncover parallel or differing developments in technical change during the recent phase of quota abolishment and volatile milk prices.

The studies in chapters 5 and 6 suggest the need for further research that considers sector heterogeneity and differentiated innovation indicators to evaluate the effects of innovation on firm performance. This could be enabled by the upcoming availability of new and more informative datasets. For example, the dataset of the Community Innovation Survey employed in chapter 5 will incorporate a panel structure in the near future, which facilitates accounting for firm-specific heterogeneity. For other studies, emphasis must be placed on sample size since a viable treatment of endogeneity in regression models is crucial for robust results in quantitative analyses.

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