Producer Implications of Agricultural Policy Trends: Empirical Studies at Farm Level

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List of Abbreviations

AES	Agri-environmental schemes
ATE	Average treatment effect
CAP	Common Agricultural Policy
CPAD	State Council Leading Group Office of Poverty Alleviation and Development
DID	Difference-in-differences
EU	European Union
FADN	Farm Accountancy Data Network
FE	Fixed effects
GDP	Gross domestic product
GHG	Greenhouse gas
GMM	Generalised method-of-moments
IDF	Input distance function
ITT	Intent-to-treat
IV	Instrumental variable
MCMC	Markov chain Monte Carlo
ODF	Output distance function
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PSE	Producer Support Estimate
RTS	Returns to scale
SEC	Scale efficiency change
TC	Technical change
TE	Technical efficiency
TEC	Technical efficiency change
TFP	Total factor productivity
TT	Terms of trade
WTO	World Trade Organisation

Abstract

Agricultural policies across the world aim to increase agricultural productivity and to improve the environmental sustainability of farming (Sterly et al., 2018). In the European Union (EU), market deregulations require farms to cope with increased cost pressure and price volatility. In subsistence economies, imperfect credit markets have been identified as a major obstacle to farm productivity growth. At the same time, there is long-standing concern that current farming practices cause environmental harm (Tilman et al., 2002). Thus, the EU and countries world-wide implemented agri-environmental programmes that aim to incentivise farmers to adopt more sustainable practices. The goal of this dissertation is to provide empirical evidence on farm production responses to policy developments that are related to agricultural productivity and environmental sustainability.

To this end, the dissertation presents four empirical studies that aim to contribute to the understanding of micro-level production behaviour with respect to agricultural policy developments. The first empirical study is concerned with the effects of sugar market deregulation on farm profitability and productivity. This sector is particularly relevant, as it has been the last heavily regulated agricultural market in the EU. The empirical results show that resource reallocation has contributed to sector productivity growth following a reform in 2006 and that the reallocation efficiency varies across regions with distinct ownership structures in the sugar processing industry. The second study measures diversification economies in the dairy sector, which also underwent significant deregulation efforts in the past decade. The results confirm that diversification can be an effective strategy to foster competitiveness in dairy farming. Furthermore, the study shows that small farms tend to benefit from diversification between milk and livestock production, whereas large farms are better off diversifying between milk and crop production. The third empirical study shifts the attention to subsistence farming in rural China. In developing regions, access to credits is essential for smallholder farms to benefit from the increasing market orientation of agricultural policies (FAO, 2002). The empirical results suggest that relaxing credit constraints improves productivity via both technical efficiency gains and technical change. While the first three studies are largely concerned with farm productivity and economic performance, the fourth study examines farm production responses to agri-environmental policies. Based on a structural profit function model, this study presents elasticities of output supply, input demand and land allocation with respect to agri-environmental subsidies. The results indicate that current EU agri-environmental programmes reduce fertiliser use and shift crop production from cereals to protein crops. Finally, two supplementary studies investigate the relationships between different farming practices and environmental sustainability. Overall, the results of this dissertation underline the importance of the empirical evaluation of agricultural policy developments that considers the heterogeneity of farms and the specifics of the markets in which they operate.

Zusammenfassung

Weltweit zielt Agrarpolitik darauf ab, die landwirtschaftliche Produktivität zu steigern und die ökologische Nachhaltigkeit der Landwirtschaft zu verbessern (Sterly et al., 2018). In der Europäischen Union (EU) erfordern Marktderegulierungen von den landwirtschaftlichen Betrieben, mit erhöhten Kostendruck und Preisschwankungen umzugehen. In Subsistenzwirtschaften wurden unvollständige Kreditmärkte als erhebliches Hindernis für das Wachstum der landwirtschaftlichen Produktivität identifiziert. Gleichzeitig besteht seit langem die Sorge, dass derzeitige landwirtschaftliche Praktiken Umweltschäden verursachen (Tilman et al., 2002). So haben die EU und Länder auf der ganzen Welt Agrarumweltprogramme eingeführt, die BetriebsleiterInnen Anreize bieten sollen, nachhaltigere Praktiken anzuwenden. Ziel dieser Dissertation ist es, empirische Belege für die Reaktionen landwirtschaftlicher Betriebe auf politische Entwicklungen zu liefern, die sich auf die landwirtschaftliche Produktivität und die Umweltnachhaltigkeit beziehen.

Dazu präsentiert die Dissertation vier empirische Studien, die zum Verständnis mikroökonomischer Produktionsentscheidungen in Folge aktueller agrarpolitischer Entwicklungen beitragen sollen. Die erste empirische Studie befasst sich mit den Auswirkungen der Deregulierung des Zuckermarktes auf die Profitabilität und Produktivität landwirtschaftlicher Betriebe. Dieser Sektor ist besonders relevant, da er den letzten stark regulierten Agrarmarkt in der EU darstellte. Die empirischen Ergebnisse zeigen, dass eine Reallokation der Ressourcen nach der Marktreform in 2006 zum Produktivitätswachstum des Sektors beigetragen hat und dass die Effizienz dieser Reallokation in Regionen mit verschiedenen Eigentümerstrukturen in der zuckerverarbeitenden Industrie unterschiedlich stark ausgeprägt ist. Die zweite Studie analysiert Diversifizierungseffekte im Milchsektor, einem weiteren Sektor, der in den letzten zehn Jahren erhebliche Deregulierungsmaßnahmen erfahren hat. Die Ergebnisse bestätigen, dass Diversifizierung eine wirksame Strategie zur Steigerung der Wettbewerbsfähigkeit in der Milchviehhaltung sein kann. Die Studie zeigt auch, dass kleine Betriebe von einer Diversifizierung zwischen Milch- und Tierproduktion profitieren, während es für große Betriebe lohnenswert ist, die Betriebszweige Milch- und Pflanzenproduktion zu kombinieren. Die dritte empirische Studie verlagert die Aufmerksamkeit auf die Subsistenz-Landwirtschaft im ländlichen China. In Entwicklungsregionen ist der Kreditzugang für Kleinbauern essentiell ist, um von einer zunehmenden Marktorientierung der Agrarpolitik zu profitieren (FAO, 2002). Die empirischen Resultate dieser Studie weisen darauf hin, dass eine Lockerung der Kreditbeschränkung die landwirtschaftliche Produktivität durch Steigerung der technischen Effizienz sowie durch technischen Wandel verbessert.

Während sich die ersten drei Studien insbesondere mit der Produktivität und der Wirtschaftlichkeit landwirtschaftlicher Betriebe befassen, betrachtet die vierte Studie landwirtschaftliche Produktions-

entscheidungen in Folge agrarumweltpolitischer Anreize. Basierend auf einem strukturellen Gewinnfunktionsmodell werden in dieser Studie die Elastizitäten von Produktionsangebot, Faktornachfrage und Anbauentscheidungen in Bezug auf Agrarumweltzahlungen dargestellt. Die Ergebnisse zeigen, dass aktuelle EU-Agrarumweltprogramme den Düngemittelverbrauch reduzieren und die Pflanzenproduktion von Getreide auf Eiweißpflanzen verlagern. Abschließend werden in zwei ergänzenden Studien die Zusammenhänge zwischen unterschiedlichen landwirtschaftlichen Praktiken und ökologischer Nachhaltigkeit untersucht. Insgesamt unterstreichen die Ergebnisse dieser Dissertation die Bedeutung einer empirischen Bewertung der agrarpolitischen Entwicklungen unter Berücksichtigung der Heterogenität der landwirtschaftlichen Betriebe sowie der Märkte, in denen sie agieren.

Part I

Introduction

1

Agricultural Policy and Producer Implications

Contrary to other sectors, agricultural production is exposed to natural influences that are mostly beyond the individual producers' control, such as weather conditions or pest pressure. Furthermore, the prices of agricultural commodities are substantially more volatile than the prices of other commodities. At the same time, agricultural production relates to critical questions that affect the entire society. First, a substantial growth in food production is needed to meet future food demand (Fouré, Bénassy-Quéré and Fontagné, 2013). Taking into account both population and economic growth, Gouel and Guimbard (2019) estimate that the demand for food will increase by 47 % until 2050. Second, agricultural production is inherently related to producer and consumer welfare through income and food price effects. Globally, nearly 30 % of the workforce is employed in agriculture, the majority being located in developing regions. Thus, increasing agricultural productivity is essential to reducing poverty among smallholder farm households (Irz et al., 2001) and to enhancing overall economic growth via structural transformation (Bustos, Caprettini and Ponticelli, 2016). Third, farming and food production also relate to environmental sustainability. At present, agriculture is one of the largest producers of environmental pressures and significantly contributes to climate change, biodiversity loss, soil erosion and water pollution (Foley et al., 2011).

For these reasons, agricultural policies all over the world aim to tackle a wide range of problems and developments related to agricultural and food production. There is broad consensus that the sector must become more productive and environmentally sustainable (OECD, 2020a, p. 19). The following chapter provides an overview of global agricultural policies in this regard. Since the empirical studies contained in this dissertation focus on the European Union (EU) and the People's Republic of China (hereafter, "China"), Chapter 1.2 highlights agricultural policy developments in these regions. Finally, I summarise the empirical literature on the farm-level effects of these policy developments in Chapter 1.3.

1.1 Overview of global agricultural policies

Heterogeneous climatic and economic conditions make the agricultural sector highly diverse across countries. Nevertheless, challenges are broadly the same across the globe: "lagging farm incomes, increasing resource constraints (land, water) and environmental concerns (including climate), and a rapidly increasing future food demand" (Sterly et al., 2018, p. 13). In nearly all countries, agriculture and food policies involve large government interventions. The Organisation for Economic Co-operation and Development (OECD) distinguishes between producer support (market price support and budgetary transfers to producers), consumer support (market and budgetary transfers to consumers) and general services support such as infrastructure investments or knowledge and innovation systems (OECD, 2016) and provides estimates of different support categories for 37 OECD countries, five non-OECD EU Member States, and twelve emerging economies.[1] In 2019, the total support estimate in these countries amounted to EUR 530 billion (OECD, 2020b). As shown in Figure 1-1, support to producers (Producer Support Estimate, PSE) accounts for the largest part of support. The figure also reveals a significant increase in agricultural support payments between 2008 and 2015, primarily driven by growing producer support. This development is largely caused by changes in emerging economies, where total support payments increased more than tenfold in this period. Relative to their gross domestic product (GDP), however, the selected emerging countries allocated on average 0.35 % to agricultural support agriculture while OECD countries spent 0.59 % in 2019 (OECD, 2020b).

The largest portion of producer support is contributed by market price support and payments based on output or unconstrained input use, even though they slightly declined from 73 % in the period 2000–2002 to 69 % in the period 2017–2019. These measures are considered as the potentially most distorting forms of support, as they "have the greatest tendency to retain farmers in uncompetitive and low-income activities, harm the environment, stifle innovation, slow structural and inter-generational change, and weaken resilience" (OECD, 2020a). Domestic market support results in gaps between farm-gate prices and world market prices. In the period 2017–2019, producers received prices 6 % higher than world market prices at the global average, compared to nearly 14 % in the period 2000–2002 (OECD, 2020a), implying a slow trend away from the most protective towards more market-oriented policies. The highest gaps between farm-gate and world market prices in the past years have been observed for rice, sugar, wheat and milk (Sterly et al., 2018). For example, sugar producers in the EU and the US have received prices between two and three times the world market price, making sugar one of the most distorted commodity markets in the world (Elobeid and Beghin, 2006). The deregulation of the EU sugar market, starting with a market reform in 2006 until the abolishment of the sugar quota in 2017, resulted in declining prices for EU sugar producers. In Chapter 3, we empirically show how this policy development affected the productivity and profitability of sugar beet farming. The dairy sector has been another commodity sector highly distorted by global agricultural policies (Knips, 2005). Similar to the sugar market, production quotas for milk production in the EU have been abolished in 2015. Chapter 4 evaluates diversification economies in dairy farming that may help dairy farms cope with the increased competition.

[1] The included emerging countries are Argentina, Brazil, China, Costa Rica, India, Indonesia, Kazakhstan, the Philippines, the Russian Federation, South Africa, Ukraine and Viet Nam.

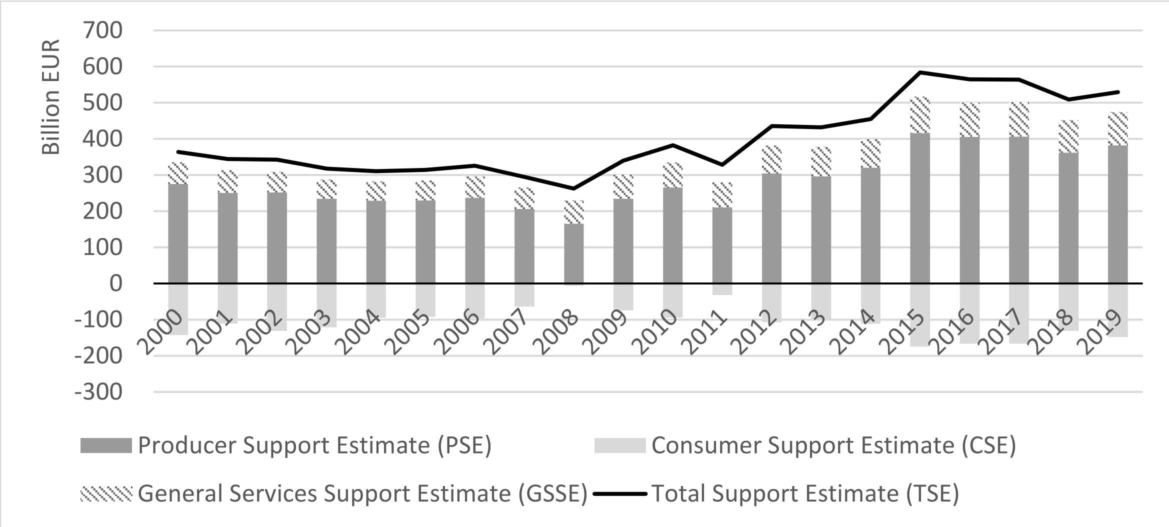

Figure 1-1. Estimates of support to agriculture in the OECD and 12 emerging countries (*Source of data:* OECD, 2020b)

Credit concessions constitute another globally important form of farm support. These policies aim to improve the credit access for farmers by reducing interest rates, the extension of repayment periods, debt write-offs or government guarantees on agricultural loans (OECD, 2016). In Brazil, agricultural credit is considered the major policy instrument for family farms, while other countries with important shares of credit support in the agricultural budget include Costa Rica, Canada, Australia, and Argentina (OECD, 2020a). In the United States, the Department of Agriculture guarantees the repayment of loans to banks, allowing new entrants into agriculture and helping farmers with limited resources (Sterly et al., 2018). Limited access to financial resources is a major challenge especially, but not exclusively, for smallholder farms in developing and emerging countries. While past studies showed that improving credit access increases the partial productivity of smallholder farming (for example, in terms of revenues per unit of land), we show that this is also the case for the total factor productivity (TFP) using the empirical case of rural China (see Chapter 5).

Countries across the globe are also increasingly implementing policy measures that address the challenge of the environmental sustainability of agriculture. The focus of such policies is mainly on mitigating the negative environmental impacts of agriculture (DeBoe et al., 2020). As summarised by Sterly et al. (2018), minimum standards in land management and animal husbandry have been introduced or revised, and increased interest in organic farming and the promotion of biofuels and biomaterial has been observed. An important policy area in this context is the regulation of agricultural chemicals. As indicated by OECD (2020a), Argentina, Brazil and the EU implemented new regulations on the approval or use of pesticides in 2019. Individual EU member countries have introduced regulations to reduce nitrogen runoffs and ammonia emissions, and Japan amended its Fertiliser Regulation Act in the same year. Other countries, such as Australia, China, and India, introduced measures to reduce the use of all chemical inputs (OECD, 2020a). Chapter 6 provides empirical evidence on the extent to which green policies, such as agri-environmental schemes (AES), affect fertiliser usage in the EU.

Finally, reducing the impact of agriculture on climate change has gained increasing attention in global agricultural policies. The OECD (2020a) summarises major policy developments in this area: While many countries have prioritised the mitigation of greenhouse gas (GHG) emissions, only New Zealand and Ireland introduced legally binding targets for the reduction of agricultural GHGs. The EU presented strategies to achieve net zero GHG emissions by 2050. Individual member countries implemented national climate change or climate change adaptation plans that include agriculture, or introduced programmes designed to reduce agricultural GHG emissions. Targets to reduce GHG emissions from the agricultural sector are also set by Korea, and the government of Norway negotiated a climate agreement for agriculture with farmers' organisations. Support to climate change adaptation is especially provided by Mexico (information on weather forecast and most appropriate adaptation practices), Costa Rica (credit system to respond to climate change related disasters) and the United States of America (better equipment of farmers to reduce the environmental footprint of US agriculture) (OECD, 2020a). Lamb et al. (2016) advocate for land-sparing strategies (i.e., increasing agricultural yields and restoring natural habitats on spared land) to reduce agricultural emissions. Along these lines, we find that GHG emission efficiency in dairy farming can be improved by supporting sustainable intensification in Stetter, Wimmer and Sauer (2020). The structural type of agriculture, however, does not seem to have an essential impact on sustainable farming practices: contrary to anecdotal beliefs, we show in Wuepper, Wimmer and Sauer (2020) that small family farming does not unequivocally lead to the adoption of more environmentally friendly farming practices compared to large, industrial farming.

1.2 Agricultural policy trends in the EU and China

This subchapter provides a more detailed description of agricultural policy developments in the EU and China, two regions where farmers faced significant structural and policy changes in the last decade. The EU and China are major agricultural producers, accounting for 9 and 33 % of worldwide gross production value in 2016, respectively (FAOSTAT, 2020). With 2 % in the EU and 8 % in China (ILOSTAT, 2020), however, the share of agriculture in total GDP is significantly different between the regions. At the same time, the share of agriculture in employment is 5 % in the EU and 28 % in China (ILOSTAT, 2020), indicating considerably higher agricultural labour productivity in the former. Figure 1-2 compares overall producer support in percentage of gross farm receipts (%PSE) between China and the EU. Since 1992, %PSE has largely decreased in the EU and increased in China. However, the support in China remains below the level in the EU. The focus of the EU agricultural policy was on supporting farmers since the implementation of the Common Agricultural

Policy (CAP) in 1962. China's agricultural policy shifted from taxing to subsidising and protecting agriculture only in the last decade (Huang, J. and Yang, 2017). Recognising the market distorting effects of price intervention programmes, both the EU and China have shifted their policies from market support to direct payment programmes. Both regions are also increasingly implementing policies that promote the environmental sustainability of agricultural production. The following sections give short overviews on the development of agricultural policies in the EU (1.2.1) and China (1.2.2).

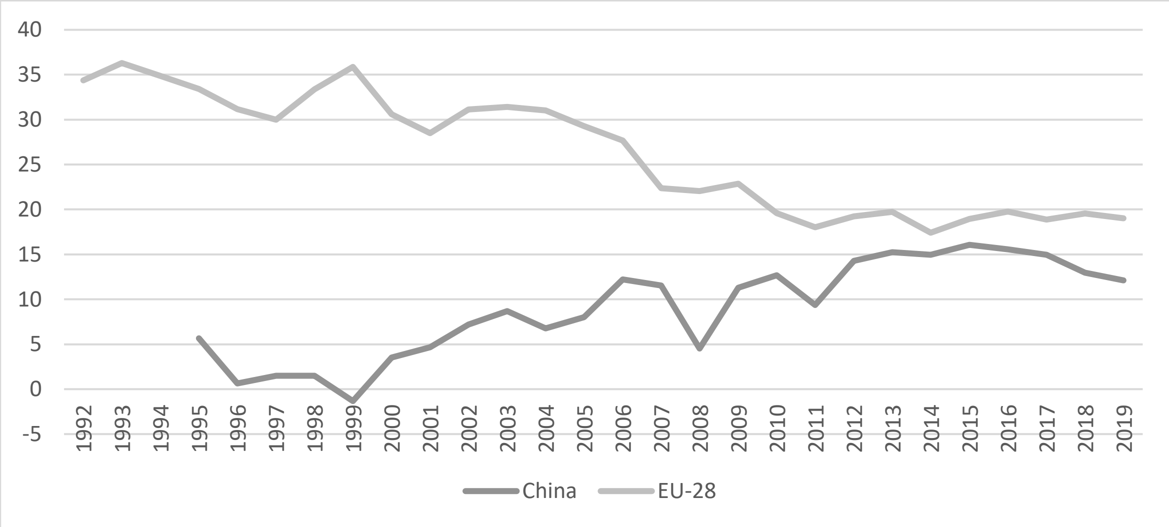

Figure 1-2. Producer support in % of gross farm receipts in China and the EU, 1992–2019 (*Source of data:* OECD, 2020b)

1.2.1 Agricultural policy development in the EU

The CAP is the EU's main instrument to steer agricultural production. Today, its budget amounts to EUR 59 billion per year, or nearly 40 % of the EU total budget. Since its implementation in 1962, the CAP has developed through several reforms to align with changing societal demands (Pe'er et al., 2017). In the 1950s, a major concern in Europe was to increase food production (Fennell, 1973). Thus, the primary objectives of the CAP, specified in article 39 in the Treaty of Rome in 1957, were to provide a fair and stable income to farmers and to ensure food supply at reasonable prices. To achieve this, the main policy measure in the early years of the CAP was price support for domestic producers. However, the choice of price support without structural policies has faced criticism from its beginnings as it contradicted the goal of reasonable food prices, could not solve the farm income problem and created overproduction (Zobbe, 2001). In the 1980s, supply controls were introduced to address increasing production surpluses and the associated increasing budget demands. These efforts included the introduction of milk quotas in 1984 and of the set-aside incentive scheme in 1988. Requiring farmers to take part of their land out of production, the set-aside programme sought to provide environmental benefits in addition to reducing overproduction. With the MacSharry reform in 1992, the CAP shifted from market support to producer support to align the CAP with the standards of the World Trade Organization (WTO) (Pe'er and Lakner, 2020). In particular, coupled price supports for cereals and beef were reduced and compensated for by direct payments to farmers (Sterly et al., 2018). Taking into account increasing environmental concerns, direct payments were made contingent on minimum standards regarding the environment, safety and animal health. As these direct payments were based on a farm's area allocation to different crops, they were not fully decoupled from production. Thus, the process of decoupling of payments was continued with the Fischler Reform in 2003 by introducing the Single Payment Scheme in 2005 (Klaiber, Salhofer and Thompson, 2017). As opposed to preceding direct payments, payments under this scheme are based on the farm's or the region's historical entitlements or a hybrid model thereof (Klaiber, Salhofer and Thompson, 2017). To further address environmental challenges, 30 % of these payments were linked to greening measures that go beyond the minimum standards of good agricultural practice with the latest reform in 2013: crop diversification, maintenance of permanent pastures, and promotion of Ecological Focus Areas (Pe'er et al., 2017). During this reform period (2014–2020), two of the EU's most distorting agricultural policy instruments were phased out: the milk production quota in 2014 and the sugar production quota in 2017.

Figure 1-3 summarises the most important steps in the history of the CAP, illustrating the gradual shift from the policy focus on food security and producer support towards sustainability concerns and policy efficiency. Nonetheless, it remains important to acknowledge that up to today, direct payments aimed primarily at securing farmers' income are accountable for 70 % of the CAP budget (Pe'er and Lakner, 2020).

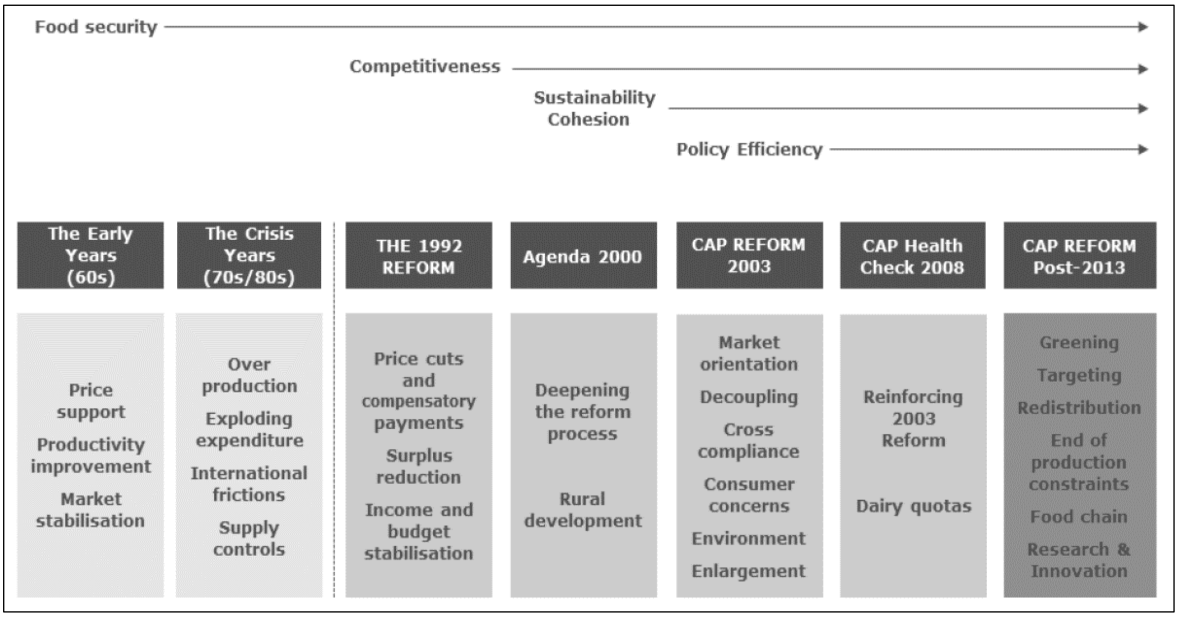

Figure 1-3. Historical development of the CAP since 1962

(*Source:* Adopted from the European Commission by Sterly et al., 2018, p. 21)

1.2.2 Agricultural policy development in China

The agricultural policy framework emerges from several documents that are periodically released by the Chinese government. The 13th Five-Year Plan issued by the government presents key orientations of agricultural policies for the period 2016–2020, focusing on agricultural modernisation, such as supporting the development of new types of agribusiness or strengthening the adoption and use of information technologies (OECD, 2020a). In addition, the annually released "Policy Document No. 1" classifies agricultural and rural development as top priority (OECD, 2020a).

Between 2003 and 2013, the average farm size in China increased from 0.57 to 0.78 hectare (Huang, J. and Ding, 2016). Despite the recent emergence of land cooperatives and company-run farms, Chinese agriculture is still characterised by small-scale farming. China's agricultural sector has undergone substantial changes since the late 1970s, resulting in annual growth rates of 4.6 % over more than three decades (Huang, J. and Yang, 2017). According to these authors, the growth was driven by institutional reforms (implementation of the household responsibility system in 1978), technology changes through public R&D investments, market reforms and trade liberalisation. The market and trade reforms included a reduction of average import tariff rates from 42 to 24 % between 1992 and 1998 before China's accession to the WTO in 2001 (Baylis, Fan and Nogueira, 2019). Nevertheless, the agricultural sector in China faces significant challenges today. Similar to the global perspective discussed above, the main challenges are lagging farmers' income, threats on food security, and environmental degradation. For example, the rural income was about 2.7 times below the urban income in 2014 and 60 million people lived under poverty in the same year (Huang, J. and Yang, 2017). At the same time, increasing rural labour wages reduce the international competitiveness of Chinese agriculture (Wang, X. et al., 2016). As a result, China became a net food importer in 2004, raising concerns on food security (Huang, J. and Yang, 2017). Finally, the growth of the agricultural sector in the past decades came at the cost of environmental sustainability (Zhang, F., Chen, X. and Vitousek, 2013; Lu, Y. et al., 2015).

Various policy measures have been introduced in recent years to address these challenges: In 2004, direct subsidies were introduced to improve farmers' income and food security. These include direct grain subsidies, input subsidies, subsidies for purchasing agricultural machinery, and subsidies for credit (Huang, J. and Yang, 2017; OECD, 2020a). The main sources of income support for farmers, however, are price intervention programmes. Minimum purchase prices for rice and wheat were introduced in 2004 and 2006, respectively. In the following years, the Temporary Storage Programme was introduced for maize, soybean, rapeseed, cotton and sugar. Increasing price support between 2009 and 2014 resulted in large price gaps between domestic and global prices, costly storage building for the government, and economic disadvantages for domestic downstream industries (e.g. livestock sector or textile or garment industries) (Huang, J. and Yang, 2017). Thus, price intervention for soybean and cotton was replaced by the target price policy, under which farmers are compensated by payments covering the difference between pre-determined target prices and actual market prices. Regarding maize production, a pilot reform was introduced in 2016 that replaced price supports by direct payments based on the area planted (Huang, J. and Yang, 2017; OECD, 2020a). This policy trend to shift from market support to producer support is similar to the process in the CAP of the EU, which started with the MacSharry reform in 1992. The OECD (2019) concludes that payments based on area planted reflect the policy trend towards long-term productivity growth and sustainability and recommends to further decouple production from subsidies by making the latter conditional on a historical area basis and on environmentally-friendly production practices.

Such agri-environmental objectives are currently addressed in the National Agricultural Sustainable Development Plan for the period 2015–2030 (OECD, 2020a). It involves natural resource protection, environmentally friendly farming practices and focusing on the quality and efficiency of production. Plans to control GHG emission are also included in the 13th Five-Year Plan, including the reduction of methane emissions in the agricultural sector. China also released commitments to reduce GHG emissions in response to its ratification of the Paris Agreement on Climate Change and follows a zero growth strategy in fertiliser and pesticide use (OECD, 2020a). Soil quality degradation has also been recognised as a result of the excessive use of modern inputs (Liu, Y., Wen and Liu, X., 2013). To monitor and improve the soil quality, the Soil Pollution Prevention and Control Law was introduced in 2019, and payments are due if farmland is returned to forests and if degraded grassland is excluded from grazing (OECD, 2020a).

1.3 Microeconomic evidence on policy developments

Governmental policies affect microeconomic decision-making by changing prices and incentives for firms, for example via regulations, tariffs, taxes or subsidies. By setting the framework under which firms maximise profits or utility, these policies aim to affect firm's production behaviour, such as supply of outputs, demand for inputs, choice of technology and innovation activities. The empirical assessment of the effects of agricultural policies is particularly important, as they affect a heterogeneous group of actors (e.g. farmers and buyers) and commonly involve multiple goals (e.g. competitiveness and sustainability). As stated by Esposti and Sotte (2013), the increasing complexity of agricultural policies requires a careful evaluation of the effects with respect to the stated objectives. Thus, rigorous empirical insights into the behaviour and response of farmers to changing policies are needed to support evidence-based policymaking (e.g. Sauer and Vrolijk, 2019).[2]

[2] Evidence-based policy-making seeks to use objective evidence about what works to design policy measures. While the idea to inform decisions by knowledge is not new, the concept has gained increasing attention in the field of social sciences in the 1990s (Marchi, Lucertini and Tsoukiàs, 2016).

As described in Chapter 1, agricultural policies around the world, including the EU and China, tend to be shifted away from the most protective towards more market-oriented measures. The first step towards market orientation is often the reduction of trade barriers and price support measures. As documented in various empirical works, such policy reforms shift productive activities from less productive firms towards more productive ones, increasing the aggregate productivity of the sector (see, e.g. Eslava et al., 2004 for the manufacturing sector in Colombia and Frick and Sauer, 2018 for the dairy farm sector in Germany). Individual farmers also benefit from increased allocative efficiency if the production portfolio is based on market prices, as shown by Brauw, Huang, J. and Rozelle (2004) for trade liberalisation in China.

Chapter 1.2 further outlined that both the EU and China have (partially) replaced trade barriers and price support measures by area-related direct payments to compensate farmers for potential income losses. While such policies allow prices to be determined by market forces, they still impact production decisions as they incentivise farmers to grow crops with the highest area payments (see, e.g., Lacroix and Thomas, 2011). With the CAP reform in 2003, the EU went one step further and decoupled agricultural payments from production decisions (see Chapter 1.2.1). Empirical studies addressing decoupled payments from a microeconomic perspective show that these payments affect output decisions only marginally (e.g. Burfisher, Robinson, S. and Thierfelder, 2000; Goodwin and Mishra, 2006; Weber, J. G. and Key, 2012). However, as shown by Serra (2006) and Sckokai and Moro (2006), decoupled payments may affect output supply and input demand by reducing the degree of risk faced by the farmers. The risk aversion of farmers has been quantified using experimental methods by Menapace, Colson and Raffaelli (2013), for example.

Although market price support and subsidies linked to production levels are considered harmful for the environment (OECD, 2020a), far less empirical studies exist that assess the effect of the policy development towards more market orientation on sustainability. The study by Laborde Debucquet et al. (2020) suggests that overall productivity growth has only a small effect on environmental sustainability due to a rebound effect caused by an expansion of output, and that policies that directly target environmental benefits are more effective. For example, it has been shown that AES in the EU successfully reduce the purchase of fertiliser and pesticides (e.g. Pufahl and Weiss, C. R., 2009; Arata and Sckokai, 2016). Mennig and Sauer (2020) find that AES participation reduces the productivity of dairy farms, but no significant effect was found for crop farms. From a microeconomic perspective, agri-environmental programmes are most efficient if the marginal revenue from project participation equals the marginal cost (including forgone market income). If a programme requires only minor changes in the farm production plan, farmers gain from windfall effects, reducing the cost-effectiveness of the programme (Chabé-Ferret and Subervie, 2013).

To benefit from the trend towards more market orientation and open trade, it is particularly important for farms in developing and emerging countries to increase productivity as they compete with farmers abroad. Improving credit access is essential to achieve this (FAO, 2002). As described in Chapter 1.1, preferential credits are an important policy tool to support farmers. Microeconomic models show that under binding credit constraints, the marginal value product of the inputs is higher than the price of inputs, resulting in suboptimal input usage (Petrick, 2004). In line with this theoretical result, the empirical literature finds that credit access increases production (Feder et al., 1990; Foltz, 2004; Briggeman, Towe and Morehart, 2009; Petrick, 2004), investment (Foltz, 2004; Carter and Olinto, 2003; Berhane and Gardebroek, 2011), partial productivity (Guirkinger and Boucher, 2008; Dong, Lu, J. and Featherstone, 2012; Reyes et al., 2012; Ciaian, Fałkowski and Kancs, 2012) and household consumption (Berhane and Gardebroek, 2011).

1.4 Aims, scope and structure of this thesis

As discussed above, countries across the world face similar challenges in the agricultural sector, including lagging farm incomes, increasing food demand, and environmental concerns (Sterly et al., 2018). The OECD (2020a) concludes that the agricultural sector must become more productive and environmentally sustainable to meet these challenges. Thus, empirical research is required to assess how current agricultural policies affect farmers' performance and production strategies. In this dissertation, I analyse agricultural sectors that have been subject to large deregulation measures in the past years from a farm-level perspective, focusing on competitiveness and productivity as well as environmental sustainability effects. The primary objective of the dissertation is to provide empirical insights into farm responses to changing policy environments in order to inform evidence-based policymaking.

The four embedded empirical studies (Chapters 3 – 6) address farm performance and management strategies in different policy contexts. Based on microeconomic production theory, econometric techniques are used to obtain theoretically consistent and unbiased estimates, from which implications for both policy and management are derived. The studies address different farming sectors at various geographic levels: Bavaria, Germany, three selected EU member states and China.

The empirical studies contribute to the existing literature on agricultural policy and production decisions in several ways. As outlined in the previous chapter, there is empirical evidence that market deregulation promotes structural change and results in higher aggregate productivity. However, the effects of the EU sugar market deregulation on farm performance and resource reallocation have not been studied yet. **Chapter 3** closes this gap in the literature by examining the effects of the 2006 sugar market reform on profitability and (aggregate) productivity of sugar beet producing farms. Furthermore, the literature shows that decoupled subsidies are less market distorting than output price support. In turn, the trend away from most protective measures requires farmers to increase their competitiveness to remain in business. **Chapter 4** shows that on-farm diversification can be an effective strategy to reduce production costs. The empirical case of this study is dairy farming, the second sector besides the sugar market that experienced large deregulation measures in the EU in the last decade. For smallholder farms in developing countries, improving credit access to increase productivity is essential to benefit from increased market orientation (FAO, 2002). Existing literature shows that improving credit access can increase land and labour productivity of farms. However, these *partial* productivity measures do not consider changes in other inputs, and empirical evidence on credit access and *total* factor productivity is scarce. Therefore, **Chapter 5** contributes to the literature by assessing the effect of improved credit access on TFP, using data from a field experiment in rural China.

While higher productivity can contribute to environmental sustainability as it allows to produce the same amount of output with less resources, the remaining studies address environmental outcomes more directly. **Chapter 6** evaluates the effect of green policies in the EU on farm-level output- and input decisions as well as area allocation. This study extends the literature by showing that current agri-environmental schemes reduce cereal and maize production in favour of protein crops and that production elasticities vary substantially across the three selected countries (France, Germany and the UK). Finally, **two supplementary studies** examine how different farm practices and structures are related to environmental sustainability: intensive vs. extensive farming technologies and small family farming vs. large industrial farming.

Table 1-1 summarises the four empirical studies embedded in the dissertation as well as the two supplementary articles that have been co-authored by the author of this dissertation. The table specifies each article's main research question, the empirical case and data as well as the applied methods. The remainder of the dissertation is organised as follows. Chapter 2 introduces the methodological approaches applied in the empirical work. Chapters 3 – 6 present the embedded empirical studies, which address producer implications of agricultural policy developments at various regional levels (Bavaria, Germany, EU, China) and various sectors (dairy farming, sugar beet production, crop farming, small-scale and subsistence agriculture). Chapter 7 summarises all six empirical studies (four embedded and two supplementary studies), highlighting authors' contributions. Finally, Chapter 8 provides a discussion across all dissertation topics in relation to the existing literature and concludes by providing policy implications, limitations and scope for further research.

Table 1-1. Overview of the empirical studies

Title	Main research question	Empirical case / data	Methods
a) Empirical studies embedded in the dissertation			
1. Profitability Development and Resource Reallocation: The Case of Sugar Beet Farming in Germany (Chapter 3)	What is the impact of the 2006 sugar market reform on aggregate productivity in beet production?	German crop farms with sugar beet production; Farm accountancy data from 2004 to 2013	Theoretically consistent index approach to compute productivity and profitability change; System generalised method-of-moment (GMM) estimator to identify drivers of resource reallocation
2. Diversification Economies in Dairy Farming – Empirical Evidence from Germany (Chapter 4)	What is the cost-saving potential of farm diversification in dairy farming?	Bavarian dairy farms; Farm accountancy data from 2000 to 2014	Input distance function approach; Bayesian estimation technique to impose theoretical consistency; Two-stage least square fixed effects instrumental variable regression to explain cost complementarities
3. Credit Access and Farm Productivity: Evidence from a Field Experiment in Rural China (Chapter 5)	What is the causal effect of credit access on total factor productivity?	Smallholder farms in five provinces in China; Household panel data from a survey in 2010, 2012 and 2014	Production function and frontier approaches to estimate productivity / productivity growth. Levinsohn-Petrin (2003) proxy-variable approach to control for endogeneity; Difference-in-difference estimation to identify treatment effects
4. Green Policies and Farm Production Decisions in Selected EU Member States (Chapter 6)	How do agri-environmental subsidies affect production choices and land allocation between crops?	Crop farms in France, Germany and the UK; Farm accountancy data from 1995–2016	Profit function approach with Cholesky factorisation to impose theoretical consistency; System of profit equations estimated with iterated feasible generalised nonlinear squares
b) Additional co-authored articles cited in the dissertation			
5. Is small family farming more environmentally sustainable? Evidence from a spatial regression discontinuity design in Germany (Summary in Chapter 7)	Do small family farms use more environmentally sustainable farming practices than their larger counterparts?	German farms (focus on farms within 130 km of the historical inner-German border for identification purposes); Farm Structure Survey in 2010	Regression discontinuity design to identify the causal effect of small family farming on various farm practices
6. Production Intensity and Emission Efficiency – A Latent-Class Meta-frontier Approach (Summary in Chapter 7)	How do intensive and extensive production technologies compare in GHG emission efficiency?	Bavarian dairy farms; farm accountancy data from 2005 to 2014	Eco-efficiency concept combined with latent class stochastic frontier analysis, followed by stochastic meta-frontier estimation

2

Conceptual Framework and Methodological Overview

Insights into production technologies and behaviour of producers are essential to evaluate how policies and market conditions affect production and performance. Hence, the empirical studies in this dissertation largely rely on applied production analysis. This chapter presents an overview of the applied methods, focusing on both microeconomic production theory and econometric applications.

2.1 History of thought

Starting with the work by Cobb and Douglas (1928), production functions were used to study the functional distribution of income between capital and labour at the macroeconomic level (Greene, 2008). At the microeconomic level, empirical production studies were pioneered by Dean (1951), Johnston, J. (1960) and Nerlove (1963), all focusing on cost rather than production functions. In his seminal work, Nerlove (1963) highlighted the dual relationship between cost and production functions and laid the groundwork for investigating production measures such as factor-demand and supply elasticities, input substitutability, or economies of size, scale and scope.

While the early production and cost function literature was primarily interested in describing the production structure, Debreu (1951) and Farrell (1957) developed the notion that firms may deviate from the frontier isoquant. Aigner and Chu (1968) combined parametric estimation and linear programming techniques to find parameter values that envelope the observed data. In their seminal papers, Aigner, Lovell and Schmidt, P. (1977) and Meeusen and van Den Broeck (1977) proposed to estimate the stochastic frontier model with parametric distributional assumptions for the composite error term. These models have been extended in various ways, and many specifications for different inefficiency distributions exist. For example, Pitt and Lee (1981) propose a random effects model with time invariant inefficiency to take advantage of panel data. Battese and Coelli (1992) propose a time-varying inefficiency model by describing firm-specific inefficiency term as a function of time. Battese and Coelli (1995) extended the model to include inefficiency determinants. More recent variants of the stochastic frontier model focus on the separation of time-invariant inefficiency and firm heterogeneity, such as the Kumbhakar, Lien and Hardaker (2014) model.

Besides stochastic frontier models, deterministic approaches to constructing the frontier exist. The most common technique is data envelopment analysis. The fundamental difference between the stochastic and the deterministic approach is that the latter generates the frontier by observed data, so that some firms are efficient by construction. Since the empirical studies in this dissertation all make use of stochastic approaches, the deterministic ones are not described further.

2.2 Primal and dual approaches

Primal production models consider combinations of output and input vectors measured in physical quantities, which are feasible given the underlying technology. Typical examples are the production function or various forms of distance functions. With the primal approach, the underlying technology can be described without making any assumption about the economic behaviour of the firm (Coelli et al., 2005, p. 47). Dual models, on the other hand, involve economic variables (e.g. prices, costs, revenues, or profits) and the choice of the model depends on the appropriate behavioural assumption. For example, if the behavioural objective of cost minimisation is made, the technology can be represented by the cost function. The duality theory, pioneered by Shephard (1953), describes the link between the production model and the various economic models (Färe and Primont, 1995). Since both approaches are applied in the empirical studies of the dissertation, they are described in more detail in the following.

2.2.1 Primal approach

The **production function** describes the physical transformation of inputs (such as material, labour, capital) into outputs. Formally, a production function is a mathematical representation of the technology that converts inputs into outputs. In the single output case, this is

$$q = f(x), \tag{2-1}$$

where q denotes output and $x = (x_1, x_2, \dots x_j)'$ is a $j \times 1$ vector of inputs.

As described in Chambers (1988), a well-defined production function is characterised by the following properties:

a) Non-negativity: $f(x)$ is finite, non-negative, real-valued and single-valued for all non-negative and finite x
b) Weak essentiality: $f(0) = 0$, i.e. the production of positive output is impossible without the use of at least one input
c) Monotonicity in x: $f(x^0) \geq f(x^1)$ for $x^0 > x^1$ (i.e., non-decreasing in x)
d) Differentiability: $f(x)$ is continuous and twice-differentiable everywhere
e) Quasi-concavity in x: The input requirement set $V(y) = \{x | f(x) \geq y\}$ is a convex set, implying quasi-concavity of $f(x)$
f) Non-emptiness: The set $V(y)$ is closed and non-empty for any $y > 0$

Some of these properties are illustrated in the left panel of Figure 2-1. The non-negativity condition is satisfied since q are non-negative and finite real numbers for all x on the horizontal axis. Weak essentiality is also fulfilled as the function includes the origin. Furthermore, the function is monotonically increasing in x, implying that an increase in inputs leads to a non-negative change in outputs, or marginal products $MP_i = \partial f(x)/\partial x_i$ are non-negative. In some real-world settings, however, the monotonicity condition may be violated due to an overuse of certain inputs. In agriculture, for example, fertiliser may reduce the output if it is used excessively. Concavity is violated between the origin and the first horizontal curve in Figure 2-1. Coelli et al. (2005) call the segment of the production function where all theoretical properties are satisfied the *economically feasible region* of production, because it is expected that rational behaving decision-makers will choose a production plan that lies within this segment. However, due to regulatory matters or restricted access to certain inputs (e.g. land in the agricultural case), firms may well be located in a region with increasing marginal products.

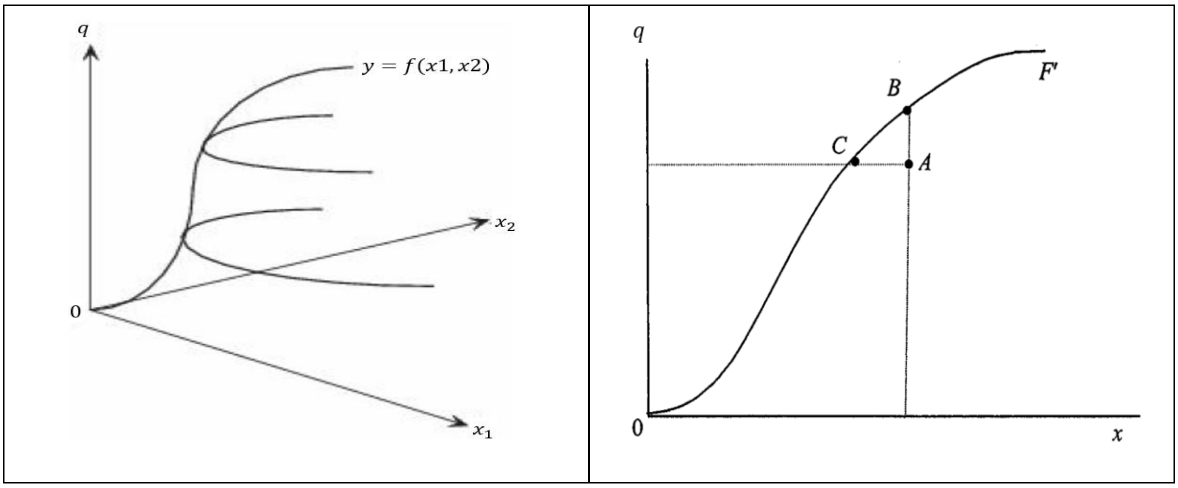

Figure 2-1. Production function with one output and two inputs (left) and production frontier with technical efficiency (right)

(*Sources:* Kumbhakar, Wang, H.-J. and Horncastle, 2015, p. 11 and Coelli et al., 2005, p. 4)

The production function in equation (2-1) represents the average expected output given input quantities. As such, it does not account for the fact that some firms may be inefficient. By contrast, the **production frontier** represents the maximum attainable output given inputs:

$$q = f(x) \times TE \quad , \tag{2-2}$$

where $0 < TE \leq 1$ represents technical efficiency. In the right panel of Figure 2-1, firms B and C are operated at the production frontier and hence are technically efficient ($TE = 1$). Firm A, on the other hand, is technically inefficient ($TE < 1$). For example, it could expand output without altering its input use by moving towards firm B (output-oriented view) or reduce inputs whithout changing the output produced by moving towards firm C (input-oriented view).

A limitation of the production function and frontier approaches is that they only accommodate single-output technologies. With multiple outputs, the technology can be represented in form of **distance functions**. For this purpose, the production possibility set is defined as the combination of all technologically feasible input and output combinations. Under the assumption of weak disposability of outputs, the technology set can be specified by the Shephard (1953, 1970) output distance function (ODF) as

$$D^O(q,x) = \inf_{\theta}\left\{\theta > 0: \frac{q}{\theta} \epsilon\, P(x)\right\} . \tag{2-3}$$

In equation (2-3), $P(x)$ is the set of producible outputs for the input vector x. The use of infimum rather than minimum is necessary because the minimum may not be achieved if q is a vector of multiple outputs (Färe and Primont, 1995, p. 9). Under weak disposability of outputs, the ODF fully characterises the producible output set, i.e. $q \in P(x)$ if and only if $D^O(q,x) \leq 1$.

Analogously, the Shephard (1953, 1970) input distance function (IDF) describes how the input vector can be proportionally contracted, holding the output vector constant:

$$D^I(q,x) = \sup_{\lambda}\left\{\lambda > 0: \frac{x}{\lambda} \epsilon\, V(q)\right\} , \tag{2-4}$$

where $V(q)$ is the input requirement set for producing the output vector q. Since the input vector belongs to the input isoquant if and only if $D^I(q,x) = 1$, the IDF exactly characterises the input isoquant. If weak disposability of inputs is assumed, the entire input requirement set can be characterised by the IDF (Färe and Primont, 1995, p. 21). Because the IDF is applied in the second empirical study of this dissertation (Chapter 4), its properties are described here in more detail. From the theoretical considerations of the production technology set, several properties of a well-behaved IDF can be derived (Färe and Primont, 1995; Coelli et al., 2005):

a) Weak essentiality: $D^I(0,x) = 0$ for all x in $\mathbb{R}_+^N$
b) Monotonicity: $\partial D^I(q,x)/\partial x_i \geq 0$; : $\partial D^I(q,x)/\partial q_i \leq 0$ (i.e., non-decreasing in x and non-decreasing in q)
c) Linear homogeneity: For $\omega > 0$, $D^I(q,\omega x) = \omega D^I(q,x)$
d) Concavity in x (due to convexity of the input requirement set)
e) Quasi-concavity in q (due to the convexity of the producible output set)
f) If the input vector x belongs to the input requirement set ($x \in L(q)$), then $D^I(q,x) \geq 1$
g) If the input vector belongs to the boundary of the input requirement set, then $D^I(q,x) = 1$

Monotonicity in x and q requires the first derivative of the IDF with respect to x to be positive and the first derivative with respect to y to be negative. Concavity in x follows from the convexity of the input requirement set. It requires the Hessian matrix of the IDF to be negative semidefinite (see

Technical Appendix). Quasi-concavity in q requires the principal minors of the bordered Hessian matrix to be non-positive. This property follows from the convexity of the producible output set, which is not always assumed in empirical applications, such as in Coelli and Perelman (2000), Nemoto and Furumatsu (2014) or Kumbhakar, Wang, H.-J. and Horncastle (2015).

Figure 2-2 illustrates the IDF for different input and output quantities. The black curve indicates the input isoquant with $D^I(q,x) = 1$. Firms located on this curve are technically efficient. Firms located on the dark grey area are technically inefficient ($D^I(q,x) > 1$) while the surface in light grey indicates the technologically infeasible area ($D^I(q,x) < 1$). It can also be seen that the distance measure is increasing in inputs (left panel) and decreasing in outputs (right panel).

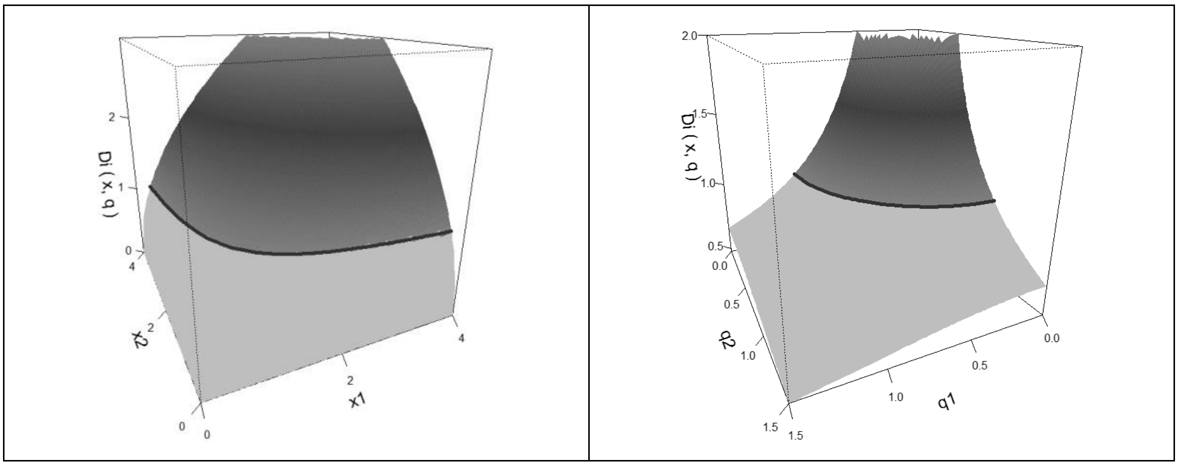

Figure 2-2. Graphical illustration of input distance functions for different input quantities (left) and output quantities (right)

(*Source:* Henningsen, 2019, pp. 293 and 296)

It is noteworthy that the inverse of the input distance measure returns the input-oriented measure of technical efficiency in Debreu (1951) and Farrell (1957). Besides efficiency measurement, distance functions are also useful to derive and decompose productivity indices. Chapter 2.3 below describes this in detail.

2.2.2 Dual approach

Under the assumption of cost-minimising behaviour, the technology can also be represented by the **cost function**. That is, the cost function can be used to study the characteristics of the underlying technology. The cost function defines the minimal cost involved for any predetermined output q given input prices w:

$$c(w,q) = \min_{x \geq 0}\{w'x : x \in V(q)\} \tag{2-5}$$

Equation (2-5) shows that the cost function incorporates technological restrictions. By definition, a well-defined cost function is non-negative (i.e., $c(w,q) > 0$ for $w > 0$ and $q > 0$), non-decreasing in w (i.e., if $w^1 > w^2$, then $c(w^1,q) \geq c(w^2,q)$), concave and continuous in w, positively linearly homogeneous (i.e., for $\mu > 0$, $c(\mu w,q) = \mu c(w,q)$), non-decreasing in q (i.e., if $q^1 \geq q^2$, then $c(w,q^1) \geq c(w,q^2)$), and involves no fixed costs (i.e., $c(w,0) = 0$) (Chambers, 1988, pp. 50-56). Under these conditions, the dual relationship between the IDF and the cost function can be described as (Färe and Primont, 1995, p. 47):

$$C(q,w) = \min_{x\geq 0}\{w'x: D^I(x,q) \geq 1\} \tag{2-6}$$

Because of the dual relationship between the IDF and the cost function, it is possible to derive cost function parameters from IDF parameters and vice versa. For example, Hajargasht, Coelli and Rao (2008) use the envelope theorem and Shephard's (1953) lemma to recover the matrix of cost function second-order derivatives from the IDF:

$$C_{qq} = C\{D_q D_q' - D_{qq} + D_{qx}[D_{xx} + D_x D_x']^{-1} D_{xq}\} \ , \tag{2-7}$$

where subscripts indicate derivatives. In the second empirical study (Chapter 4), we use this relationship to estimate cost complementarities between various output pairs based on an IDF specification.

In other applications, it may be more reasonable to assume a profit-maximizing behaviour of firms, i.e. both inputs and outputs are chosen by the decision-maker. Under this assumption, the technology can be represented by the **profit function**. The profit function defines the maximum attainable profit given output prices p and input prices w:

$$\pi(p,w) = \max_{y\geq 0} p'q - c(w,q) \tag{2-8}$$

Representing the profit function in this way illustrates that profit maximisation involves cost minimisation. (Chambers, 1988, p. 121). Drawing upon the properties of a well-behaved cost function, it can be shown that a well-behaved profit function is non-negative (i.e., $\pi(p,w) > 0$ for $p > 0$ and $w > 0$), non-decreasing in p (i.e., if $p^1 > p^2$, then $\pi(p^1,w) \geq \pi(p^2,w)$), convex and continuous in (p,w), positively linearly homogeneous (i.e., for $\mu > 0, \pi(\mu p, \mu w) = \mu\pi(p,w)$), and non-increasing in w (i.e., if $w^1 \geq w^2$, then $\pi(w^1,p) \leq \pi(w^2,p)$) (Chambers, 1988, pp. 121-124). Further, if $\pi(p,w)$ is differentiable in p and w, Hotelling's (1932) lemma implies that the partial derivatives of the profit function with respect to the output (input) price are the profit-maximising supply and derived demand functions:

$$q(p,w) = \frac{\partial\pi(p,w)}{\partial p} \tag{2-9}$$

$$x(p,w) = -\frac{\partial\pi(p,w)}{\partial w} \tag{2-10}$$

Thus, specification of the profit function allows deriving well-behaved supply and demand equations. Convexity of the profit function ensures that the output supply functions are increasing in p and input demand functions are decreasing in w. The fourth empirical study (Chapter 6) employs this approach to estimate the supply and demand elasticities of crop farms in selected EU member countries in the context of agri-environmental policies.

2.3 Productivity and profitability

Productivity is an important concept to measure and compare the performance of firms. Essentially, productivity measures how much output is produced from a given set of inputs. *Partial* productivity measures include output per unit of labour (i.e., labour productivity) or output per unit of land (i.e., land productivity or yield). However, partial productivity measures are incomplete as they do not consider the use of other inputs, such as other capital inputs or materials. Since partial productivity measures are affected by the use of the excluded inputs, measures of *total* factor productivity are more suitable for performance measurement (e.g. Coelli et al., 2005, p. 62; Syverson, 2011). Formally, TFP is defined as the ratio of aggregate outputs (Q) to aggregate inputs (X):

$$TFP = \frac{Q}{X} \tag{2-11}$$

One possibility to aggregate inputs and outputs is in terms of values. This requires the use of appropriate price indices so that differences in productivity are not confounded by differences in prices. A comprehensive discussion of appropriate price indices is provided in O'Donnell (2012a). Another way of aggregation is to use output elasticities as weights for inputs. For example, with K production inputs X_{kit} and output Q_{it}, TFP can be defined as (e.g. Syverson, 2011)

$$TFP_{it} = A_{it} = \frac{Q_{it}}{X_{1it}^{\alpha_1} + X_{2it}^{\alpha_2} + \cdots + X_{Kit}^{\alpha_K}} \quad , \tag{2-12}$$

where i and t are subscripts for production units and time, α_k denotes the k-th input's output elasticity and A_{it} is a factor-neutral shifter of the production function. As such, TFP indicates variations in the firms' output that are not explained by differences in input use.

In empirical work, the interest often lies in measuring productivity *change* rather than productivity levels. A straightforward way is to compare input changes to output changes using input and output quantity indices, such as Laspeyres, Paasche or Törnqvist indices. TFP indices based on output and input changes are summarised under the term Hicks-Moorsteen indices (Diewert, 1992; Coelli et al., 2005, p. 66). Another popular method to measure productivity change between production units and over time is the Malmquist TFP index. It was introduced by Caves, Christensen and Diewert (1982), who proposed a TFP index based on Malmquist IDFs and ODFs. The output-oriented Malmquist TFP index between period s and period t is defined as the geometric average of two distance measures based on period-t and period-s technologies (Coelli et al., 2005, p. 68):

$$m_o(q_s, q_t, x_s, x_t) = \left[\frac{D_s^O(q_t, x_t)}{D_s^O(q_s, x_s)} \times \frac{D_t^O(q_t, x_t)}{D_t^O(q_s, x_s)}\right]^{0.5} \tag{2-13}$$

If firms are allowed to be inefficient, i.e. $D_s^O(q_s, x_s) \leq 1$ and $D_t^O(q_s, x_s) \leq 1$, the index in (2-13) can be decomposed as (Coelli et al., 2005, p. 70):

$$m_o(q_s, q_t, x_s, x_t) = \frac{D_t^O(q_t, x_t)}{D_s^O(q_s, x_s)} \times \left[\frac{D_s^O(q_t, x_t)}{D_t^O(q_t, x_t)} \times \frac{D_s^O(q_s, x_s)}{D_t^O(q_s, x_s)}\right]^{0.5} \quad , \tag{2-14}$$

where the first term represents technical efficiency change (TEC) and the term in square brackets represents technical change (TC). Thus, the Malmquist TFP index captures TEC and TC as sources of productivity change. Indeed, these are the only sources of productivity change if the technology exhibits constant returns to scale (RTS). However, if the technology is characterised by varying RTS, productivity is also affected by the scale of production (Balk, 2001). Output-oriented scale efficiency is described as the ratio between the output distance value relative to the (hypothetical) constant-returns-technology (D_t^{*O}) and the output distance value relative to the (actual) constant-returns-technology (D_t^O) (Balk, 2001, p. 165):

$$SE_t^O(q, x) = \frac{D_t^{*O}(q, x)}{D_t^O(q, x)} \tag{2-15}$$

Scale efficiency change (SEC) is then defined as the ratio of scale efficiency between two periods. Using again the geometric average of both reference technologies results in the following measure for scale efficiency change:

$$SEC = \left[\frac{D_t^O(q_t, x_t)/D_t^{*O}(q_t, x_t)}{D_t^O(q_s, x_s)/D_t^{*O}(q_s, x_s)} \times \frac{D_s^O(q_t, x_t)/D_s^{*O}(q_t, x_t)}{D_s^O(q_s, x_s)/D_s^{*O}(q_s, x_s)}\right]^{0.5} \tag{2-16}$$

Taken together, the individual components of productivity growth can be summarised as an index for TFP change (TFPI) as follows:[3]

$$\begin{aligned} TFPI = {} & \frac{D_t^O(q_t, x_t)}{d_s^O(q_s, x_s)} \times \left[\frac{D_s^O(q_t, x_t)}{D_t^O(q_t, x_t)} \times \frac{D_s^O(q_s, x_s)}{D_t^O(q_s, x_s)}\right]^{0.5} \\ & \times \left[\frac{D_t^O(q_t, x_t)/D_t^{*O}(q_t, x_t)}{D_t^O(q_s, x_s)/D_t^{*O}(q_s, x_s)} \times \frac{D_s^O(q_t, x_t)/D_s^{*O}(q_t, x_t)}{D_s^O(q_s, x_s)/D_s^{*O}(q_s, x_s)}\right]^{0.5} \\ = {} & TEC \times TC \times SEC \end{aligned} \tag{2-17}$$

The obtained productivity index can be evaluated using either explicit distance measures or derivative-based techniques (Coelli et al., 2005, p. 300). In empirical study 3 (Chapter 5), we use derivative-

[3] Another source of productivity change, which is not discussed here for reasons of space, is output mix efficiency. This concept is discussed in Balk (2001) and O'Donnell (2012b), for example.

based techniques to decompose productivity change into the three components of TEC, TC and SEC, following Kumbhakar and Lovell (2000), Alvarez, del Corral and Tauer (2012) and Mennig and Sauer (2020).

The focus so far was on output and input quantities to measure productivity and productivity change. Profitability, on the other hand, includes price information and is defined as the ratio of revenue over cost:

$$PROF = \frac{Q \times P}{X \times W} \ , \tag{2-18}$$

where P and W denote aggregate prices. A straightforward index to compare profitability across two periods s and t is (O'Donnell, 2012b)

$$PROFI_{st} = \frac{PROF_t}{PROF_s} = \frac{Q_t \times P_t}{X_t \times W_t} \times \frac{X_s \times W_s}{Q_s \times P_s} = \frac{PI_{st}}{WI_{st}} \times \frac{QI_{st}}{XI_{st}} = TTI_{st} \times TPFI_{st} \ . \tag{2-19}$$

Thus, profitability change can simply be decomposed into a terms of trade (TT) index and a productivity index. From equation (2-19), it is also clear that if firms face the same input and output prices, differences in profitability reflect differences in productivity.

Figure 2-3 illustrates the relationship between productivity, efficiency, and profitability. The curve passing through the origin and firms E, K, and G represents the production frontier, indicating the maximum output that can be obtained with a given amount of inputs under a given technology. Firm A is technically inefficient, because it is operated below the production frontier. Productivity is given by the ratio of outputs to inputs, i.e. by the slope of a line from the origin through the firm's point of production. In the present example, firm E maximises productivity, followed by firms K, G and A. Profits, on the contrary, are maximised where the isoprofit line $q = \frac{\pi_{it}^*}{P_{it}} + \frac{W_{ot}}{P_{it}} \times X$ is tangent to the production frontier (firm K). For lower ratios of input to output prices, the profit maximising point would move from firm K towards firm E as the slope of the isoprofit line becomes steeper. Thus, this example illustrates that higher productivity does not necessarily lead to increased profit, and that less favourable ratios of output and input prices imply that firms with profit-maximising behaviour move towards the productivity-maximising point of production.

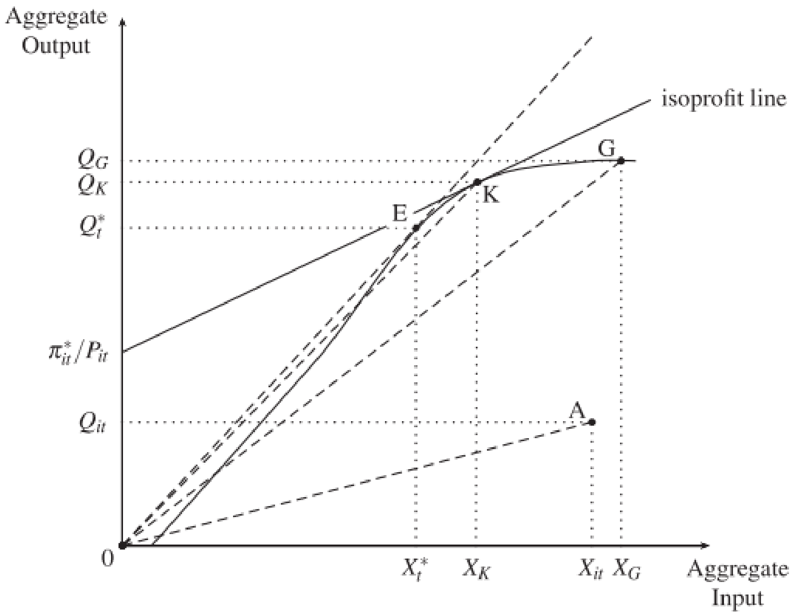

Figure 2-3. Productivity, profitability, and efficiency
(*Source:* O'Donnell, 2012b)

Evaluating and decomposing profitability changes allows examining whether profitability changes are driven by productivity changes or by external factors such as input and output prices. Policy changes, such as replacing protective agricultural policies by more market oriented ones, often affect prices faced by domestic farms. Therefore, both profitability and productivity changes are important in the evaluation of policy changes. The first empirical study in this dissertation (Chapter 3) evaluates such changes in sugar beet farming after the 2006 sugar market reform.

2.4 Econometric methods

To estimate the stochastic production frontier following Aigner, Lovell and Schmidt, P. (1977) and Meeusen and van Den Broeck (1977), it can be written it in its parametric form using panel data:

$$\begin{aligned} \ln q_{it} &= f(x_{it};\beta) + v_{it} - u_{it} \\ &= x_{it}^{'}\beta + v_{it} - u_{it} \end{aligned} \tag{2-20}$$

where x_{it} is a vector inputs used by the i-th firm at time t in logarithmic form; β is a vector of unknown parameters to be estimated; v_{it} is an idiosyncratic error term accounting for omitted variables, measurement errors and functional form misspecifications; and u_{it} is a non-negative one-sided error term associated with technical inefficiency. By imposing linear homogeneity in inputs and defining $\ln D^{i}{}_{it} = u_{it}$, the IDF can also be written in the form of a stochastic frontier model (see Chapter 4 in detail):

$$-\ln x_{1_{it}} = f\left(\frac{x_{it}}{x_{1_{it}}}, q_{it}; \beta\right) + v_{it} - \ln D^{i}{}_{it} \tag{2-21}$$

Equations (2-20) and (2-21) can be estimated with maximum likelihood techniques by making assumptions on the distributions of the error terms. The inefficiency term can be assumed either time-invariant (Pitt and Lee, 1981) or time-varying (Battese and Coelli, 1992) and it can also be modelled as a function of exogenous variables (Battese and Coelli, 1995). In Chapter 5, we employ the Kumbhakar, Lien and Hardaker (2014) model that separates firm heterogeneity from persisting and time-varying inefficiency.

Introduced by van Den Broeck et al. (1994), stochastic frontier models can also be estimated using Bayesian methods (see Technical Appendix), as applied and explained in detail in Chapter 4. Bayesian estimation techniques are particularly useful to incorporate restrictions such as regularity conditions, as will be discussed in 2.4.2 below. Before that, I describe how endogeneity concerns are addressed in this dissertation.

2.4.1 Endogeneity in production models

Endogeneity in production frontier models arises if any of the independent variables (i.e. production inputs) are correlated with any of the two (or both) error terms (Amsler, Prokhorov and Schmidt, P., 2017). Unobserved productivity shocks are common reasons for correlations between inputs and the error term v_{it} if producers respond to positive shocks with higher input use, for example. As a remedy, Olley and Pakes (1996) suggested to proxy unobserved productivity shocks with investment in the estimation of production functions. Levinsohn and Petrin (2003) proposed to use intermediate inputs instead, since investment often occurs with a time lag and takes the value zero for a large portion of observations in many data sets. In the third empirical study (Chapter 5), we apply this approach to the estimation of a production function for smallholder farms in rural China.

Regarding the estimation of the IDF in (2-21) as a special form of stochastic frontiers, input ratios are exogenous under the assumption of allocative efficiency (Kumbhakar, 2013; Sipiläinen, Kumbhakar and Lien, 2014; Tsionas, Kumbhakar and Malikov, 2015). However, if the inefficiency term u_{it} reflects management skills, input and output quantities will be correlated with u_{it} so that ordinary least squares (OLS) estimators are biased. In Chapter 4, we therefore follow Griffiths, W. E. and Hajargasht (2016) to explicitly model the correlation between time-invariant firm averages of outputs and input ratios. As such, the model is an extension of the Mundlak (1978) random effects model with correlated effects.

2.4.2 Theoretical consistency of production models

To specify the relationships between the economic variables, a functional form has to be chosen as an approximation to the true (but unknown) technical relationship between inputs and outputs. Lau (1986) provides five criteria to guide the selection of the functional form: theoretical consistency (capability to possess the theoretical properties introduced in 2.2), domain of applicability (the set of independent variables where theoretical consistency is satisfied), flexibility (a function is second-order flexible if it provides a second-order Taylor's approximation to any arbitrary function), computational facility (e.g. linearity in parameters) and factual conformity (consistency with known empirical facts). Theoretical consistency is particularly important to facilitate a meaningful economic interpretation of the econometric results (see Sauer, 2006; Sauer, Frohberg and Hockmann, 2006). In practice, it is not guaranteed that econometrically estimated functions are consistent to economic theory. However, different econometric techniques exist to impose curvature on the estimated functions, for example by using *ex post* procedures (e.g. Henningsen and Henning, 2009), constrained maximum likelihood methods (e.g. Bokusheva and Hockmann, 2006) or Bayesian Markov chain Monte Carlo (MCMC) techniques (e.g. O'Donnell and Coelli, 2005).

In this dissertation, two different techniques are used to impose regularity conditions on the primal IDF (Chapter 4) and on the dual profit function (Chapter 6). The selection was made based on the functional forms of the respective functions applied. The IDF applied in Chapter 4 is estimated using a translog functional form, introduced by Christensen, Jorgenson and Lau (1971, 1973) because it is second-order flexible (Diewert, 1974) and it can easily be transformed to its estimable form of equation (2-21) by imposing linear homogeneity. However, the translog functional form cannot be restricted to globally satisfy monotonicity without destroying its flexibility (Diewert and Wales, 1987). Therefore, we use a Bayesian estimation technique to impose regularity on selected data points to make the function theoretically consistent at a large share of data points while maintaining its flexibility. This is along the lines of Ryan and Wales (2000), who demonstrate that imposing concavity at a single data point can result in satisfaction of concavity at most data points in the sample. In particular, we restrict the posterior probability of the unknown parameters by assigning a likelihood value of zero to all parameter draws that violate either monotonicity or concavity conditions at the selected data points as proposed by Terrell (1996) and Griffiths, W. E., O'Donnell and Cruz (2000) for the case of cost functions. O'Donnell and Coelli (2005) provide an extension to distance functions, using a random-walk Metropolis-Hastings algorithm.

The profit function in Chapter 6 is estimated using a normalised quadratic functional form suggested by Berndt, Fuss and Waverman (1977). This functional form is flexible, linear homogeneous and has a Hessian matrix of constants (e.g. Shumway, 1983). In addition, it accommodates negative profit values as opposed to the translog functional form (Moschini, 1988). The constant Hessian matrix allows imposing convexity globally without sacrificing its flexibility.

To be convex in prices, the Hessian matrix of second-order derivatives of the profit function must be positive semidefinite (see Technical Appendix). As shown by Lau (1978), every positive semidefinite matrix $\boldsymbol{A}$ has a Cholesky factorisation with non-negative Cholesky values in the form $\boldsymbol{A} = \boldsymbol{LDL}'$, where $\boldsymbol{L}$ is a unit lower triangular matrix, $\boldsymbol{L}'$ is its transpose and $\boldsymbol{D}$ is a diagonal matrix holding the Cholesky values d_i:

$$\boldsymbol{A} = \boldsymbol{LDR} = \boldsymbol{LDL}' = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ L_{21} & 1 & & 0 \\ \vdots & \vdots & \ddots & \vdots \\ L_{N1} & L_{N2} & \cdots & 1 \end{bmatrix} \times \begin{bmatrix} d_1 & 0 & \cdots & 0 \\ 0 & d_2 & & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & d_N \end{bmatrix} \times \begin{bmatrix} 1 & L_{21} & \cdots & L_{N1} \\ 0 & 1 & & L_{N2} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix} \quad (2\text{-}22)$$

Therefore, to impose convexity on the profit function, it is sufficient to constrain the Cholesky values to be non-negative (Lau, 1978). Alternatively, for positive Cholesky values, one can split the diagonal matrix $\boldsymbol{D}$ evenly between $\boldsymbol{L}$ and $\boldsymbol{L}'$ and write the Cholesky factorisation as $\boldsymbol{A} = \boldsymbol{CC}'$, where $\boldsymbol{C}$ is a lower triangular matrix with elements $a_{ji} = 0$ for $i < j$ (Strang, 1976, p. 241). Then, estimating the reparametrised model with parameters in $\boldsymbol{C}$ instead of parameters in $\boldsymbol{A}$ yields the convex profit function. This technique is due to Wiley, Schmidt, W. H. and Bramble (1973) and was adopted to the estimation of cost functions by Diewert and Wales (1987). As noted by Diewert and Wales (1987), the procedure is equivalent to the one suggested by Lau (1978).

For example, with three outputs or inputs, the Hessian matrix of second-order derivatives of a quadratic profit function can be decomposed as

$$\begin{aligned} \boldsymbol{A} &= \begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} \\ \alpha_{12} & \alpha_{22} & \alpha_{23} \\ \alpha_{13} & \alpha_{23} & \alpha_{33} \end{bmatrix} = \begin{bmatrix} \gamma_{11} & 0 & 0 \\ \gamma_{12} & \gamma_{22} & 0 \\ \gamma_{13} & \gamma_{23} & \gamma_{33} \end{bmatrix} \times \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ 0 & \gamma_{22} & \gamma_{23} \\ 0 & 0 & \gamma_{33} \end{bmatrix} \\ &= \begin{bmatrix} \gamma_{11}\gamma_{11} & \gamma_{11}\gamma_{12} & \gamma_{11}\gamma_{13} \\ \gamma_{11}\gamma_{12} & (\gamma_{12}\gamma_{12} + \gamma_{22}\gamma_{22}) & (\gamma_{12}\gamma_{13} + \gamma_{22}\gamma_{23}) \\ \gamma_{11}\gamma_{13} & (\gamma_{12}\gamma_{13} + \gamma_{22}\gamma_{23}) & (\gamma_{13}\gamma_{13} + \gamma_{23}\gamma_{23} + \gamma_{33}\gamma_{33}) \end{bmatrix} = \boldsymbol{CC}' \ . \end{aligned} \quad (2\text{-}23)$$

For estimation of the profit function with convexity imposed, the quadratic terms of the regression equation are then written as $n'(\boldsymbol{CC}')n$, where n are output or input prices (i.e., *net*put prices).

The described conceptual framework and empirical methods are used in the following four empirical studies to examine farm-level responses to agricultural policy developments. Chapter 3 uses an index-based approach to measure productivity and profitability. Chapter 4 and 5 employ primal production models (IDF and production functions/frontiers, respectively) while Chapter 6 applies the dual profit function. In all chapters, particular attention is paid to the economic consistency of the estimated econometric models.

Part II

Empirical Studies

3

Profitability Development and Resource Reallocation: The Case of Sugar Beet Farming in Germany*

Abstract. Following the 2006 reform of the European Union sugar market, and in anticipation of the quota abolition, a reallocation of sugar production has occurred. Using a Lowe quantity index, we evaluate the productivity and profitability of sugar beet farming in Germany from 2004 to 2013. The results show that an increase in total factor productivity partly compensated for losses in terms of trade. Moreover, the contribution of production reallocation to sector productivity growth varied across regions with distinct ownership structures of sugar processing companies. These findings have implications for policy and industry, as it transitions to a liberalised market.

Keywords: Beet production, Lowe index, resource reallocation, sector productivity, sugar market reform, terms of trade

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* This article is published as Wimmer, S. and Sauer, J. (2020). Profitability Development and Resource Reallocation: The Case of Sugar Beet Farming in Germany. *Journal of Agricultural Economics* 71(3): 816–837 under a Creative Commons License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited. The version of record is available online at: https://doi.org/10.1111/1477-9552.12373. Stefan Wimmer is the main author of this contribution. He developed the research idea and the study design, performed the statistical analysis and wrote the article. Johannes Sauer improved the article with his feedback and suggestions throughout the entire process.

3.1 Introduction

The abolition of the sugar quota in 2017 constitutes a turning point for the sugar sector in the European Union (EU). Because the industry is now allowed to produce unlimited amounts of sugar, the demand for sugar beet is expected to increase, at least in the short term. On the other hand, domestic sugar prices are increasingly linked to world market prices, which have been far below the EU's sugar price in the EU in the past. In addition, production and use of isoglucose (high-fructose corn syrup) as a substitute increases the economic pressure on the sugar beet industry. Therefore, questions arise about the EU sugar sector's response to the new market situation without quota and whether sugar beet farming will remain profitable in the future. To prepare the sector for an era without quotas, a reform of EU sugar policies was implemented in 2006. Most importantly, minimum prices for sugar and sugar beets were stepwise reduced, and a voluntary restructuring scheme was introduced to buy back production quotas from sugar companies. The goal of the reform was to encourage less competitive manufacturers to reduce production (e,g, Szajner et al., 2016). Substantial consolidation in the EU sugar sector has taken place with a decline in the number of sugar processing factories by 42 % between 2005/06 and 2015/16 while the harvested area dropped by 69 % and beet production declined by only 30 % (CEFS, 2016).

While increased sugar beet yields indicate productivity gains in sugar beet production, output per area of land is only a partial measure of productivity that ignores the use of other inputs such as seed or labour. Our objective is twofold. First, we evaluate changes in profitability and total factor productivity (TFP) for sugar beet production in Germany during the deregulation of the EU sugar market, both at the individual farm level and at the aggregate level. Second, we examine the role of delivery rights with respect to productivity-enhancing resource reallocation. Generally, policy reforms increase sector productivity if productive activities shift from less productive firms towards more productive ones (e.g. Eslava et al., 2004). Thus, it can be expected that resource reallocation is more efficient in regions where delivery rights can be effectively traded among farmers.

To achieve these objectives, we use farm-level data for German sugar beet producers from the EU Farm Accountancy Data Network (FADN) for the years 2004 to 2013. We decompose profitability change into TFP change and changes in terms of trade (TT) using a Lowe quantity index proposed by O'Donnell (2012b). This index is particularly suitable to our application because it allows consistent comparison across time and space. We then evaluate the contribution of average farm productivity change (within-effect) and reallocation of production between farms with distinct productivity levels (between-effect) on aggregate productivity growth, and test whether the contribution of the between-effect has increased after the 2006 reform.

O'Donnell (2012b) applied the Lowe index to decompose agricultural profitability change into changes in TFP and TT using state-level data in the US. The results illustrate that declines in TT are associated with increases in TFP, in line with profit-maximising behaviour of farms. More recently, the index has been applied by Mugera, Langemeier and Ojede (2016) to investigate sources of farm-level profitability change in a sample of Kansas dairy farms. They find that TFP change is the main driver of profitability change at the farm level. The effect of market deregulation on aggregate productivity change and reallocation of activities has been studied by Frick and Sauer (2018) for the dairy sector. They provide evidence that abolition of milk quota contributed to a more efficient resource allocation across dairy farms and thus increased sector productivity. Previous studies concerned with sugar market liberalisation primarily analyse production and trade effects *ex ante* (e.g. Elobeid and Beghin, 2006; Frandsen, 2003; Gohin and Bureau, 2006; Poonyth, 2000). To the best of our knowledge, only two studies address production responses and profitability at the farm-level. For a sample of Belgian sugar beet farms in 2002, Buysse et al. (2007) predict that Belgian sugar beet production will decline by 13 % in response to the 2006 reform, reducing aggregate farm gross margins by 8 %. Bogetoft et al. (2007) show that under an efficient quota allocation, EU market liberalisation would lead to a 25 % decline in Danish sugar beet production while aggregate profits were predicted to fall by 70 %. In a different context, Wu, Devadoss and Lu, Y. (2003) study technical efficiency of sugar beet farms in Idaho, and Thirtle (1999) and Amadi, Piesse and Thirtle (2004) compute changes in TFP for sugar beet from 1954 to 1996 in the UK.

Our article contributes to the literature in three ways. First, we investigate farm-level changes in profitability and productivity following the 2006 reform from an *ex post* perspective. Second, we examine the effect of deregulation in the sugar market on resource reallocation and sector productivity in beet production, which has attracted little attention in previous literature. Third, our empirical case of Germany provides unique insights into how the delivery relationships between farmers and processing factories may affect the reallocation process, because the three major sugar processing companies differ in their ownership structures and, as a result, have different mechanisms to allocate delivery rights to farmers. The results are also relevant in the larger European context, as Germany is one of the EU's major sugar producers besides France, the UK and Poland, and the pace of the sector's consolidation process has been similar to the EU-15 average (see section 2).

The article is structured as follows. In the next section, we provide a brief description of the history of EU sugar policies. The economic framework in Section 3.3 describes our methods to compute profitability change and to decompose aggregate productivity into the within- and between-effects. Section 3.4 outlines the empirical framework, including the evaluation of drivers of resource reallocation with a particular focus on delivery relationships. In Section 3.5, we describe the data and Section 3.6 presents the results. Finally, Section 3.7 discusses the results and offers implications for policy and industry.

3.2 Sugar policy in the European Union

The EU's common market organisation (CMO) for the sugar sector was introduced in 1968 to stabilise the sugar market and to ensure living standards for EU sugar beet growers.[4] Along with quantitative supply restrictions imposed by a sugar quota system, support prices for producers were set at a level substantially higher than the world market price. The quota was subdivided into A- and B-quota, and the minimum price for sugar beet produced for A-quota was set at a higher level than the minimum price for beet produced for B-quota. A-quota sugar was primarily used for domestic consumption, but the remaining sugar was exported with subsidies (Poonyth, 2000). Further, out-of-quota sugar (C-sugar) could be exported at the world market price or carried over to the following year. By EU legislation, the supply quota was distributed across Member States, which allocated A- and B-quota across processing factories. The factories, in turn, issued delivery rights to beet growers (Burrell et al., 2014).

Entering into force in 1995, the Uruguay Round Agreement on Agriculture required the EU to limit subsidised sugar exports, while the quota system and price mechanisms remained in place (Frandsen, 2003; Poonyth, 2000). Sugar policies remained largely unchanged despite major CAP reforms in the past decades. However, in 2005, the WTO ruled that C-sugar exports do not qualify as unsubsidised even though they were sold at world-market prices. The members of the WTO panel argued that minimum prices for A- and B-sugar cross-subsidises the production of C-sugar by covering the factories' fixed costs (Burrell et al., 2014; Gohin and Bureau, 2006). As a result, the EU implemented a significant reform of the sugar policies in 2006.

This reform involved the replacement of public intervention storage, the conflation of A- and B-quotas, and the introduction of a limit on out-of-quota sugar exports. Most importantly, the minimum prices for white sugar and quota beet were gradually reduced by 36 % and 20 %, respectively. To compensate for their income loss, farmers received 64 % of the price cut as part of the single farm payment. Since Germany has adopted the dynamic hybrid model for implementation of the single payment scheme, entitlements within a region were harmonised over time. Therefore, not only beet growers, but also farms without sugar beet production benefited from this compensation. Further, a voluntary compensation system worth €5.4 billion was introduced to facilitate the restructuring of the sector. With this programme, the EU offered to buy back quota at fixed prices (e.g. 730 EUR/tonne in the marketing year 2006/07) from sugar companies that – in turn – had to compensate farmers who lost delivery rights following this restructuring process. Germany, for example, returned 15.2 % of their quota, amounting to more than 500,000 tonnes of sugar. Other countries, such as Bulgaria, Ireland and Latvia, ceased sugar production completely. In total, the EU sugar quota decreased from

[4] Council regulations No 1009/67EEC

17.5 to 13.3 million tonnes between 2006/07 and 2010/11 (Burrell et al., 2014). Because the EU-wide quota reduction was sufficient to comply with WTO regulations, the Commission refrained from further mandatory quota cuts (Nolte, Buysse and van Huylenbroeck, 2012). Finally, supply quotas were prolonged in the 2006 reform until 2015 with no commitment for further renewal in the 2006 reform. The understanding in the market was that quotas would be abolished thereafter (Burrell et al., 2014).

With the 2013 CAP reform, a final decision was made to abolish the quota system in 2017, along with minimum prices and export restrictions, to further liberalise the EU sugar sector. Thus, while sugar companies were encouraged to reduce production in the 2006 reform, they are now allowed to increase production beyond their former quota levels. In an *ex ante* analysis, Nolte, Buysse and van Huylenbroeck (2012) forecast that EU sugar production would increase from 13.3 (excluding out-of-quota sugar) to 15.5 million tonnes by 2019/20 without the quota system. Along with the sugar quota abolition, restrictions on the production of isoglucose are also repealed. The European Commission estimates that isoglucose production in the EU will increase to 10 % of the sweetener market by 2026 (DG AGRI and JRC, 2016), which is about twice as much as before the quota abolition. Notwithstanding the elimination of quota, delivery rights continue to be used to coordinate the supply and demand of sugar beet between processing companies and beet growers. The sugar processing companies differ in their approaches to the issue and distribution of delivery rights due to different organisational forms (see below).

Figure 3-1 illustrates price movements in the EU domestic market, compared to world market prices, between 2006 and 2019 as well as EU reference prices. While the 2006 EU price for white sugar was almost twice as high as the world market price, it dropped after implementation of the 2006 reform but then recovered after 2010 with an increase of the world market price. Now, EU and world market sugar prices are increasingly linked to each other.

The deregulation of the sugar market had a significant impact on the structure of the EU sugar industry. According to the European Association of Sugar Manufacturers (CEFS, 2016), the number of sugar processing factories in the EU declined from 189 in 2005/06 to 109 in 2015/16 (42 %). In the same period, beet production declined by 30 % from 128 million tonnes to 89 million tonnes, and sugar production went down by 25 %, from 20 million tonnes to 15 million tonnes (including out-of- quota production). In Germany, the number of factories decreased by 23 %, beet production by 11 %, and sugar production by 27 % (CEFS, 2016).

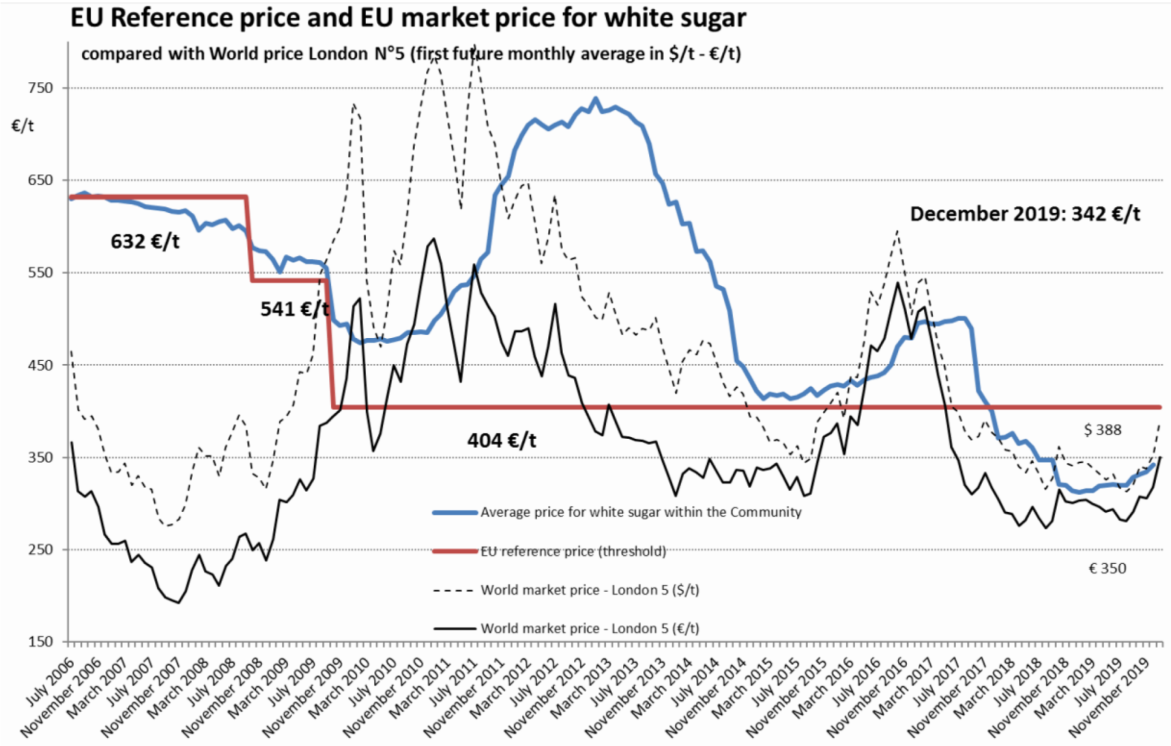

Figure 3-1. The EU reference price and white sugar market price, compared with the World Price London No. 5
Source: Committee for the Common Organisation of Agricultural Markets, 27 February 2019.

3.3 Economic framework

3.3.1 Profitability and productivity

The link between productivity and profitability is illustrated in Figure 3-2, where (aggregate) output is plotted against (aggregate) input. The curve through the origin and points A, B and C represents the production frontier. The points A, B and C represent the output-input combinations of three different farms (or one farm in three periods). Productivity is given by the ratio of aggregate output Q to aggregate input X. In the present example, farm A maximises productivity. In contrast, profitability is maximised where the isoprofit line is tangent to the production frontier (farm B). On the other hand, farm C is both less productive and less profitable than farm B. Note that the slope of the isoprofit line varies with the ratio of input prices to output prices: If input prices increase more than output prices, the slope becomes steeper, moving profit-maximising farm B closer to the productivity-maximising point of production.

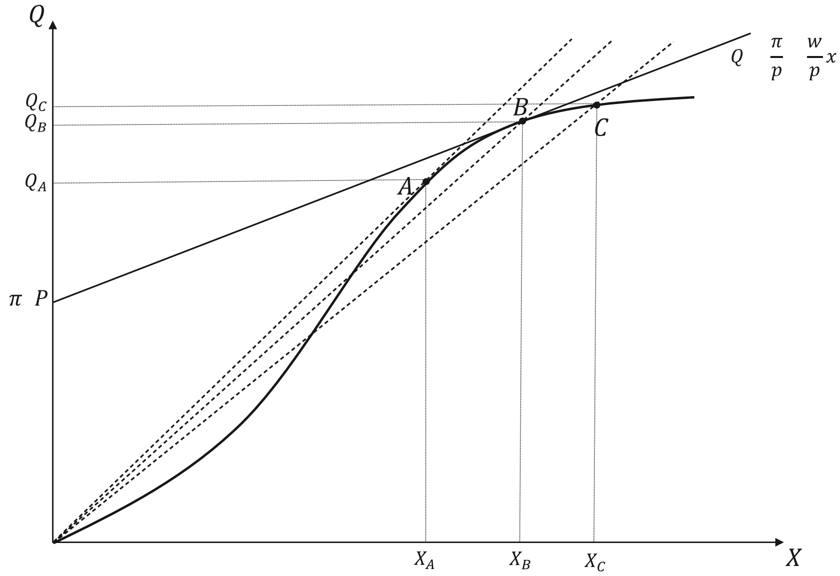

Figure 3-2. Productivity and profitability

With aggregate output price P and input price W, profitability of farm i in period t is defined as $PROF_{it} = (P_{it}Q_{it}) \,/\, (W_{it}X_{it})$. Comparing the profitability of farm i in period t with the profitability of farm h in period s, the profitability index is defined as (O'Donnell, 2012b):

$$\begin{aligned} PROFI_{hsit} &= \frac{PROF_{it}}{PROF_{hs}} = \frac{P_{it}Q_{it}}{W_{it}X_{it}} \times \frac{W_{hs}X_{hs}}{P_{hs}Q_{hs}} \\ &= \frac{PI_{hsit}}{WI_{hsit}} \times \frac{QI_{hsit}}{XI_{hsit}} = TTI_{shit} \times TFPI_{hsit} \end{aligned} \tag{3-1}$$

Equation (3-1) shows that the profitability index can be decomposed into a productivity index and an index for terms of trade. In our empirical application to sugar beet production, we consider one output (sugar beet) and multiple inputs. Therefore, only inputs have to be aggregated to calculate the TFP index in equation (3-1). We use a linear aggregator function that O'Donnell (2012b) attributes to Lowe (1822). O'Donnell (2012a) shows that in contrast to the commonly used Laspeyres, Paasche, Fisher and Tornqvist indices and their EKS[5] counterparts, the Lowe index satisfies all economically relevant axioms from index number theory, including the transitivity and identity axioms. These two axioms guarantee that direct and indirect comparisons of two observations yield the same value change and that the index takes a value of one if respective outputs and inputs are unchanged between two observations. Therefore, the Lowe index is particularly useful for our comparisons of sugar beet productivity and profitability across both time and space. Conceptually, the Lowe quantity index consists of values for different baskets of goods, evaluated using the same set of reference prices. For one output (sugar beet) and multiple inputs, we obtain:

[5] Named after Eltetö and Köves (1964) and Szulc (1964) who computed unweighted geometric averages of Fisher indices to ensure transitivity.

$$QI_{hsit} = \frac{q_{it}}{q_{hs}}$$

$$XI_{hsit} = \frac{X(x_{it})}{X(x_{hs})} = \frac{w_0^{'}x_{it}}{w_0^{'}x_{hs}} \tag{3-2}$$

$$TFPI_{hsit} = \frac{QI_{hsit}}{XI_{hsit}} = \frac{q_{it}}{q_{hs}} \times \frac{w_0^{'}x_{hs}}{w_0^{'}x_{it}}$$

An important decision to be made is the choice of the reference prices. O'Donnell (2012b) uses sample mean values as reference prices w_0 and emphasises that the chosen prices should reflect the relative importance that decision-makers place on different outputs and inputs. Mugera, Langemeier and Ojede (2016) use the farm with maximum TFP in a certain year as reference farm. In our analysis, reference prices are sample median values because of their robustness in the presence of possible outliers.

3.3.2 Productivity decomposition

As noted by Mahler (1994), rigidities in the quota market have prevented an efficient reallocation of beet production for a long time. To investigate if resource allocation became more efficient after the 2006 reform, we decompose TFP following Olley and Pakes (1996) where sector productivity at time t is defined as an output share-weighted average of firm-level productivity. We define output share as the portion of sugar beet produced by an individual farm in the respective region. Given productivity (TFP_{it}) and output share (σ_{it}) of farm i at year i, sector-level productivity TFP_t is decomposed as follows:

$$TFP_t = \sum_{i=1}^{N} \sigma_{it} TFP_{it} = \overline{TFP}_t + \sum_{i=1}^{N} (\sigma_{it} - \bar{\sigma}_t)\,(TFP_{it} - \overline{TFP}_t) \tag{3-3}$$

The first term represents the unweighted mean productivity of farms in a specific year (within-effect), and the second term is denoted as a covariance term (between-effect). If there is no correlation between productivity and output share, the covariance term is zero and sector-level productivity is equal to the average, unweighted firm-level productivity. If more productive farms have a higher market share than less productive farms, sector-level productivity exceeds the unweighted average. On the other hand, if more productive farms hold a lower market share than their counterparts, sector-level productivity is below the unweighted average. This representation provides a straightforward way to derive the sources of sector productivity growth over time: changes in unweighted, average productivity describe changes generated within farms ('within-change'), while changes in the covariance term reflect productivity change stemming from reallocation of market shares ('between-change'). In other words, it analyses the relative contribution of growth at the farm level, e.g. due to technical progress or an increase in production efficiency, and growth by reallocating production away from less productive towards more productive farms.

3.4 Empirical implementation

3.4.1 Allocation of inputs

As usual in data from bookkeeping records, our data do not report input use for individual crops but aggregated over all farm outputs. Focusing on specialised sugar beet farms only – as in Wu, Devadoss and Lu, Y. (2003) – is not possible because farms are restricted to planting beet on no more than 30 % of their utilised agricultural area. To calculate TFP for an individual crop[6], we need to estimate input allocation among individual crops. For variable inputs (crop specific inputs and other inputs), we employ the 'behavioural approach' proposed by Just et al. (1990) exploiting the fact that land allocation per crop is observed in the data set.[7] The underlying assumption is that farmers make decisions on land allocation and the ratio between variable inputs and land, while they behave as if the production technology is characterised by constant returns to scale. They are assumed to receive and follow similar recommendations by, for example, extension services (in terms of 'quantity per hectare'), and deviations from the average ratios are possible due to seasonal (e.g. economic or weather conditions) and farm-specific (e.g. soil quality and farmers' ability or perceptions) variations.[8] Thus, the total use of input j, which is observed in the data set, can be expressed as (Just et al., 1990):

$$X_{jit} = \sum_{k=1}^{K} \left[a_{kj} + \beta_{ji} + \gamma_{jt}\right] \times L_{kit} + \epsilon_{jit} \ , \tag{3-4}$$

where a_{kj} denotes the average use of input j for producing the k^{th} output, β_{ji} is the i^{th} farm's deviation, and γ_{jt} captures the time effect. Furthermore, L_{kit} is the land used to produce crop k by farm i in year t, and ϵ_{jit} is the error term to account for statistical noise. After estimating (3-4) using ordinary least squares (OLS) regression, the allocation of input j to crop k is calculated as

$$\widehat{X}_{kjit} = \left[\hat{\alpha}_{kj} + \hat{\beta}_{ji} + \hat{\gamma}_{jt}\right] L_{kit} \ . \tag{3-5}$$

At this point, it must be emphasised that farm heterogeneity may cause endogeneity problems in input allocation equations (Carpentier and Letort, 2012). For example, farmers whose input use for

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[6] It is more common to find crop-specific TFP measures at the aggregate level, for example in Jin et al. (2002) who possess data on crop-specific inputs for Chinese provinces. In the non-agricultural sector, Cherchye et al. (2013) and Walheer (2019) estimate product-specific productivity with observed input allocations.

[7] More recently, this approach has been applied by Serra et al. (2009)

[8] An alternative approach is to model input use as a function of input and output prices based on profit-maximising behaviour. This approach and its results are outlined in Appendix 2. The resulting crop-specific input usage shows unreasonably large standard deviations. The rigid specification ruling out substitution between inputs may be one reason for these econometric results. We opt for the behavioural approach because it yields far more reasonable crop-specific input usage (see section 5).

a specific crop is above the population's average may allocate less land to this crop because it is less profitable to them. In this case, crop-specific input use affects land allocation, and thus the acreage levels in equation (3-4) would be correlated with the error term. However, if crop margins within farms are positively related, the heterogeneity bias does not significantly affect individual acreage decisions. Given the lack of valid instruments for individual acreage levels, we are not able to test for the potential endogeneity. We trust that the heterogeneity bias has only a limited impact on the results, as was also the case in the empirical application in Carpentier and Letort (2012). Nevertheless, this qualification must be kept in mind when interpreting the results. For fixed inputs (labour and capital), on the other hand, we use revenue shares from sugar beet as weights similar to Foster, Haltiwanger and Syverson (2008) and Collard-Wexler and Loecker (2015). With observed revenue shares, however, we would endogenously obtain higher values of TFP in times of low prices. Therefore, to avoid misleading conclusions about productivity and profitability development, we calculate revenue shares using each farm's average crop prices over the whole period of the study.[9]

3.4.2 Drivers of resource reallocation

The delivery relationship between beet growers and sugar processing factories differs across German regions. Three major sugar companies, distinguished by their ownership structure, operate sugar factories in Germany. *Südzucker* (henceforth company 1) and *Nordzucker* (company 2) are joint-stock companies (in German: *Aktiengesellschaft*) that mainly run factories in southern and northern Germany, respectively. The stocks of company 1 are publicly traded and the major shareholder is a farmers' cooperative. In exchange for their capital contribution to the sugar company, the farmers hold delivery rights, which can be sold or lent out to other farmers. In contrast, the stocks of company 2 are not publicly traded, and delivery rights arise only from stock possession. Finally, *Pfeifer & Langen* (company 3) is a private business that operates sugar factories in the west of Germany. Even though delivery rights are usually linked to agricultural land, there is no binding commitment to any capital contributions. From economic theory, resource allocation is most efficient if there is a free market for delivery rights. Thus, we expect to find productivity-enhancing reallocation primarily in the catchment areas of company 1 where delivery rights can be traded and of company 3 where delivery rights are not linked to capital contributions.

[9] As a robustness check, we applied the behavioural approach by Just et al. (1990) for fixed inputs as well, making the same assumption as for variable inputs. This procedure did not change any of the main results.

To explore the potentially different effect of the sugar reform in 2006 on resource reallocation, we regress the farm-level covariance term ($Cov_{it} = (TFP_{it} - \overline{TFP}_t)(\sigma_{it} - \bar{\sigma}_t)$) on a set of explanatory variables, motivated by Lin, Y.-C. and Huang, T.-H. (2012) and Frick and Sauer (2018):[10]

$$\begin{aligned} Cov_{it} &= \beta_0 + \beta_1 \times Cov_{i,t-1} + \beta_2 \times Comp1_i + \beta_3 \times Comp3_i \\ &+ \beta_4 \times (Comp1_i \times Post - reform_t) + \beta_5 \times (Comp3_i \times Post - reform_t) \\ &+ \beta_6 \times UAA_{it} + \beta_7 \times Shbeet_{it} + \sum_t \beta_t \times Year_t + \epsilon_{it} \end{aligned} \tag{3-6}$$

The dependent variable (Cov_{it}) represents the contribution of resource allocation towards sector productivity for each farm observation. A higher value represents more efficient resource allocation (i.e. more productive farms hold a higher market share). Therefore, a positive coefficient of explanatory variables indicates a positive relationship with resource allocation. We include the lagged value of the covariance term ($Cov_{i,t-1}$) as explanatory variable, because we expect both productivity and market shares to be persistent over time due to the use of long-term delivery rights. Further, $Comp1$ and $Comp3$ are dummy variables for the catchment areas of company 1 and company 3 (e.g. $Comp1 = 1$ if the farm is located in the catchment area of company 1, 0 otherwise). Our primary interest lies in the heterogeneous effect of the 2006 market reform across the catchment areas of the three companies, represented by interaction terms between dummy variables for the reform ($Post - reform = 1$ if year > 2006, 0 otherwise) and catchment areas. Company 2 is used as reference, so that parameters β_4 and β_5 capture the heterogeneous effects of the 2006 reform on productivity-enhancing production reallocation in the catchment areas of companies 1 and 3 in comparison to the catchment area of company 2. We further control for the utilised agricultural area (UAA) as a proxy for farm size and for the share of farmland devoted to sugar beet production ($Shbeet$). Finally, we include a set of year dummies. The ϵ_{it} is a composite error term, consisting of fixed effects, μ_i, and idiosyncratic shocks, v_{it}.

Using lagged values of the dependent variable as regressors induces endogeneity because the lagged variable is correlated with the fixed effect μ_i (Nickell, 1981). In addition, utilised agricultural area and land share of sugar beet may be endogenous in our specification, because the covariance term includes a performance measure (productivity). Consequently, estimating (3-6) with OLS methods would yield biased estimates. Arellano and Bond (1991) and Blundell and Bond (1998) designed GMM estimators that are particularly useful when there are no instrumental variable candidates available other than lagged values of endogenous variables (Roodman, 2009). We employ the system-GMM approach by Blundell and Bond (1998), because it is more efficient and allows inclusion of time-invariant regressors, so that the linear terms of catchment areas in our model specification are

[10] Lin, Y.-C. and Huang, T.-H. (2012) use cross-sectoral rather than firm-level covariances.

not omitted. With this system-GMM procedure, the levels equation in (3-6) is simultaneously estimated with its first-difference transformation, where endogenous variables are instrumented with first-differenced lagged variables. However, the lagged variables are only valid instruments if there is no autocorrelation between the idiosyncratic error terms (e.g. Roodman, 2009). To make sure that this is the case in our estimation, we employ the Arellano and Bond (1991) test for autocorrelation. Finally, we use the Sargan (1958) and Hansen (1982) tests of overidentifying restrictions to confirm that the used instruments are uncorrelated to the error term.

3.5 Sample and data description

For the empirical analysis, we use farm accountancy data for specialised crop farms in Germany obtained from the EU Farm Accounting Data Network (FADN) covering the years 2004 to 2013 and amounting to a total of 16,717 observations. In our time period, 1,940 farms produce sugar beet at least once. Of these farms, 87 % produce beet in every year, 12 % cease beet production and 4 % start beet production.[11] In total, there are 8,749 farm observations with sugar beet production. The average yield of sugar beet varies between 57 tonnes per hectare in 2006 and 73 tonnes per hectare in 2011 and the yearly fluctuations are very similar to the population averages in Germany.

Farm-level productivity and profitability of sugar beet production are calculated considering five inputs and their respective price indices: land, labour, capital, crop-specific inputs (seed, fertiliser and pesticides), and other inputs (fuel, electricity, contract work, insurance and other farming overheads).[12] Land is measured in hectares and labour is measured in annual working hours, including both paid and unpaid labour. Capital usage is proxied by depreciation costs. Crop-specific inputs and other inputs are also measured in costs. All monetary values are deflated using agricultural price indices from the German statistics agency (Destatis) to obtain implicit quantities.

The price for sugar beet is directly observed in the data set. Input price indices for crop-specific inputs and other inputs are computed using weighted average cost shares. The price for capital is calculated as the sum of the rental price of acquisition, measured by dividing the financial expenses by the debt, and the rate of depreciation obtained by dividing depreciation costs by the initial value of capital (Frahan et al., 2011). Finally, prices for land (both owned and rented) and labour (both paid and unpaid) are calculated as district-specific (NUTS 2) values using the farm-level data on land rental prices and prices for hired labour, respectively. In both cases, farm-level prices below the 5 % and

[11] The shares add up to slightly more than 100 because some farms seize and start again or vice versa during the study period.

[12] Another source of (opportunity) costs can arise from the possession of delivery rights. While they do play a role for the farmers in making production decisions, they are not included in our measure of productivity and profitability, which only considers the use (and thus cost) of physical inputs and outputs.

above the 95 % percentiles are not included in the calculation of regional averages to be robust against potential outliers.

Summary statistics for the variables used in the analysis are provided in Table 3-1. The use of crop-specific inputs and other variable inputs were estimated using equations (3-4) and (3-5) based on our entire FADN sample (n = 16,717) to exploit as much information as possible. We report the estimated per hectare use (implicit quantities, or constant costs, measured in EUR) of these inputs for distinct crop categories in Table 3-5 in the Appendix. Below this table, we present cost estimates by a contribution margin calculator provided by the Bavarian State Research Center for Agriculture (LfL) for Bavaria. Our estimates are in line with these values, both in absolute terms and relative values across crop categories. We therefore trust that the estimated quantities are reliable.

Table 3-1. Summary statistics for variables used in the analysis

Variable	Mean	Std. Dev.	Minimum	Maximum
Sugar beet output (tonnes)	1,172.4	1,471.9	12.0	26,892.0
Sugar beet area	18.5	23.5	0.2	428.7
Labour (hours)	1,141.0	1,755.2	8.1	52,405.4
Capital (cEUR)	7,806.7	10,387.2	0.0	199,121.0
Crop-specific inputs (cEUR)	15,625.3	19,032.7	149.0	29,4102.8
Other variable inputs (cEUR)	11,135.7	14,623.5	88.0	28,4538.9
Price for sugar beets (EUR/tonne)	43.7	10.4	14.8	142.0
Rental price for land (EUR/ha)	286.9	93.0	100.8	590.3
Price of labour (EUR/hour)	9.0	1.4	3.9	12.7
Price of capital (EUR)	0.1	0.1	0.0	0.7
Price index for crop-specific inputs	1.0	0.1	0.7	1.3
Price index of other inputs	1.0	0.1	0.8	1.2
Utilised agricultural area	258.7	480.5	3.9	5,745.5
Share of land allocated to sugar beet	0.1	0.1	0.0	1.0

Note: n= 8,749; cEUR is constant Euros with base year = 2010.

3.6 Results

The unweighted averages of profitability and its components are presented in Table 3-2. We also report yield levels (tonnes per hectare land) for two reasons. First, beet output and land devoted to beet production are both directly observed in the data set and thus land productivity can be computed without estimating input allocations. Second, yield is an intuitive measure often used for benchmarking by farmers and stakeholders. This measure is inconclusive because it neglects changes in the use of other inputs and therefore does not allow conclusions about farm performance. However, it may be used as approximation, and it is interesting to see whether land productivity growth is offset by an increased use (or cost) of other inputs.

The profitability levels can be interpreted as quota rent, because they represent the residual profit after accounting for all variable and fixed inputs. Values above unity indicate that sugar beet production values exceed sugar beet production costs. This was the case in all years except for the four years following the 2006 reform (i.e. 2007– 2010). The year 2008 was the least profitable year for sugar beet farming in Germany, with a profitability level 35.0 % ((0.911.40)/1.40) below its 2004 level. During the period 2004–2008, terms of trade sharply decreased at an average rate of 9.7 %, and recovered after 2010 along with increasing profitability levels. This observation suggests that changes in profitability were largely driven by changes in terms of trade during the study period. TFP, on the other hand, shows an increasing trend. Declines in TFP (2004–2006, 2009–2010, and 2011–2013) were accompanied by yield declines, illustrating the important role of land productivity in determining TFP. Overall, profitability was 15.1 % lower in 2013 compared to 2004, despite a 15.1 % growth in TFP, at the sample mean.

Table 3-2. Unweighted averages of profitability, terms of trade, TFP and yield

Year	PROF		TT		TFP		Yield (t/ha)	
2004	1.40	(0.41)	1.43	(0.27)	1.00	(0.28)	59.67	(11.55)
2005	1.27	(0.38)	1.31	(0.26)	0.99	(0.28)	58.98	(11.41)
2006	1.10	(0.33)	1.16	(0.21)	0.95	(0.27)	57.36	(12.84)
2007	0.96	(0.28)	0.95	(0.20)	1.03	(0.31)	62.23	(13.14)
2008	0.91	(0.26)	0.88	(0.20)	1.07	(0.33)	60.92	(14.18)
2009	0.98	(0.29)	0.85	(0.21)	1.19	(0.34)	67.16	(13.36)
2010	0.92	(0.28)	0.84	(0.21)	1.11	(0.30)	63.90	(12.96)
2011	1.22	(0.32)	1.00	(0.19)	1.25	(0.33)	73.03	(13.42)
2012	1.24	(0.31)	1.05	(0.20)	1.21	(0.30)	69.58	(12.00)
2013	1.19	(0.34)	1.05	(0.22)	1.15	(0.29)	66.22	(13.71)

Note: n = 8749*;* Standard deviations are in parentheses; PROF is profitability, TT is terms of trade, TFP is total factor productivity.

The changes in TFP, profitability and terms of trade are illustrated in Figure 3-3, separated by catchment areas of the three sugar companies. These indices compare productivity, profitability and terms of trade to their respective values in 2004. Since it is not indicated in the data which factory farms deliver their beets to, we assume that each farm delivers beets to its nearest factory and exclude farms that are located at border regions.[13] This reduces the sample size from 8,749 to 6,107 observations. The figure shows that profitability closely followed changes in terms of trade in all regions. Further, it is seen that increasing TFP compensated for the loss in terms of trade. In particular, the considerable TFP growth between 2006 and 2009 counteracted profitability losses in all regions. As a result, profitability level in 2013 equals the profitability level in 2004 even though terms of trade are 20 % below the initial level in catchment area 1. In catchment areas 2 and 3, by contrast, sugar beet profitability in 2013 is about 20 % and 10 % below 2004 levels, respectively. Terms of trade, on the other hand, are 22 % below 2004 levels in 2013. Thus, reduced terms of trade were fully compensated by TFP growth in catchment area 1 and partly compensated in catchment areas 2 and 3.

[13] The procedure was assessed to be appropriate by experts from sugar beet farming associations.

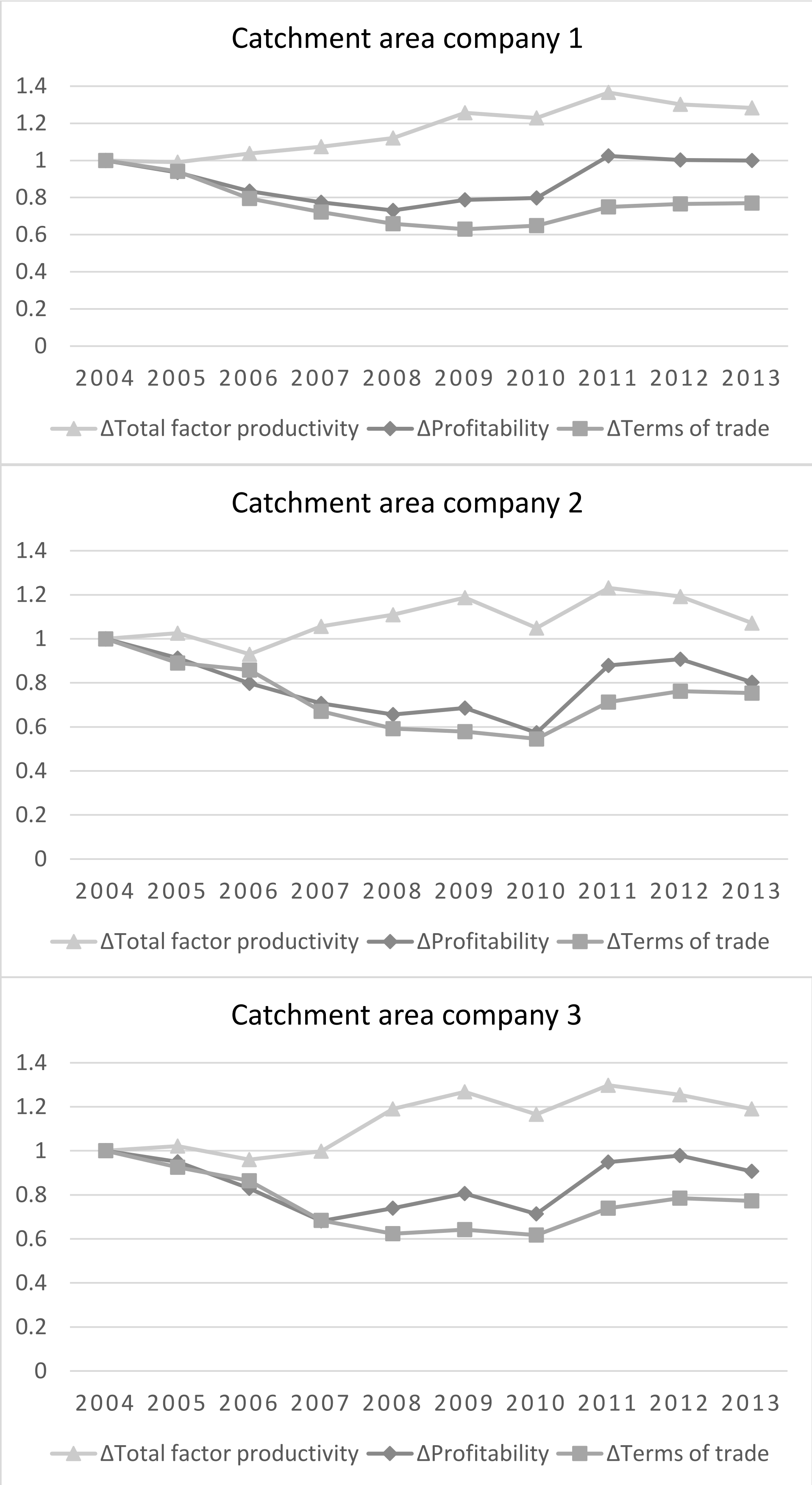

Figure 3-3. Changes in total factor productivity, profitability and terms of trade by catchment areas

3.6.1 Sector productivity

Table 3-3 reports levels of sector productivity, the within-effect (unweighted average sugar beet TFP) and the between-effect (the effect of resource allocation). The values of the average TFP are from Table 2. The positive values of the between-effect mean that – throughout the study period – farms with more productive beet production hold larger market shares than farms with lower sugar beet TFP. Therefore, sector TFP is above the unweighted average TFP in all years. Further, it can be seen that there was an increase in the between-effect in the years immediately after the 2006 reform. This indicates that resource allocation positively contributed towards sector productivity in these years. However, the value of this term is relatively unstable after the year 2009. Therefore, we cannot definitively say whether resource allocation continues to be significantly more efficient in recent years. On average, at least, the covariance term takes higher values after 2006 compared to the years previous to the reform, providing some support for the hypothesis that the reform contributed to an increase in sector productivity.

Figure 3-4 visualises the development of sector productivity, decomposed into the within-farm component and the between-farm component, along with profitability and terms of trade. The figure underlines that the contribution of the between-effect towards sector productivity became slightly more important after the 2006 reform, and that productivity growth worked against unfavourable price developments. Overall, the within-effect played a larger role in the determination of sector productivity changes than the between-effect. We investigate the contributions of the two effects over time in more detail in the following section, segmented by catchment areas of the three main sugar companies in Germany.

Table 3-3. Decomposition of aggregate sugar beet TFP

Year	Sector TFP	Within-effect		Between-effect	
2004	1.12	1.00	(89.57 %)	0.12	(10.43 %)
2005	1.10	0.99	(90.25 %)	0.11	(9.75 %)
2006	1.04	0.95	(91.02 %)	0.09	(8.88 %)
2007	1.17	1.03	(88.43 %)	0.14	(11.57 %)
2008	1.21	1.07	(88.50 %)	0.14	(11.50 %)
2009	1.32	1.19	(90.05 %)	0.13	(9.95 %)
2010	1.22	1.11	(91.22 %)	0.11	(8.78 %)
2011	1.39	1.25	(90.15 %)	0.14	(9.85 %)
2012	1.31	1.21	(92.06 %)	0.10	(7.87 %)
2013	1.26	1.15	(91.10 %)	0.11	(8.90 %)

Note: n = 8749; Numbers in parantheses are shares of sector productivity.

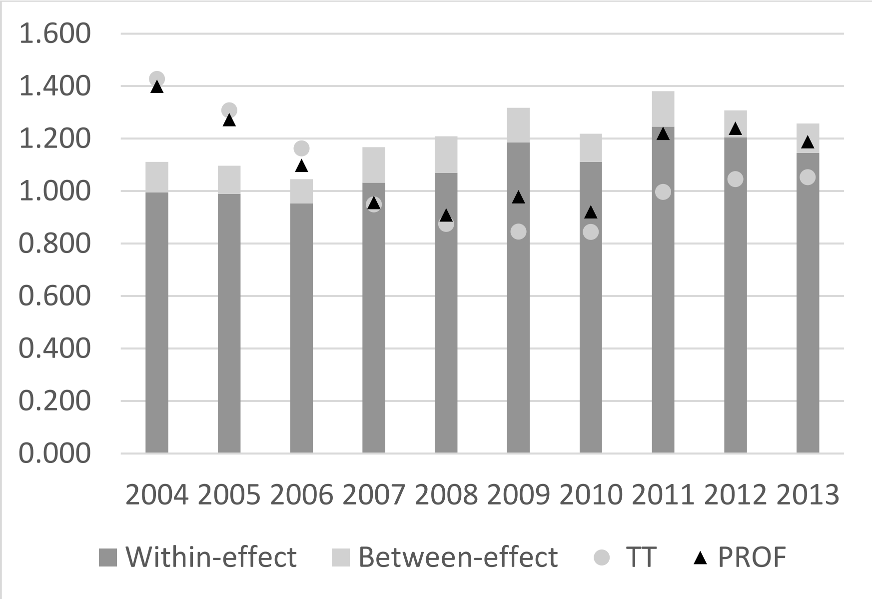

Figure 3-4. Productivity decomposition, terms of trade and profitability

3.6.2 Reallocation and ownership structure

To describe the association between ownership structures of sugar companies and the resource allocation across sugar beet growers, we calculated the decomposition of productivity in (3-3) separately for farms within catchment areas of different sugar companies. Changes in sector productivity, as well as the contributions of the within-effect and the between-effect, are illustrated in Figure 3-5. The 2004 value of catchment area of company 1 is used as the base value for all indices. The upper panel shows that sector productivity of beet growing in the catchment area of company 1 was below that in the areas of companies 2 and 3 throughout the data period. Comparing the three panels, it becomes clear that sector productivity growth was largely driven by average farm productivity growth in all regions. The contribution of the between effect is far less pronounced.

The bottom panel shows that the between-effect in the catchment area of company 2 was consistently below that of farms in the catchment areas of the other two sugar companies, indicating that the contribution of resource allocation to sector productivity was lowest in the catchment area of the company with the least transparent market for stocks and delivery rights. In the other two regions, a sudden increase in the contribution of resource reallocation to sector productivity growth is observed after 2006, the year the sugar market reform was implemented. However, a decline in the between-effect occurred towards the end of the study period, especially within the catchment area of the company 3. This is surprising because it implies that more productive farms lost market shares, or that farms with higher market shares suddenly become less productive.

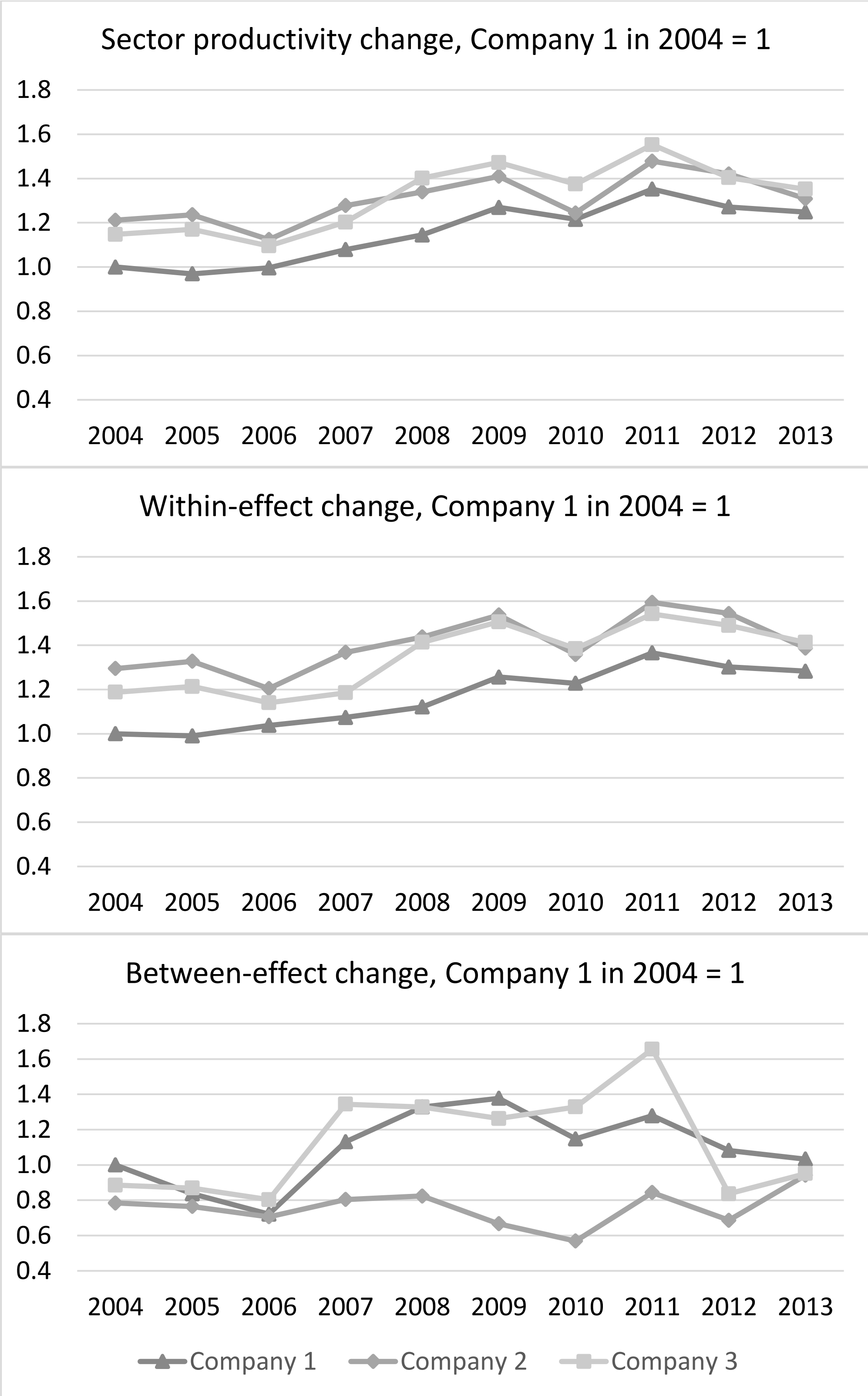

Figure 3-5. Contributors to sector productivity growth by catchment area

One possible explanation is that productivity differences between farms can vary because of production uncertainty and weather fluctuations. Further, the data show that average TFP levels as well as farm-level heterogeneity in TFP were considerably lower in 2012 than in 2011, in particular for company 3, giving less scope for sector productivity gains from efficient allocation. Nevertheless, the results indicate that resource allocation became on average more efficient after the 2006 reform. We performed the sectoral analysis for profitability levels as well. The results are shown in Figure 3-6 in the Appendix. It is plausible that the between-effect resembles the one from the productivity decomposition, as productivity change is, along with price changes, a component of profitability change. The changes in the between-effect, however, fluctuate more than those observed from the productivity decomposition, as they are confounded by year-to-year variations in the terms of trade.[14]

The results of the system-GMM estimation for the model in (3-6), reported in Table 3-4, allow us to draw statistical inferences about resource allocation in sugar beet farming. Both the Sargan (1958) and Hansen (1982) tests of overidentifying restrictions and the Arellano and Bond (1991) test of second-order autocorrelation show the desired results, namely that the null hypotheses of joint validity of instruments and no autocorrelation cannot be rejected at the usual levels of significance. The statistically significant estimate for the lagged covariance term confirms the expected persistency of the farm-level between-effect. The positive estimate for company 1 indicates that resource allocation is on average more efficient in its catchment area compared to the catchment area of company 2, even though the difference is only statistically significant at the 10 % level. This difference increased after the 2006 reform, as indicated by the significantly positive coefficient for the interaction term between the post-reform dummy variable and company 1. Both the coefficient for company 3 and its interaction term with the post-reform dummy are statistically insignificant. However, they are jointly significant at the 10 % significance level (p-value = 0.066), implying that resource allocation after the 2006 reform is more efficient in the catchment area of company 3 compared to the catchment area of company 2. Overall, the regression results show that the contribution of resource reallocation towards sector productivity growth after the 2006 reform was significantly higher in the catchment area of companies 1 and 3 compared to company 2. Finally, utilised agricultural area is positively related to the covariance term, while specialisation in sugar beet production is not statistically significant.

[14] Foster, Haltiwanger and Syverson (2008) compare the effects of productivity, prices and idiosyncratic demand on firms' survival in the manufacturing sector. Noting that more productive firms tend to charge lower prices, they use physical productivity as instrument for firm-level prices to estimate the demand function and derive producer-specific demand shocks. In our empirical case of sugar beet production, producers are price takers and demand shocks can be assumed to affect competing producers equally. Thus, we focus on cross-farm variation in productivity when analysing resource reallocation.

Table 3-4. Effect of the 2006 reform on productivity-enhancing resource reallocation

Variable	Coefficient		Std. Err.	z-statistic
One-period lag of cov	0.661	***	0.217	3.04
Company 1	4.21E-05	*	2.40E-05	1.76
Company 3	1.85E-05		1.92E-05	0.96
Post-reform x company 1	4.11E-05	**	2.05E-05	2.00
Post-reform x company 3	2.63E-05		2.43E-05	1.08
Utilized agricultural area	5.76E-07	*	3.12E-07	1.85
Land share sugar beets	4.79E-04		4.10E-04	1.17
Year 2005	7.15E-05	***	2.68E-05	2.66
Year 2006	2.68E-05		3.35E-05	0.80
Year 2007	6.88E-05	***	1.64E-05	4.20
Year 2008	8.41E-05	***	1.99E-05	4.23
Year 2009	-2.89E-05		2.21E-05	-1.31
Year 2010	-7.39E-06		1.01E-05	-0.73
Year 2011	1.79E-05		1.09E-05	1.64
Year 2012	7.98E-07		1.10E-05	0.07
Year 2013		*reference year*		
Constant	-1.77E-04		1.17E-04	-1.52
Nr. of observations	4527			
Nr. of farms	1045			
Nr. of instruments	50			
Wald test for overall significance				
Chi-squared	124.63	***		
P-value	0.000			
Arrelano-Bond test of 2nd order autocorrelation				
Z-statistic	-0.48			
P-value	0.63			
Sargan test of overidentifying restrictions				
Chi squared	38.61			
P-value	0.269			
Hansen test of overidentifying restrictions				
Chi squared	38.37			
P-value	0.278			

Note: ***, ** and * indicate 1 %, 5 % and 10 % significance levels, respectively. The dependent variable is the covariance term, representing the between-effect on sector productivity. The first year of the data is omitted due to the inclusion of the lagged value of the dependent variable. Catchment area of company 2 serves as reference for the policy effect. Results are obtained using the Blundell and Bond (1998) estimator with fifth and higher lags of endogeneous variables being used as instruments.

3.7 Discussion and conclusion

In this article, we examined changes in profitability and productivity of sugar beet farming in Germany over a 10-year period from 2004 to 2013. We decomposed profitability of sugar beet farming into total factor productivity (TFP) and terms of trade effects using a Lowe quantity index that allows consistent comparisons across times and space (O'Donnell, 2012b, 2012a). The results show that average sugar beet profitability in Germany decreased between 2004 and 2008 due to unfavourable price developments and recovered after 2010. This is in line with the low EU market prices for white sugar in the years following the 2006 reform. From 2007 to 2010, the average production value of sugar beet was below production cost, underlining the importance of single farm payments, which were increased to compensate farmers for the losses as a consequence of a reduction in the minimum price. We also observe that TFP growth partly compensated losses in terms of trade. Regarding the magnitude of TFP growth, there are very few comparable studies in the literature on sugar beet TFP growth because productivity is usually measured at the farm rather than the crop level. Two exceptions are Thirtle (1999) and Amadi, Piesse and Thirtle (2004), who use crop-specific input data for sugar beet to calculate partial and TFP indices. Thirtle (1999) finds that TFP in sugar beet production increased by 2.7 % per year between 1954 and 1992. Amadi, Piesse and Thirtle (2004) use more recent data from the same data source to analyse growth rates between 1970 to 1996. According to their estimates, TFP growth rate in the UK was 3.39 % per annum. Both studies measure the exponential growth rate, which is obtained by regressing the natural logarithm of TFP on a time trend. Applying this procedure to our TFP values, we obtain an annual growth rate of 2.83 % between 2004 and 2013, which lies between the findings of Thirtle (1999) and Amadi, Piesse and Thirtle (2004).

We further find that the contribution of production reallocation on sector productivity growth was rather low. This contradicts our expectation that liberalisation of the market would make resource reallocation more attractive. However, two mechanisms might have worked against this expectation. First, even though minimum prices for sugar beet were reduced, actual prices remained largely above the minimum, especially after 2009. Second, transaction costs for trading delivery rights quota trade may have hampered reallocation of production. To further investigate this, we compared three subregions in Germany where the dominating sugar companies differ in the mechanisms of delivery rights transfer between farms. Using a system-GMM estimator to control for potential endogeneity, we find the productivity-enhancing effect of the reform was higher in the regions where delivery rights can be traded between sugar beet growers (company 1) and where delivery rights are not linked to capital contributions (company 3).

In terms of implications for policy and industry, the results demonstrate how essential TFP growth is for maintaining beet profitability in periods of low sugar prices. As suggested by the results, a flexible and market-based approach to coordinate production allocation can be beneficial for aggregate TFP growth. For the industry, higher aggregate beet productivity would improve the competitiveness of the industry if it is reflected in lower beet prices. Generally, aggregate productivity is maximised if delivery rights are allocated to farmers who value them the most (assuming equal prices among farms), e.g. via auction markets (see Bogetoft et al., 2007). However, even though policy encouraged farmers to give up delivery rights through the voluntary restructuring scheme, the magnitude of the observed gain in our empirical example is relatively small. Thus, it is not clear whether additional administrative costs for more effectively distributing delivery rights will actually be covered by the associated gains. Considering within-farm productivity growth as the main determinant of aggregate productivity growth during the study period, promoting research and development remains an important tool to support the sector in times without sugar quota. In this context, we must note that full-time farm enterprises are overrepresented in the FADN data we use in our analysis. Hence, the average farm size in our sample is considerably larger than the German average. If small farms are on average less productive and more likely to give up or transfer delivery rights, then our results for the productivity-enhancing effect of the reform can be viewed as a lower bound measure.

There are at least three avenues for future research in this area. First, the study could be extended to further countries, especially countries where delivery rights are more easily transferred than in Germany. Second, a stronger causal linkage could be established. For instance, one could collect data from farms that are located at the border region of factories run by different companies and compare the contribution of production allocation towards sector productivity between farms that deliver to different companies. This could be done in a regression discontinuity framework (e.g. Hahn, Todd and Klaauw, 2001). Third, one could further disentangle the farm-level productivity changes into technical change and various measures of efficiency changes, as well as weather effects (see, e.g., Njuki, Bravo-Ureta, B. E. and O'Donnell, 2018). Identification of the main drivers of productivity and profitability changes at the farm level would provide additional insight into how the competitiveness of the sector can be increased.

Appendix

Appendix 1: Table and Figure

Table 3-5. Estimated per hectare use of variable inputs for distinct crop categories

	Crop-specific inputs (cEUR)	Other variable inputs (cEUR)	Sum (cEUR)	Obs.
Sugar beet	857.05	655.54	1,512.59	8,749
	(250.59)	(266.27)	(451.84)	
Cereals (e.g. wheat,	467.00	436.99	903.98	16,004
barley, grain maize)	(408.05)	(355.60)	(692.47)	
Other field crops (potatoes,	526.02	393.52	919.53	13,565
legumes, oilseed)	(357.02)	(387.65)	(678.60)	
Forage crops (e.g. corn	275.45	479.43	754.88	12,454
silage)	(341.01)	(397.25)	(672.39)	
Vegetables, wine,	829.92	747.66	1,577.58	3,869
permanent crops	(970.50)	(1019.51)	(1806.86)	
Total	519.91	500.34	1,020.25	16,717
	(528.11)	(565.84)	(996.32)	

Note: cEUR is constant Euros with base year = 2010. Standard deviations are in parentheses. Variable input costs provided by LFL are: EUR 1630 for sugar beet, EUR 870 for wheat, EUR 2790 for potatoes, EUR 660 for peas, EUR 910 for canola, EUR 990 for corn silage; for the last category, it is difficult to find representative examples (as also indicated by the large standard deviation). Categories are based on FADN standard results.

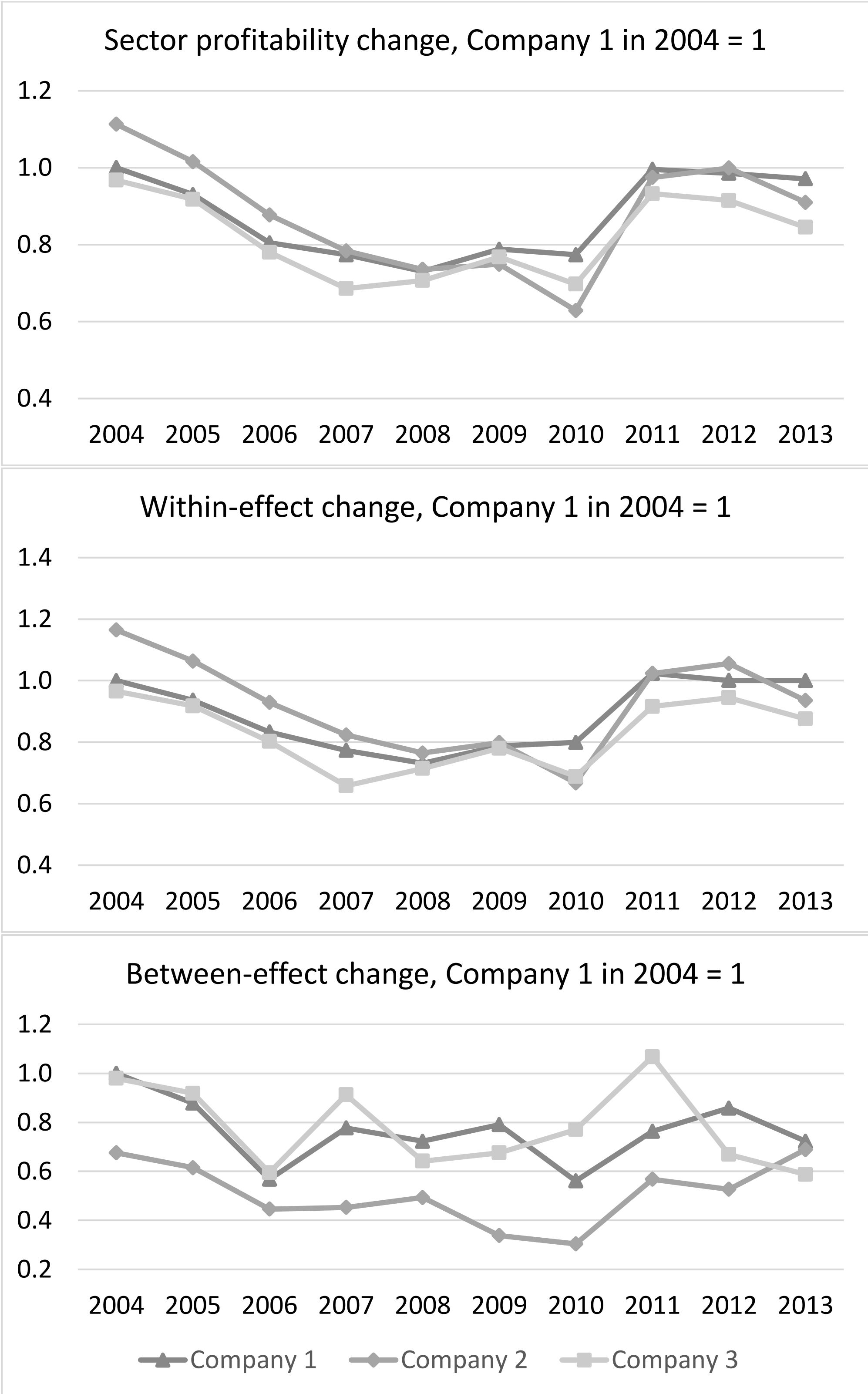

Figure 3-6. Contributors to sector profitability growth by catchment areas.

Note: Decomposition obtained with $PROF_t = \sum_{i=1}^{N} \sigma_{it} PROF_{it} = \overline{PROF}_t + \sum_{i=1}^{N}(\sigma_{it} - \bar{\sigma}_t)(PROF_{it} - \overline{PROF}_t)$.

Appendix 2: Behavioural Approach for Input Allocation

The profit maximisation approach for crop-specific input allocation relies on the assumption that farmers allocate variable inputs across a given amount of land in a profit-maximising way. At the optimum, input prices equal the marginal products for each crop produced multiplied with by output price of the corresponding crop:

$$W_{jit} = P_{kit} \frac{\partial f_{kit}}{\partial X_{kjit}}, k = 1, \dots, K; j = 1, \dots, J \tag{5-A1}$$

Using elasticities $e_{kjit} = (\partial_{kit}/\partial X_{kjit} \times (X_{kjit}/Q_{kit})$, Just et al. (1990) show that the first order conditions can be rewritten as:

$$X_{kjit} = \frac{R_{kit}}{W_{jit}} \times e_{kjit} \ , \tag{5-A2}$$

where R represents revenue. Letting elasticities vary across farms, crops and time, the authors derive the estimable form for crop-specific input allocation:

$$X_{kjit} = \sum_{k=1}^{K} [\alpha_{kj} + \beta_{ji} + \gamma_{jt}] \times \frac{R_{kit}}{W_{jit}} + \xi_{jit} \ , \tag{5-A3}$$

where again α_{kj} denotes the crop effect, β_{ji} is the farm effect and γ_{jt} is the time effect. The estimated parameters can then be used to calculate profit maximising crop-specific input use:

$$\hat{X}_{kjit} = \hat{\alpha}_{kj} + \hat{\beta}_{ji} + \hat{\gamma}_{jt} \frac{R_{kit}}{W_{jit}} \ . \tag{5-A4}$$

Applying this method to our data, we obtain the following per hectare input use:

Table 3-6. Estimated per hectare use using the behavioural approach

	Crop-specific inputs (cEUR)	Other variable inputs (cEUR)	Sum (cEUR)	Obs.
Sugar beet	1402.07	1481.19	2,883.25	8,749
	(450.24)	(599.69)	(963.66)	
Cereals (e.g. wheat,	384.86	326.14	711.00	16,004
barley, grain maize)	(157.11)	(204.43)	(302.72)	
Other field crops (potatoes,	686.80	938.24	1,625.04	13,565
legumes, oilseed)	(10996.74)	(26585.12)	(37406.17)	
Forage crops (e.g. corn	72.13	91.72	163.85	12,454
silage)	(303.18)	(362.55)	(652.14)	
Vegetables, wine,	1237.95	1469.54	2,707.49	3,869
permanent crops	(2332.65)	(2716.19)	(4595.24)	
Total	517.92	494.08	1,012.00	16,717
	(581.34)	(582.58)	(1065.78)	

Note: cEUR is constant Euros with base year = 2010; standard deviations are in parentheses

4

Diversification Economies in Dairy Farming – Empirical Evidence from Germany*

Abstract. This article explores how farm size is related to economic benefits from diversification. Using a data set pertaining to Bavarian dairy farms (2000–2014), we estimate an input distance function (IDF) to derive cost complementarities between distinct outputs. A Bayesian estimation technique is used to improve the theoretical consistency of the IDF. The results show that small dairy farms are more likely to benefit from diversification between milk and livestock production, while larger farms tend to benefit from diversification between milk and crop production. Both managerial and policy implications are discussed.

Keywords: Bayesian estimation, cost complementarities, farm diversification, input distance function, regularity conditions

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* This is a pre-copyedited, author-produced version of an article accepted for publication in the *European Review of Agricultural Economics* following peer review. The version of record [Wimmer, S. and Sauer, J. (2020). Diversification economies in dairy farming – empirical evidence from Germany. *European Review of Agricultural Economics* 47(3): 1338-1365] is available online at: https://doi.org/10.1093/erae/jbaa001. Stefan Wimmer is the main author of this contribution. Both authors developed the research idea and the study design. Stefan Wimmer performed the statistical analysis and wrote the manuscript. Johannes Sauer supervised the empirical estimation and improved the article with his feedback and suggestions throughout the whole process.

4.1 Introduction

The optimal production structure of firms in terms of size and degree of specialisation has been a central question in economics for decades. Especially in the agricultural sector, a significant structural change has been observed in recent years. While the number of farms in the EU-28 decreased by 28 per cent from 14.5 million in 2005 to 10.5 million in 2016, the average farm size increased by 40 per cent from 11.9 to 16.6 hectares (Eurostat, 2019). This trend towards larger but fewer farms is often viewed critically by society. In order to slow down structural change and to support rural development, the European Union (EU) promotes farm activities going beyond agricultural production such as farm tourism or direct marketing. However, the concept of diversification is not limited to activities taking place outside agricultural production. Since our primary interest is in structural change for agriculture, which is commonly defined by the number of farms and the average farm size expressed in utilised agricultural area, we focus on farm diversification within agricultural production, for example the joint production of livestock products and cash crops.

This article aims to investigate how structural change interacts with diversification economies. Specifically, we ask the question whether the pattern of diversification economies varies across farm size. For example, one could expect that large farms benefit from different output combinations compared to small farms due to labour-saving technologies or different skill requirements. If this were true, structural change would not only imply larger farms but also farms with different output compositions. To empirically test for diversification economies, we apply a stochastic input distance function (IDF) to a sample of dairy farms in Bavaria, a federal state in southern Germany, distinguishing between four farm outputs: milk; livestock production (i.e. meat); crops; and other outputs such as energy production, farm tourism, or the provision of contract services. Diversification economies are then measured as cost complementarities between individual outputs, which are obtained from the estimated parameters of the IDF (Hajargasht, Coelli and Rao, 2008). We trust that the results from our empirical study are relevant for the entire European dairy sector, because approximately 23 per cent of the milk in Germany and 5 per cent of the milk in the EU-28 were produced in Bavaria in 2017. Moreover, the number of specialised dairy farms, both in Bavaria and in the EU-28, decreased by an annual average rate of three per cent between 2005 and 2016 (Eurostat, 2019), indicating a similar pace of structural change in Bavaria and the EU average.

Farm diversification has been widely investigated for decades. Pope (1967) described farm diversification as a portfolio problem where the optimal choice depends on the decision maker's preference for risk and feasible production sets. Consistent with risk theory, Pope and Prescott (1980) found that wealthier farmers and corporations are more specialised. Mishra, El-Osta and Sandretto, C. L. (2004) found a positive relationship between farm enterprise diversification and sole ownership, and a negative relationship between diversification and off-farm income. Chavas and Di Falco (2012) estimated the role of economies of scope as well as production risk management in diversification-related decisions at the farm-level in Ethiopia where no other insurance mechanism was available. In our article, we focus on cost savings through output diversification that occurs from the technological relationships of outputs and inputs. As shown by Chambers and Voica (2017), production decisions do not depend on risk preferences if off-farm income opportunities are available and functioning financial markets exist. These may be reasonable assumptions in the context of farms in Bavaria, where more than 60 per cent of farms are operated part-time. However, if the assumption of functioning financial markets does not hold, risk-averse farmers may choose a different output and input mix than risk-neutral farmers (see, e.g., Kumbhakar, 2002). Hence, we emphasise that diversification can still be a strategy to reduce risk, but other opportunities such as hedging, insurance, contracting or the use of risk-reducing inputs also exist (Just and Pope, 2003). As discussed below, our methodology does not rely on the assumption of cost-minimising behaviour.

A popular approach to empirically measure diversification benefits is estimating economies of scope based on a cost function approach. Economies of scope exist when costs can be saved by jointly producing multiple outputs (Baumol, Panzar and Willig, 1988). For example, Fernandez-Cornejo et al. (1992) found economies of scope between various combinations of milk, cattle, crop, and hog production in Germany. Wu and Prato (2006) showed that scope economies exist between crop and livestock production in Missouri, U.S.A., even though they are challenged by a reduction of allocative efficiency due to joint production. Melhim and Shumway (2011) found that the degree of scope economies decreases with farm size, implying that larger farms have fewer incentives to diversify their production compared to smaller farms. Studies estimating economies of scope for non-agricultural sectors include Cantos and Maudos (2001), Farsi, Fetz and Filippini (2007), and Triebs et al. (2016). Estimating a cost function to elicit scope economies is problematic if input price data are not accessible or lack sufficient variation across firms. Thus, several studies that measure diversification economies have preferred to make use of a distance function as an alternative approach to model multi-output technologies. However, these studies mainly focused on output complementarities (or synergies), which does not consider cost-minimising input use adjustments on the farms when altering output compositions. Hence, it is only a lower-bound estimate of scope economies (Coelli and Fleming, 2004). For instance, Coelli and Fleming (2004) evaluated diversification economies between coffee, subsistence food and cash food production for Papua New Guinea; Morrison Paul and Nehring (2005) assessed the impact of output complementarities on farm performance in the United States; and Chavas and Di Falco (2012) found complementarities among different field crops for Ethiopian farms.

Contrary to these studies, we exploit the duality relationship between the cost function and the IDF to evaluate *cost* complementarities between distinct outputs as proposed by Hajargasht, Coelli and Rao (2008). To the best of our knowledge, Fleming and Lien (2009) is the only study that applies this method to the farm sector.[15] They estimate cost complementarities in Norwegian agriculture, restricting the analysis to the sample mean of the data. We extend the literature by providing an in-depth analysis of cost complementarities at the farm-level, allowing us to derive implications on the pattern of diversification economies across farm size and to identify farm characteristics that may enhance or prevent farms from operating at the optimal level of output combination. Our second contribution is the imposition of regularity conditions on the IDF using a Bayesian estimation framework following O'Donnell and Coelli (2005), which improves its consistency to economic theory. This is particularly important in this application, as the derivation of cost complementarities from the parameters of an IDF depends on duality theory.

The remainder of the article is organised as follows. In Section 4.2, we describe the conceptual framework of diversification economies and the duality relationship between cost and IDF functions. Section 4.3 presents the data and descriptive statistics. The empirical framework, including the imposition of regularity conditions on the IDF, is introduced in Section 4.4. The results are presented and discussed in Section 4.5 and Section 4.6 concludes.

4.2 Conceptual framework

The analysis of economies of multi-product firms has drawn a lot of attention since the seminal works by Baumol (1977), Willig (1979) and Baumol, Panzar and Willig (1988). These authors define economies of scope to exist when costs for a multi-output firm are lower than costs for multiple firms producing the same amount of output separately, i.e.,

$$C\left(\sum_{m} q_m, w\right) < \sum_{m} C(q_m, w) \quad , \tag{4-1}$$

where C denotes costs, q_m is the m-th output, and w is a vector of input prices. This definition of economies of scope compares the production cost of diversified firms with the production cost of fully specialised firms. Chavas and Kim (2010) provide an extended version for the evaluation of economies of diversification allowing for partial specialisation and also for specialisation in a subset of outputs. In our paper, we focus on cost complementarities between distinct outputs, which Coelli et al. (2005, p. 30) call *product-specific economies of scope*:

[15] A related concept is firm flexibility, which contains the primal measure for economies of scope by Hajargasht, Coelli and Rao (2008) as one component (Renner, Glauben and Hockmann, 2014). The application in Renner, Glauben and Hockmann (2014) is to farms in Poland.

$$Comp_{mn} = \frac{\partial^2 C(q,w)}{\partial q_m \partial q_n}, \qquad m \neq n \tag{4-2}$$

Equation (4-2) describes how the marginal costs of producing one good respond to producing an additional unit of another good. If this expression is negative for a specific firm, the firm experiences cost complementarities between outputs m and n. As shown by Baumol, Panzar and Willig (1988, pp. 75-79), cost complementarities are a sufficient condition for the existence of economies of scope as defined by equation (4-1). They arise from the presence of public inputs that can be used for different production processes without additional costs, once they are acquired for the production of one good (e.g. managerial knowledge). Another source of scope economies is the presence of shared inputs (Baumol, Panzar and Willig, 1988), representing the role of fixed costs and their changes under alternative specialisation schemes. Thus, even without cost complementarities, economies of scope may exist. Nevertheless, evaluating cost complementarities in (4-2) is preferred over the direct estimation of economies of scope in (4-1) in our empirical application for several reasons. First, it does not require evaluating the estimated function outside the data range in situations where only diversified firms are observed (e.g. Saal et al., 2013). Second, it allows the use of functional forms that cannot accommodate zero values, such as the popular translog function. Third, the measure in (4-2) can be estimated based on the first and second derivatives of the IDF following Hajargasht, Coelli and Rao (2008). Estimating a cost function is problematic if input price data are not accessible (e.g., the price of capital) or if they lack variation across firms. For the empirical case used in this study, national price indices are available for several inputs but no price data exists at a sub-regional or even at the firm-level. In fact, it is reasonable to assume that input prices do not significantly differ within an individual German state. Additionally, estimating the IDF does not require us to make behavioural assumptions such as profit maximisation or cost minimisation (e.g. Coelli et al., 2005, p. 47). We therefore use the duality relationship between the cost function and the IDF to recover cost complementarities defined in equation (4-2) from the IDF (Hajargasht, Coelli and Rao, 2008).

The Shephard (1953, 1970) IDF describes the degree to which a firm can contract its input vector such that a given output can be produced. To define the IDF, let $q \in R_+^N$ be a firm's output vector and $x \in R_+^N$ its vector of inputs. Then, the input requirement set $L(q)$ of the production technology T is given by

$$L(q) = \{x: (q,x) \in T\}. \tag{4-3}$$

The IDF is formally represented by

$$D^I(q,x) = max \left\{\lambda: \frac{x}{\lambda} \in L(q)\right\}. \tag{4-4}$$

In equation (4-4), λ is a scalar between 1 and infinity. Firms with $\lambda = 1$ are technically efficient, because they operate on the boundary of the input requirement set. If $\lambda > 1$, it is possible to produce the same amount of output with less input and therefore these firms are characterised as technically inefficient. If inputs are weakly disposable, the IDF is a perfect representation of the production technology (Färe and Primont, 1995). It is also reciprocal to the Farrell (1957) measure of input-oriented technical efficiency. The duality of IDFs and cost functions relies on theoretical properties of the IDF. To be consistent with economic theory, it must be non-decreasing in inputs, non-increasing in outputs, homogenous of degree 1 in inputs, and concave in inputs (e.g. Coelli and Perelman, 1999; Kumbhakar et al., 2008; Hirsch et al., 2020).[16] As our measurement approach depends on the duality principle, we put a particular focus on these regularity conditions in our empirical analysis.

To derive an expression for the second order derivatives of the cost function from the IDF, Hajargasht, Coelli and Rao (2008) use the following dual relationship:

$$C(q,w) = min\{w'x: D^I(x,q) \geq 1\} \tag{4-5}$$

Making use of Shephard's (1953) lemma ($x = C_w(q,w)$) and the envelope theorem, Hajargasht, Coelli and Rao (2008) show that the matrix of cost function second order derivatives, C_{qq}, is given by

$$C_{qq} = C\{D_q D_q' - D_{qq} + D_{qx}[D_{xx} + D_x D_x']^{-1} D_{qx}\} \ , \tag{4-6}$$

where D_x and D_q are vectors of first derivatives with respect to x and q, respectively, and D_{qx}, D_{xx}, and D_{qq} are matrices of second-order derivatives. In conjunction with equation (4-2), cost complementarities between outputs m and n exist if

$$\frac{1}{C}\frac{\partial^2 C(q,w)}{\partial q_m \partial q_n} = \frac{\partial D^I}{\partial q_m}\frac{\partial D^I}{\partial q_n} - \frac{\partial^2 D^I}{\partial q_m \partial q_n} + \begin{bmatrix} \frac{\partial^2 D^I}{\partial q_m \partial x_1} & \cdots & \frac{\partial^2 D^I}{\partial q_m \partial x_K} \end{bmatrix} \times$$
$$\begin{bmatrix} \frac{\partial^2 D^I}{\partial x_1^2} + \frac{\partial D^I}{\partial x_1}\frac{\partial D^I}{\partial x_1} & \cdots & \frac{\partial^2 D^I}{\partial x_1 \partial x_K} + \frac{\partial D^I}{\partial x_1}\frac{\partial D^I}{\partial x_K} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 D^I}{\partial x_K \partial x_1} + \frac{\partial D^I}{\partial x_K}\frac{\partial D^I}{\partial x_1} & \cdots & \frac{\partial^2 D^I}{\partial x_K^2} + \frac{\partial D^I}{\partial x_K}\frac{\partial D^I}{\partial x_K} \end{bmatrix}^{-1} \begin{bmatrix} \frac{\partial^2 D^I}{\partial x_1 \partial q_n} \\ \vdots \\ \frac{\partial^2 D^I}{\partial x_K \partial q_n} \end{bmatrix} < 0, m \neq n \ , \tag{4-7}$$

where K is the number of inputs. It is worth emphasising that the second order partial derivatives of the distance function with respect to two distinct outputs are interpreted as diversification economies or output synergies by Coelli and Fleming (2004) to differentiate from scope economies. While the

[16] Quasi-concavity in outputs is also often listed as regularity condition of the IDF. However, while concavity in inputs is derived from the convexity of the input requirement set, quasi-concavity is derived from the convexity of the producible output set (e.g. Nemoto and Furumatsu, 2014). The latter is not necessarily assumed in our sample of dairy farms, nor is it assumed for the derivation of the dual measure of economies of scope in Hajargasht, Coelli and Rao (2008).

simple measure of the second-order derivative assumes the input mix to be fixed (Coelli and Fleming, 2004), the expression in (4-7) allows variable inputs to be adjusted to the cost-minimising input mix.

4.3 Sample and descriptive statistics

Accounting data for farms located in Bavaria, a federal state in the southeast of Germany, were obtained from the Bavarian State Research Centre for Agriculture for the years 2000–2014. These data are annually collected based on a rotating sample consisting of commercial farms as part of the German contribution to the EU Farm Accountancy Data Network. To ensure that the sample is representative for commercial agricultural holdings, it is stratified according to region, type of specialisation and economic size. Following Kellermann and Salhofer (2014) and Frick and Sauer (2018), we consider dairy farms as farms that obtained at least two-thirds of total revenue from dairy production and more than two-thirds thereof from milk sales at the yearly average. This ensures a rather homogenous technology for the econometric estimation of the IDF but still provides a considerable range of farming activities for the evaluation of diversification economies. Farms with no more than two consecutive observations are dismissed to properly account for farm heterogeneity in the empirical estimation. Finally, 24 farm observations were identified by the BACON algorithm (Billor, Hadi and Velleman, 2000), which detects outliers in multivariate data based on Mahalanobis distances (Weber, S., 2010). Farms with at least one outlier appearance were dismissed from the sample, as well as farms with less than five cows or less than five hectares to exclude “hobby” farms. The resulting (unbalanced) panel dataset consists of 1,647 farms and a total of 18,772 observations. Figure 4-1 illustrates farm-level revenue shares of different production activities over the whole data period. Milk production accounted for the major portion of farm revenue with a 70.9 per cent share, on average. Livestock sales intrinsically linked to milk production (mainly calves and old dairy cows) and revenue from downstream fattening of cattle contributed 15.4 per cent and 4.4 per cent of total farm revenue, respectively. A very small portion of farms were also engaged in the production of other animals such as hogs or chickens, but their contribution to total farm revenue was almost zero (0.8 per cent). Even though nearly half of the farms produced crops for sale, their revenue contribution was also rather small. On average, crop sales accounted for 3.5 per cent of total revenue. Finally, all other outputs – including the provision of services, tourism, or electricity – contributed to about 5.0 per cent of total farm revenue, on average.

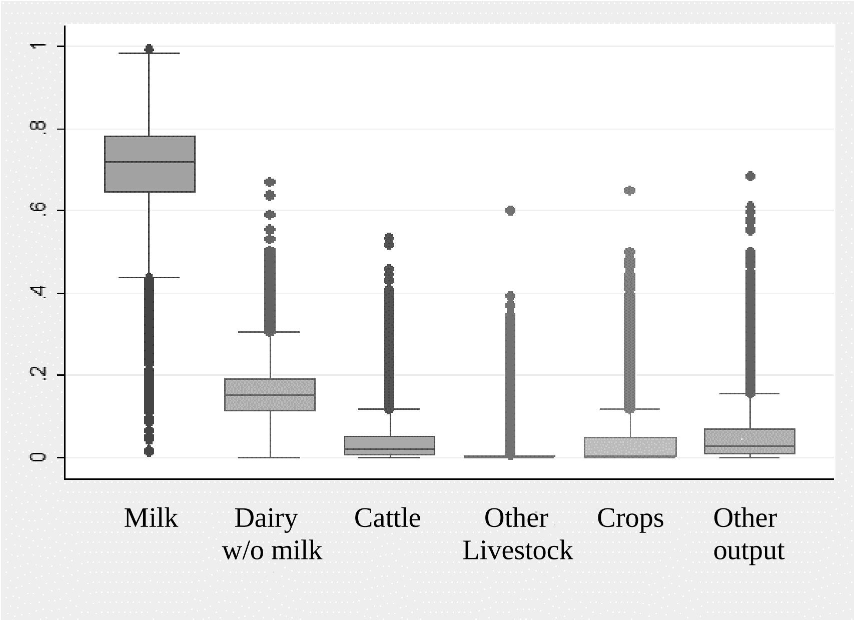

Figure 4-1. Farm-level revenue shares from different outputs (2000–2014)

For the estimation of the empirical model, we aggregated the outputs into four main groups: milk production ($Q1$), livestock production ($Q2$), crop production for sale ($Q3$) and other output ($Q4$). Inputs were aggregated into five categories. Land ($X1$) is measured in hectares of utilised agricultural area. Labour ($X2$) reflects the number of annual working units. Intermediate inputs ($X3$) capture expenses on animal-specific inputs (e.g., feed and veterinary inputs), crop-specific inputs (e.g., seed, fertiliser, pesticides, and other crop material), and other inputs such as electricity, fuel, or heating material. Cows ($X4$) represent the yearly average number of dairy cows on the farm. Finally, capital ($X5$) is proxied by depreciation costs (e.g. Sauer and Latacz-Lohmann, 2015; Mennig and Sauer, 2020). All outputs and monetary inputs are measured in terms of revenues or expenses, respectively, deflated by their specific nationwide price indices from the Destatis database with 2010 being used as the base year. This way, we obtain implicit quantities, which also reflect quality differences. As discussed in Reinhard, Lovell and Thijssen (1999), dividing the revenue (or expenses) by price indices, which do not vary across farms, cancels out price differences that result from variations in quality. This is particularly important in milk production, as the farm-gate milk price varies according to fat and protein content of the milk. The summary statistics of all variables used in the analysis – including farm and farmers' specific characteristics – are presented in Table 4-1.

Table 4-1. Summary statistics for variables used in the analysis

Variables	Unit	Mean	St. Dev.	Min	Max
Milk	1,000 c€	84.76	50.91	0.34	599.02
Livestock	1,000 c€	22.90	14.78	0.28	276.93
Crops	1,000 c€	5.22	11.10	0.00	156.67
Other output	1,000 c€	3.27	6.02	0.00	367.11
Land	ha	44.63	25.23	5.56	291.77
Labour	AWU	1.57	0.46	0.25	4.97
Interm. inputs	1,000 c€	45.69	26.95	4.20	284.70
Cows	Amount	38.00	18.27	5.00	182.24
Capital	1,000 c€	25.18	16.76	0.01	152.06
Farmer's age		48.55	9.69	19.00	92.00
Higher educ.	1 if farmer has higher agricultural education (master craftsman diploma or university degree), 0 otherwise	0.27	0.45	0.00	1.00
Full-time	1 if farm is operated full-time, 0 otherwise	0.95	0.22	0.00	1.00
Rev. share milk	Percentage	0.71	0.11	0.01	0.99
Rev. share livestock	Percentage	0.21	0.08	0.01	0.84
Rev. share crops	Percentage	0.04	0.06	0.00	0.65
Rev. share other outputs	Percentage	0.05	0.07	0.00	0.68
Share grassland	Percentage	0.58	0.29	0.00	1.00
Avg. field size	ha	3.70	3.28	0.01	71.49

n = 18,772
Note: c€ = constant Euros (2010), ha = hectares, AWU = annual working units

4.4 Empirical framework

4.4.1 Estimation of input distance function

To empirically estimate the IDF in a parametric framework, it has to be transformed, since the distance D^I is not observable. Following Lovell et al. (1994), we normalise D^I by one of the inputs to impose linear homogeneity with respect to inputs as required by economic theory. Homogeneity implies that $D^I(q, \omega x) = \omega D^I(q, x)$ for any $\omega > 0$. Using land (x_1) as normalising factor and setting $\omega = 1/x_1$ yields $D^I\left(q, \frac{x}{x_1}\right) = D^I(q, x)/x_1$. For the translog functional form with four outputs q and five inputs x, this implies

$$\ln\left(\frac{D_{it}^{I}}{x_{1it}}\right) = \alpha_0 + \sum_{m=1}^{4} \alpha_m \ln q_{mit} + \sum_{k=2}^{5} \beta_k \ln\left(\frac{x_{kit}}{x_{1it}}\right)$$
$$+\frac{1}{2}\sum_{m=1}^{4}\sum_{n=1}^{4} \alpha_{mn} \ln q_{mit} \ln q_{nit} + \frac{1}{2}\sum_{k=2}^{5}\sum_{l=2}^{5} \beta_{kl} \ln\left(\frac{x_{kit}}{x_{1it}}\right) \ln\left(\frac{x_{lit}}{x_{1it}}\right) \tag{4-8}$$
$$+\sum_{m=1}^{4}\sum_{k=2}^{5} \gamma_{mk} \ln q_{mit} \ln\left(\frac{x_{kit}}{x_{1it}}\right) + \sum_{z=1}^{14} \zeta_z r_{zit} + \sum_{t=2001}^{2014} \delta_t\, year_t = TL(\cdot) \ ,$$

where subscripts i and t denote farm and time. In addition to input and output variables, we control for farm and farmers' specific characteristics (age, education, whether or not the farm is operated full-time, and agro-ecological zones to reflect differences in soil quality) in the vector r and for year-specific effects in the dummy variables $year_t$. The coefficients α, β, γ, ζ and δ are parameters to be estimated. Because of its logarithmic form, equation (4-8) can be rearranged to the estimable form

$$-\ln x_{1it} = TL(\cdot) - u_{it} + v_{it} \ , \tag{4-9}$$

where v_{it} is an independently and identically distributed error term with a mean of zero and a variance of σ_v^2, and $u_{it} = \ln D_{it}^{I}$ is a one-sided error term that is also independently and identically distributed but truncated at the mean to reflect inefficiency. The standard error term v_{it} captures omitted variables (such as weather influences), measurement errors, and functional form errors. To allow firm-specific technical inefficiency to vary over time, we adopt the approach proposed by Battese and Coelli (1992) by modelling $u_{it} = \left(u_i \exp\left(-\eta(t-T)\right)\right)$, where η is another parameter to be estimated.

The translog functional form is widely used in the estimation of Shephard distance functions because of its flexibility and the ease of the imposition of homogeneity (see, e.g., Coelli and Perelman, 2000; Plastina and Lence, 2018; Hirsch et al., 2020).[17] A significant drawback is that it cannot accommodate zero values in any of the output and input variables. While evaluating cost complementarities does not require plugging in zero values into the estimated distance function (see also Saal et al., 2013), there are farms in our sample that do not produce all of the four outputs. To facilitate the logarithmic transformation, some studies replace zero values with arbitrarily small positive values (e.g. Morrison Paul, Johnston, W. E. and Frengley, 2000). Battese (1997) argues that this procedure causes biased estimates if there is a significant number of observations with zero values and proposes the inclusion of dummy variables indicating whether a specific variable is zero or greater than zero. We follow this approach and define $d_{crops} = 0$ if $y_{crops} > 0$ and $d_{crops} = 1$ if $y_{crops} = 0$. The logarithm of crop

[17] The quadratic functional form, by contrast, permits the imposition of the translation property and is therefore preferred for the directional distance function defined by Chambers, Chung and Färe (1996, 1998). A comparison between a translog Shephard (1953, 1970) distance function and a quadratic directional distance function is provided in Färe, Martins-Filho and Vardanyan (2010).

output is then constructed as $\ln q_{crops} = \ln\big(max(q_{crops}, d_{crops})\big)$. The same method is applied to the output category of other output. Recent applications of this approach include Villano et al. (2015) and Katuwal, Calkin and Hand (2016) for estimating stochastic frontiers and Rasmussen (2010) and Qushim et al. (2018) for estimating IDFs.[18]

4.4.2 Bayesian estimation technique

To empirically estimate the IDF in (4-9), we selected a Bayesian framework for two reasons: First, the dual measure of economies of scope as defined in equation (4-7) is a complex non-linear function of the estimated parameters of the IDF. The Bayesian approach provides a more convenient way to compute standard deviations for the resulting scope measures compared to the frequentist approach, as it allows us calculating credibility intervals based on the results from numerous successive draws from the posterior distribution. Second, the Bayesian approach offers an intuitively appealing method to impose regularity conditions on a translog IDF without sacrificing the flexibility of the functional form (O'Donnell and Coelli, 2005). We adopt a stochastic frontier model with farm-specific individual effects as described in Koop (2003). Following this approach, we use independent Normal-Gamma priors for the coefficients of the IDF and a hierarchical prior for the inefficiencies. The inefficiency parameter follows an exponential distribution. For a more rigorous explanation of the priors used, please refer to Koop (2003, p. 170). The likelihood function depends on distributional assumptions for the error terms. In the following, T_i denotes the number of observations for the i-th farm to account for the unbalanced panel data set, ι_T is a T-vector of ones, and h is the error precision $1/\sigma^2$. The standard error assumptions are: v_i is normally distributed around 0_T with the covariance matrix $h^{-1}I_T$; v_i and v_j are independent for $i \neq$ j, and all variables are independent of the error terms. In the stochastic frontier model, it is further assumed that u_i and v_j are independent of each other for all i and j. These assumptions imply the likelihood function

$$p(Y|\beta, h, u) = \prod_{i=1}^{N} \frac{h^{\frac{T_i}{2}}}{(2\pi)^{\frac{T_i}{2}}} \left\{exp\left[-\frac{h}{2}(y_i - X_i\beta + u_i\iota_T)'(y_i - X_i\beta + u_i\iota_T)\right]\right\} \quad , \qquad (4\text{-}10)$$

where the dependent variable is represented by Y, X is the vector of independent variables, and β is the vector of unknown parameters to be estimated. Statistical inference about the marginal posterior distributions of β is made by repeatedly drawing sample observations from the posterior distribution $p(\beta|Y)$ using MCMC based methods. A burn-in period of 5,000 replications followed by 10,000 sampling replications proved to be sufficient for model convergence and provided consistent estimates for the parameters of interest.

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[18] We also estimated the IDF for the subsample of farms producing all four outputs and found that the estimated parameters and corresponding elasticities are very similar. The results are available from the authors upon request.

In the unrestricted model, we make use of the basic Gibbs sampler, a sampling algorithm that draws from the joint posterior density by sampling from a series of conditional posteriors (see Gelfand and Smith, A. F. M. (1990) for a detailed explanation). In the restricted version of the model, we employ a Metropolis-Hastings algorithm that assigns zero weights to all likelihood values for proposed vectors of parameters where the monotonicity or curvature conditions are violated as described in O'Donnell and Coelli (2005). To be non-increasing (non-decreasing) in outputs (inputs), the first ordinary derivatives of the translog IDF have to be non-positive (non-negative):

$$\frac{\partial D^I}{\partial q_m} = \frac{\partial \, ln \, D^I}{\partial \, ln \, q_m} \times \frac{D^I}{q_m} = \left(\alpha_m + \sum_n \alpha_{mn} \, q_n + \sum_k \beta_{mk} \, x_k \right) \times \frac{D^I}{q_m} \leq 0 \tag{4-11}$$

$$\frac{\partial D^I}{\partial x_k} = \frac{\partial \, ln \, D^I}{\partial \, ln \, x_k} \times \frac{D^I}{x_k} = \left(\beta_k + \sum_l \beta_{kl} \, x_l + \sum_m \gamma_{mk} \, q_m \right) \times \frac{D^I}{x_k} \geq 0 \tag{4-12}$$

For the function to be concave in x, the following Hessian matrix must be negative-semidefinite:

$$M_{inp} = \begin{bmatrix} D^I_{x_1x_1} & D^I_{x_1x_2} & \cdots & D^I_{x_1x_5} \\ D^I_{x_1x_2} & D^I_{x_2x_2} & \cdots & D^I_{x_2x_5} \\ \vdots & \vdots & \ddots & \vdots \\ D^I_{x_5x_1} & D^I_{x_5x_2} & \cdots & D^I_{x_5x_5} \end{bmatrix} \tag{4-13}$$

with

$$D^I_{x_kx_l} = \frac{\partial^2 D^I}{\partial x_k \partial x_l} = \left(\beta_{kl} + \frac{\partial \ln D^I}{\partial \ln x_k} \times \frac{\partial \ln D^I}{\partial \ln x_l} - \delta_{kl} \frac{\partial \ln D^I}{\partial \ln x_k} \right) \times \frac{D^I}{x_k x_l},$$

$$\delta_{kl} = 1 \; if \; k = l, 0 \; otherwise.$$

In the estimation procedure, we impose concavity by restricting the k^{th}-order principle minors (a total number of 31) of the Hessian matrix to be non-positive for k odd and non-negative for k even (Simon and Blume, 1994, p. 514). Note that the functional form is an approximation to the unknown true functional form that has been chosen because of its flexibility. If inputs and outputs are weakly disposable, the true functional form cannot be translog, because the translog IDF is never globally non-decreasing in inputs and non-increasing in outputs.[19] Therefore, to maintain the flexibility of the function, we impose regularity on selected representative data points only. Ryan and Wales (2000) argue that imposing constraints on an appropriate reference point can lead to a satisfaction of the regularity conditions at most data points in the sample. When imposing the conditions on the sample mean of each variable, we observed only a minor improvement in the adherence to the regularity conditions. Motivated by Griffiths, W. E., O'Donnell and Cruz (2000), who imposed the regularity conditions on 23 representative price points in a cost function framework, we then chose to divide

[19] For a translog function to globally satisfy curvature and monotonicity, it must reduce to a Cobb-Douglas function.

each input and output variable into their nine data deciles. This choice proved computationally feasible, maintained the flexibility of the functional form, and resulted in considerable improvement to the amount of farm observations satisfying regularity conditions. The procedure was empirically implemented based on Griffin and Steel, M. F. J. (2007) using the *rjags* package of the statistical software *R* (Plummer, Stukalov and Denwood, 2019).

4.4.3 Endogeneity in distance functions

Concerns have been raised in the literature regarding performing an unbiased estimation of distance functions – or stochastic frontiers in general – since the explanatory variables could be correlated with the error terms u and v. As noted above, the economic formulation of distance functions does not rely on behavioural assumptions. Econometrically, however, we have to consider that some variables may be endogenous. In the estimable form of the IDF (equation (4-9)), input ratios and output levels appear as regressors. Therefore, when estimating the IDF, it is often assumed that outputs are predetermined and firms chose inputs to minimise costs (e.g. Renner, Glauben and Hockmann, 2014 in the agricultural sector). In this case, outputs are exogenous and inputs are endogenous. The ratios of inputs, on the other hand, are exogenous if allocative inefficiencies do not exist (Kumbhakar, 2013; Sipiläinen, Kumbhakar and Lien, 2014; Tsionas, Kumbhakar and Malikov, 2015).[20] For example, Tsionas, Kumbhakar and Malikov (2015) demonstrate that input demand functions are functions of input price ratios and outputs, which are both exogenous under cost minimisation, and that input ratios are affected neither by the inefficiency term nor by stochastic productivity shocks. This result is in line with earlier studies by Schmidt, P. (1988) and Mundlak (1996) who argue that input ratios are exogenous even under expected profit maximisation (see also Brümmer, Glauben and Thijssen, 2002). Sipiläinen, Kumbhakar and Lien (2014) further demonstrate that even without making any behavioural assumptions, ratios of assumingly endogenous variables are not endogenous if they are affected by u and v in the same way. Output levels, on the other hand, may be considered exogenous if they are limited by a production quota (Kumbhakar, 2013), as it was the case for the main output (milk) during the data period of our empirical application. This argument has been used in Frahan et al. (2011) for the use of a cost function to represent the production technology of dairy farms, for example. Contrary to many previous studies, we do not want to rely on the assumption of cost minimising behaviour in the estimation of the IDF, especially given risk considerations in the choice of the output portfolio, as discussed above. Moreover, Kumbhakar (2013) argues that results from IDF models may be biased if the inefficiency term u reflects management skills which are known by the

[20] In the presence of allocative inefficiencies, the authors state that input ratios are not exogenous. However, allocative efficiency is implicitly assumed in the derivation of cost complementarities from the IDF in Hajargasht, Coelli and Rao (2008).

producer but unknown to the econometrician. In this case, input and output quantities would be correlated with u and the results would suffer from simultaneity bias. Therefore, we check for endogeneity in the estimation of the IDF by following Griffiths, W. E. and Hajargasht (2016) who propose Bayesian estimation tools for dealing with endogeneity in stochastic frontier models.[21] Specifically, the inefficiency term is transformed so that it takes a lognormal distribution, which is then explained by time-invariant farm averages of outputs and input ratios denoted by the vectors $\bar{q}$ and $\bar{\tilde{x}}$, respectively:

$$H(u_i) = \rho_0 + \rho_q \bar{q}_i + \rho_{\tilde{x}} \bar{\tilde{x}}_i + e_i \tag{4-14}$$

The error term e_i is assumed to satisfy $e_i \sim i.i.d.\, N(0, \lambda^2)$ and $H(u_i) = \ln(u_i)$ ensures that u_i has a lognormal distribution. As such, the model is an extension of the Mundlak (1978) random effects model with correlated effects, which has been more recently used to account for endogeneity by Chavas and Di Falco (2012), for example. In our application, the posterior standard deviations for the parameters ρ_q and $\rho_{\tilde{x}}$ are quite large compared to their posterior means (see Table 4-7 in the Appendix), which points towards exogenous regressors (Griffiths, W. E. and Hajargasht, 2016). Hence, we conclude that the distance function can be estimated using conventional stochastic frontier techniques as, for example, in Renner, Glauben and Hockmann (2014), Hailu and James Deaton (2016), and Plastina and Lence (2018).[22]

4.4.4 Explaining cost complementarities

After estimating cost complementarities for each farm observation using equation (4-7), we explore their relationship to selected farm-specific factors. We are particularly interested in the effect of farm size in order to assess how the structural change towards larger farms affects diversification economies. Farm size ($size$) is proxied with the number of dairy cows. We further control for the degree of specialisation ($spec$), since highly specialised farms are likely to benefit more from increasing the level of diversification compared to farms that are already diversified. When explaining cost complementarities between milk and livestock, we use the revenue share of milk as a proxy for specialisation. For the output pairs milk-crops and milk-other output, we use the share of the second output

[21] Other strategies to deal with endogeneity in stochastic frontier analysis include estimation of equation systems using GMM techniques (Kumbhakar, Asche and Tveteras, 2013), Cholesky decomposition of the error term (Kutlu, 2010; Tran and Tsionas, 2013) or use of the copula formula (Amsler, Prokhorov and Schmidt, P., 2016). The advantages and disadvantages of each of them are discussed in Orea and Zofío (2017).

[22] Plastina and Lence (2018) develop a four-equation system that consists of the IDF and instrumented input quantity ratios to account for possible endogeneity. Consistent with our results, they find that cross-equation correlations are of minor importance and continue the analysis with the results from the single-equation IDF model.

to avoid misconceptions about its importance in the output portfolio.[23] Additional explanatory variables are the share of grassland ($shgrass$), average field size ($fieldsize$), the farmer's age (age), and two dummy variables indicating whether the farmer has a higher agricultural education[24] ($educ$) and whether the farm is operated full-time ($fulltime$). Finally, a time variable ($time$) is included to test whether farms approached a more optimal level of diversification over time. Thus, the equation to be estimated takes the following form:

$$\begin{aligned} comp_{mn} = \varphi_0 + \varphi_1\, size + \varphi_2\, size^2 + \varphi_3\, spec + \varphi_4\, shgrass \\ + \varphi_5\, fieldsize + \varphi_6\, age + \varphi_7\, educ + \varphi_8\, fulltime \\ + \varphi_9 time + \epsilon, \qquad m \neq n \end{aligned} \tag{4-15}$$

where $comp_{mn}$ denotes complementarity between two distinct outputs m and n, φs are parameters to be estimated and ϵ is the error term. Time and farm subscripts have been omitted to avoid notational clutter. Equation (4-15) is estimated as fixed effects model to account for time-invariant unobserved variables. Nevertheless, farm size and level of diversification may be endogenous, since they are likely chosen by the farmer in response to experienced cost complementarities. If this were true, the error term would be correlated with these variables and OLS regression would yield biased parameter estimates. Therefore, we follow Hirsch et al. (2020) and examine which of these variables are indeed endogenous by applying the Davidson and Mackinnon (1993) test for exogeneity, an augmented Durbin-Wu-Hausman test. Exogeneity is tested by regressing potentially endogenous variables on all exogenous variables. Then, the residual is included in the regression of the original model. If the parameter estimate of the residual is statistically significant, the null hypothesis of exogeneity is rejected. In this case, we use time lags of the identified endogenous variables as instruments in a two-stage least squares fixed effects instrumental variable (IV-FE) regression. To make sure that the lagged variables are valid instruments, we assess whether the instruments are orthogonal to the errors using the Sargan-Hansen test of over-identifying restrictions (Sargan, 1958; Hansen, 1982). The relevance of the instruments is evaluated using the minimum eigenvalue statistic (Cragg and Donald, 1993). To obtain heteroscedasticity-robust estimates, standard errors are clustered at the farm level.

4.5 Results and discussion

4.5.1 Input distance function and regularity

Prior to estimation of the IDF, all inputs and outputs have been divided by their means so that first-order coefficients can be interpreted as elasticities at the sample mean. Table 4-6 in the Appendix presents the posterior means and 95 per cent credibility intervals for the IDF parameters obtained

[23] For example, the revenue share of milk could be relatively low even if the share of the other output (e.g. crops) is also low, if the farm produces a larger share of livestock or other outputs.
[24] i.e., a master craftsman diploma or university degree

from Bayesian MCMC simulation for both the unrestricted and the restricted model. The land variable is used as numeraire, and parameters for variables containing the numeraire are recovered after the estimation by making use of the homogeneity conditions as outlined in Coelli and Perelman (1999), for example. The posterior means of the first-order coefficients show the expected signs and the parameter estimates only marginally differ between the unrestricted and restricted model: a one-per cent-increase in milk production decreases the distance to the efficient border by 0.49 per cent in both the unrestricted and restricted model at the sample mean, all other variables being held constant. With respect to inputs, a one per cent-increase in land (x_1), for example, is associated with a 0.21 per cent increase in the distance in both models. The main differences between the restricted and the unrestricted model are visible in the input cross terms – especially in the squared terms of land and cows, respectively – and in the interaction term between land and labour. In both models, technical efficiency is around 0.75 at the sample mean, indicating that – holding input use constant – the average farm could increase output by 25 per cent if it was fully efficient. Finally, the technology shows increasing returns to scale (RTS = 1.81) at the sample mean. The magnitude is similar to other studies evaluating economies of scale based on IDFs. For example, Atsbeha, Kristofersson and Rickertsen (2012) report RTS = 1.57 for a sample of Icelandic dairy farms and Sipiläinen, Kumbhakar and Lien (2014) find RTS = 1.51 for Norwegian and RTS = 1.71 for Finnish dairy farms. Moreover, Nehring et al. (2009) estimate scale elasticities (the inverse of our measure of RTS) of 0.65 (i.e., RTS = 1.54) for conventional and 0.44 (i.e., RTS = 2.27) for pasture-based dairy farms at the sample mean. For German dairy farms, and using output distance functions, Brümmer, Glauben and Thijssen (2002) find slightly increasing returns to scale (RTS=1.08) and Skevas, Emvalomatis and Brümmer (2018) slightly decreasing returns to scale (RTS=0.88). While RTS in our study are considerably higher, it must be noted that dairy farms in our Bavarian sample are considerably smaller than the German average. For example, dairy farms in Skevas, Emvalomatis and Brümmer (2018) produce 42 per cent more milk than farms in our sample.

The descriptive statistics of farm-level distance elasticities with respect to outputs and inputs are displayed in Table 4-2, along with the percentage of regularity violations of monotonicity and concavity. Recall that in the restricted model, the regularity conditions have not been imposed at all observations but only at the sample mean and nine data quantiles to maintain the flexibility of the function. While the violations of the monotonicity condition are quite similar between the two models, there is a substantial improvement in the curvature of the function: the share of data points where the function is not concave in inputs decreases from 28 per cent in the unrestricted model to 6 per cent in the restricted one. In total, imposing regularity conditions on the IDF cuts the share of observations inconsistent with economic theory in half, from 40 per cent to 19 per cent. The similarity of the parameters and elasticities in the unrestricted and restricted version of the model indicate that the imposed regularity conditions are true and that duality results can be used to recover cost complementarities from the parameter estimates of the IDF. In the following, we therefore discuss the results from the restricted model only.

Table 4-2. Farm-level elasticities of the input distance function and regularity violations

	Unrestricted Model				
	Mean	Std. Dev.	Min	Max	Vio (%)
Monotonicity in outputs					**15.52 %**
Milk	-0.4878	0.0560	-0.7102	0.1380	0.01 %
Livestock	-0.0414	0.0187	-0.2185	0.0462	1.62 %
Crops	-0.0136	0.0050	-0.0343	0.0217	2.64 %
Other output	-0.0032	0.0029	-0.0168	0.0143	13.20 %
Monotonicity in inputs					**2.56 %**
Land	0.2023	0.0349	-0.0973	0.3228	0.01 %
Labour	0.1786	0.0436	0.0133	0.5029	0.00 %
Intermediates	0.1853	0.0272	0.0301	0.3021	0.00 %
Cows	0.4204	0.0277	0.2238	0.5780	0.00 %
Capital	0.0134	0.0065	-0.0444	0.0430	2.55 %
Concavity in inputs					**28.36 %**
Total violations					**40.41 %**
	Restricted Model				
	Mean	Std. Dev.	Min	Max	Vio (%)
Monotonicity in outputs					**14.07 %**
Milk	-0.4881	0.0555	-0.7110	0.1410	0.01 %
Livestock	-0.0415	0.0202	-0.2293	0.0526	2.08 %
Crops	-0.0134	0.0051	-0.0361	0.0206	2.63 %
Other output	-0.0036	0.0027	-0.0209	0.0123	10.40 %
Monotonicity in inputs					**0.58 %**
Land	0.2029	0.0368	-0.0694	0.3270	0.01 %
Labour	0.1782	0.0404	0.0275	0.4785	0.00 %
Intermediates	0.1840	0.0270	0.0284	0.3043	0.00 %
Cows	0.4197	0.0273	0.2368	0.5760	0.00 %
Capital	0.0153	0.0048	-0.0355	0.0337	0.58 %
Concavity in inputs					**5.73 %**
Total violations					**19.14 %**

n = 18,772

Note: Vio (%) is the share of farm observations with regularity violations.

4.5.2 Presence of cost complementarities

The Bayesian estimates for cost complementarities at the sample mean are presented in Table 4-3.[25] The results show that the probability of negative values of cost complementarities between milk and livestock production is slightly above five per cent. In other words, there is statistical evidence that marginal costs of milk production increase with additional output of livestock at the sample mean, i.e. it is convenient for the average farm in our sample to increase specialisation towards milk production and to reduce the engagement in cattle feeding. As explained above, economies of scope may still exist if they arise from sharable inputs, such as farm buildings, which is likely in the case of dairy production and downstream fattening. Further, no cost complementarities are found for the joint production of milk and crops at the sample mean. This could be explained by the distinct knowledge and skills required for the production of crops for sale and roughage as main feed input for dairy farms in Bavaria. In contrast, the joint production of livestock and crops results in cost savings, when evaluated at the sample mean (P>0.95). This makes intuitive sense, because crops produced for sale can also be used for downstream fattening of cattle, so these two products have related production processes and require similar management skills as public input. Moreover, crop production may benefit from high quality nutrients in form of manure, and farmers may use side products of crop production as feed for animals. This results in cost reductions through external economies (Teece, 1980).

Table 4-3. Cost complementarities evaluated at the sample mean

	Mean	Median	Std. Dev.	95 % CrI		$P(Comp_{mn}<0)$
Milk-livest.	5.55E-06	5.33E-06	3.75E-06	-1.23E-06	1.34E-05	0.0572
Milk-crops	1.33E-05	1.32E-05	4.71E-06	4.26E-06	2.30E-05	0.0026
Milk-other	2.33E-06	2.26E-06	6.20E-06	-1.01E-05	1.47E-05	0.3481
Livestock-crops	-2.51E-05	-2.51E-05	1.22E-05	-5.02E-05	-1.79E-06	0.9813
Livestock-other	-1.73E-05	-1.70E-05	1.56E-05	-4.94E-05	1.26E-05	0.8679
Crops-other	1.74E-05	1.80E-05	2.30E-05	-2.93E-05	5.97E-05	0.2170

Note: CrI and P are credibility interval and probability, respectively, both calculated based on 10,000 successive draws of the posterior distribution; $Comp_{mn}$ represents cost complementarities between outputs m and n, with negative values indicating that costs can be saved by increasing diversification.

[25] The magnitude of these estimates depend on the measurement units of inputs and outputs, because they affect the scale of the first and second derivatives of the IDF. Our measure of cost complementarities can be converted to percentage terms using the formula $(C_{q1q2}/\ C) \times (q_2/\ -D_{q1})$. For example, a 1 %-increase in the output level of livestock corresponds to a 0.02 %-increase in MC of milk at the sample mean.

For the analysis at the individual farm-level, we only focus on observations that satisfy the regularity conditions as in Hirsch et al. (2020) to avoid misleading interpretations (Sauer, 2006; Henningsen and Henning, 2009). Table 4-4 shows that negative values of cost complementarities –indicating cost savings – between milk and livestock production are present for nine per cent of observations. That is, for 91 per cent of farms in the sample, the marginal costs of milk production are increasing in response to an increase in the production of livestock. Only one per cent of the farms benefit from jointly producing milk and crops, and five per cent benefit from the joint production of crops and other outputs, such as provision of services, tourism, or electricity. For a higher number of farms (26 per cent), it is convenient to jointly produce milk and other outputs, and the vast majority benefits from combining livestock and crop production as well as production of livestock and other outputs.

Table 4-4. Cost complementarities at the farm level

	Nr. of obs.	Mean	Median	Std. Dev.	Min	Max	$Comp_{mn}$ <0 (%)
Milk-livestock	15,179	1.56E-05	5.94E-06	2.49E-04	-1.66E-02	2.28E-02	9.41 %
Milk-crops	7,197	2.23E-05	1.12E-05	8.81E-05	-3.53E-03	3.14E-03	1.22 %
Milk-other	10,761	1.18E-05	2.12E-06	6.53E-04	-6.08E-03	5.78E-02	25.51 %
Livestock-crops	7,197	-9.88E-05	-1.87E-05	4.63E-04	-1.70E-02	1.39E-03	99.93 %
Livestock-other	10,761	-9.32E-05	-2.40E-05	4.84E-04	-2.82E-02	1.31E-02	99.69 %
Crops-other	5,507	8.01E-05	1.46E-05	4.21E-04	-1.66E-02	9.02E-03	4.87 %

Note: $Comp_{mn}$ represents cost complementarities between outputs m and n, with negative values indicating that costs can be saved by increasing diversification. Only farm observations without regularity violations are included.

4.5.3 Patterns of cost complementarities

We now investigate the link between cost complementarities and the size of dairy farms as well as the level of diversification. This allows us to assess how farm size is related to economic benefits from diversification between specific outputs. Specifically, we would like to answer the question whether cost complementarities for various output pairs differs between small and large dairy farms. To visualise the relationship, cost complementarities for all output pairs that involve milk production – the main output of the farms in the sample – are plotted against the number of dairy cows on the farm and revenue shares of the corresponding output in Figures 4-2 – 4-4 in the Appendix. Following Abrate and Erbetta (2010), we categorise the observations according to the sign of the cost complementarities. Negative values of cost complementarities indicate that marginal costs of producing one good (e.g. milk) are decreasing when the output level of another good (e.g. livestock) is increased, i.e. increasing diversification is convenient. On the other hand, positive values of cost complementarities indicate that marginal costs of producing one good increase in response to increasing the output level of another good. Figure 4-2 illustrates cost complementarities between milk and livestock production. Most farm observations with negative values of cost complementarities – i.e. those that would benefit from increasing diversification – have a share of livestock revenues below 15-20 per cent. Above this threshold, we almost exclusively find observations with positive values of cost complementarities. The plot therefore indicates an optimal output share of livestock production around 15-20 per cent.[26] It is also visible that the vast majority of farm observations with negative values of cost complementarities have a herd size smaller than 50 cows. Larger farms seem to experience mainly increasing costs from diversification.

With respect to cost complementarities between milk and crops, Figure 4-3 indicates that cost savings from joint production are only realised when the crop revenue share is slightly above zero. Nearly all farms with a higher share of crop revenue could save costs by reducing crop production in favour of increased milk production. A similar pattern is found for the output pair of milk and other products (Figure 4-4). Again, most farms experiencing cost savings from the joint production gain a very small portion of revenue from other outputs.

Next, we use regression analysis to make statistical inference about the effect of farm size on the value of cost complementarities (the graphical display only distinguishes positive and negative values). Each column in Table 4-5 presents the estimation results from equation (4-15) for explaining cost complementarities between the three output pairs that include milk, the main output of dairy farms in the sample. The Davidson-MacKinnon test indicates that the degree of specialisation (i.e., the revenue shares) is endogenous in columns (1) and (2) and that farm size (as proxied with the number of dairy cows) is endogenous in column (3). Therefore, we use IV-FE regression in all models. The number of lags has been selected according to the Cragg-Donald weak identification test and the Sargan-Hansen overidentification test. Due to the test results, we trust that that the instruments are adequately selected to mitigate endogeneity concerns.

[26] This threshold is similar to what Abrate and Erbetta (2010) found in their study on the output mix in airport companies.

Table 4-5. Determinants of cost complementarities (IV-FE regression)

Variable	Cost compl. Milk-livestock (1)	Cost compl. Milk-crops (2)	Cost compl. Milk-other (3)
Number of cows	3.08E-06***	-2.37E-07	1.52E-08
	(9.90E-07)	(1.84E-07)	(2.95E-07)
Number of cows squared	-1.73E-08***	1.99E-09**	-5.24E-10
	(5.90E-09)	(9.23E-10)	(1.38E-09)
Rev. share milk	-3.13E-04***	–	–
	(8.43E-05)	–	–
Rev. share crops	–	3.16E-05	–
	–	(3.32E-05)	–
Rev. share other output	–	–	3.21E-05***
	–	–	(8.34E-06)
Share grassland	6.15E-06	2.23E-05***	-9.85E-06
	(1.09E-05)	(8.48E-06)	(6.21E-06)
Avg. field size	-7.19E-07*	-8.51E-07	1.16E-06
	(3.99E-07)	(5.38E-07)	(9.78E-07)
Age	-1.14E-07	-5.24E-08	-2.13E-08
	(8.41E-08)	(4.90E-08)	(6.91E-08)
Higher educ	-5.64E-06	3.11E-07	-3.80E-07
	(3.50E-06)	(1.04E-06)	2.18E-06
Fulltime	-1.31E-05**	-3.38E-06	-5.87E-06
	(6.33E-06)	(5.85E-06)	(1.46E-05)
Time trend	-5.70E-07**	-8.97E-07***	2.70E-07
	(2.72E-07)	(2.79E-07)	(2.20E-07)
Constant	1.62E-04***	3.13E-05***	3.70E-06
	(3.44E-05)	(1.10E-05)	(1.65E-05)
Nr. of observations	7477	5063	6218
Nr. of farms	1284	859	1153
Endogenous variables[a]	Revenue share	Revenue share	Nr. of cows, Nr. of cows sq.
Instruments (lags)	4–5	2–3	3–4
Weak identification test			
Cragg-Donald Wald F statistic	8.26	44.01	151.46
Critical value	7.25	7.25	6.28
Overidentification test			
Sargan-Hansen statistic	1.273	0.852	4.240
p-value	0.259	0.356	0.120

Note: Dependent variable is cost complementarities. Recall that negative values indicate that joint production is convenient. Heteroscedasticity-consistent standard errors (clustered at the farm level) are in parentheses. The common significance levels are used: *** = 1 %, ** = 5 %, and * = 10 %; [a]According to Davidson-MacKinnon test for exogeneity.

The parameter estimates in column (1) show that cost complementarities between milk and livestock production are increasing in the number of dairy cows at a decreasing rate. Since negative values of cost complementarities indicate that cost savings are realised by jointly producing the two outputs, this finding provides evidence that small farms benefit more from diversifying between milk and livestock production than larger farms. A potential explanation is that the combination of milk and livestock production is less capital-intensive than, for example, the combination of milk and crop production. Since smaller dairy farms tend to be less capital- but more labour-intensive, they may make better use of human capital as common input to milk and livestock, resulting in cost savings when these two products are jointly produced. Further, the parameter estimate for revenue share of milk is negative at the one per cent level of statistical significance. Thus, dairy farms with a high share of milk revenue benefit from increasing livestock production (i.e., increasing diversification), while farms with a lower share of milk revenue can benefit from increasing milk output (i.e., reducing diversification). This finding is consistent with Figure 4-2 in the Appendix and implies that there is an 'optimal level' of diversification in terms of production costs.

The estimation results for explaining cost complementarities between milk and crop production are presented in column (2). The parameter estimates for the linear and quadratic terms of dairy cows are jointly significant at the five per cent level (p-value = 0.0136). This finding indicates that large dairy farms are more likely to benefit from jointly producing milk and crops than small farms – contrary to the result for the output pair milk and livestock. As discussed above, the joint production of milk and crops may be more capital-intensive. Dairy farms with larger herd sizes may adopt technologies that are less labour-intensive (e.g. automatic milking or feeding systems), and thus more time is available for engaging in crop production, for example. On the other hand, small farms may face higher management costs when engaging in two production areas that require distinct sets of skills, and thus do not benefit when jointly producing milk and crops. The coefficient for revenue share of crops takes the expected sign (higher share of crop revenues leads to more positive values of cost complementarities between milk and crop production) but is not statistically significant.

Finally, cost complementarities between milk and other outputs are not affected by farm size (see column (3)). This may be due to the fact that other outputs comprises a range of products and cost complementarities between its individual components and the remaining outputs may be mixed and therefore cancel each other out. The share of revenue share of other outputs is positively related to the value of cost complementarities at the one per cent level of statistical significance. Again, this result confirms that dairy farms that are already highly diversified are less likely to realise additional cost savings from a further increase of the diversification level (see also Figure 4-4).

Some interesting results also arise from the parameter estimates of the farm and farmers' characteristics, which are included in the model as control variables. Primarily, the share of grassland is statistically different from zero at the 1 per cent level in column (2): a higher share of grassland is associated with less cost savings from the joint production of milk and crops. This is intuitive, because farms with high grassland shares are restricted in their production of cash crops, and hence they are better off by specialising in milk production. Farmer's age and education seem not to be related to the values of cost complementarities, but farms with larger average field size and those operated full-time are more likely to realise cost savings from jointly producing milk and livestock. Finally, the time trend reveals that farms move towards a situation characterised by cost-savings from joint production of milk and livestock as well as milk and crops over time. This observation provides support that farms improve their output portfolio with respect to the main farm outputs milk, livestock, and crops.

4.6 Conclusions

In this study, we examined cost complementarities between different farm outputs for a representative sample of Bavarian dairy farms. Cost complementarities are commonly evaluated using cost functions, but the empirical estimation is problematic if input price data is not available, as it is usually the case with farm-level accountancy data. Therefore, we follow the approach by Hajargasht, Coelli and Rao (2008), which exploits the duality relationship between cost functions and IDFs to recover parameters of the cost function from its dual IDF. Since duality relies on theoretical conditions such as monotonicity and curvature, we estimate the IDF in a Bayesian framework, which allows us to impose these regularity conditions (O'Donnell and Coelli, 2005). To maintain the flexibility of the functional form of the IDF approximation, we impose monotonicity in inputs and outputs and concavity in inputs on representative data points rather than the full sample, which results in the reduction of observations that are inconsistent with economic theory from 40 per cent to 19 per cent.

Cost complementarities describe the change in the marginal costs of producing one good in response to increasing the production level of another output. Evaluated at the sample mean, we find negative values of cost complementarities (i.e., costs can be saved by increasing diversification) between livestock and crop production, but positive values for the output pairs milk and livestock as well as milk and crops. These findings are in contrast to Fleming and Lien (2009) who do not detect any significant cost complementarities in a sample of Norwegian dairy farms. A farm-level analysis shows that highly specialised farms are more likely to realise cost savings from increasing the level of diversification than highly diversified farms, indicating that there is an optimal level of diversification in terms of associated production costs. Further, the results show that the value of cost complementarities between milk and livestock are increasing in size, but the value of cost complementarities between milk and crop production are decreasing in size. In other words, larger farms tend to benefit from jointly producing milk and crops, while smaller farms are more likely to benefit from diversification between milk and livestock production. Even though livestock production is an inherent by-product of milk production, the farmer can chose to sell side-products (i.e., male calves) immediately or to engage in down-stream fattening of the calves. The longer the calves are kept for downstream fattening, the higher is the revenue from livestock sale, and the higher is the level of diversification between milk and livestock products. This study reveals that feeding cattle is especially attractive for smaller farms as it allows them to reduce the marginal costs of milk production.

Overall, the results show that diversification benefits vary across farm size, and different output combinations are favourable for dairy farms with distinct herd sizes. These findings suggest that the preferred composition of individual farm output will change in the context of structural change in agriculture with the trend towards larger but fewer farms. The results imply that farm size needs to be taken into account in the formulation of policies related to supporting optimal farm structure. Currently, the German government supports farm diversification beyond primary agricultural production – such as farm tourism, direct marketing, or energy production – to improve the competitiveness of farms. Our study provides empirical evidence that for the dairy sector, small farms can be effectively supported by promoting diversification within primary agricultural production – in particular the joint production of milk and livestock. This could be achieved by subsidising investments into barns serving downstream fattening of cattle.

While cost complementarities provide useful insights into the benefits of diversification, they fail to detect economies of scope when they are exclusively due to shared inputs (Baumol, Panzar and Willig, 1988; Färe and Karagiannis, 2018). Hence, a limitation of our study is that it does not account for the role of fixed costs. Future empirical research on diversification economies should therefore address the importance of cost complementarities as a source of scope economies, for example by measuring the cost reduction generated by output complementarities under different diversification schemes. To this end, data on farms specialising in different output categories is needed. Finally, it must be noted that cost minimisation must not be the primary goal of dairy farmers. In contrast, they may maximise revenue or profit or – more generally – utility. While the concept of IDFs does not make any assumptions on the managerial behaviour of farmers, the performance of farmers should not be evaluated based on costs when their managerial behaviour is different (O'Donnell, 2018). In this article, we use the concept of costs as an indicator for farm competitiveness. If productivity maximisation is on the policy agenda, the effect of diversification on total factor productivity should be considered, which is subject to further research.

Appendix

Table 4-6. Bayesian estimates for unrestricted and restricted input distance functions

	Unrestricted Model				Restricted Model			
Parameter	Posterior mean	St. Dev.	95 % CrI		Posterior mean	St. Dev.	95 % CrI	
α_0 (Constant)	0.4238	0.0319	0.3817	0.4877	0.3803	0.0125	0.3602	0.4053
(Dummy for $Y3 = 0$)	0.0156	0.0021	0.0114	0.0196	0.0151	0.0021	0.0111	0.0192
(Dummy for $Y4 = 0$)	0.0076	0.0016	0.0046	0.0107	0.0087	0.0015	0.0057	0.0117
α_1 (Milk output)	-0.4945	0.0038	-0.5018	-0.4866	-0.4942	0.0038	-0.5023	-0.4866
α_2 (Livestock output)	-0.0421	0.0022	-0.0465	-0.0378	-0.0418	0.0022	-0.0464	-0.0377
α_3 (Crop output)	-0.0137	0.0011	-0.0158	-0.0116	-0.0134	0.0011	-0.0157	-0.0113
α_4 (Other output)	-0.0038	0.0007	-0.0053	-0.0024	-0.0040	0.0007	-0.0055	-0.0026
β_1 (Land)	0.2133	0.0049	0.2040	0.2229	0.2124	0.0048	0.2032	0.2218
β_2 (Labour)	0.1676	0.0034	0.1610	0.1744	0.1697	0.0032	0.1633	0.1761
β_3 (Intermediate inputs)	0.1898	0.0039	0.1821	0.1973	0.1881	0.0042	0.1797	0.1962
β_4 (Cows)	0.4149	0.0052	0.4048	0.4251	0.4137	0.0052	0.4036	0.4241
β_5 (Capital)	0.0145	0.0022	0.0103	0.0187	0.0161	0.0020	0.0123	0.0202
α_{11}(Output interactions)	-0.1131	0.0045	-0.1220	-0.1041	-0.1145	0.0041	-0.1228	-0.1066
α_{12}	0.0358	0.0031	0.0293	0.0418	0.0377	0.0032	0.0318	0.0445
α_{13}	0.0019	0.0014	-0.0008	0.0046	0.0023	0.0014	-0.0004	0.0051
α_{14}	0.0020	0.0010	-0.0001	0.0041	0.0031	0.0010	0.0012	0.0052
α_{22}	-0.0297	0.0033	-0.0360	-0.0233	-0.0294	0.0031	-0.0355	-0.0233
α_{23}	0.0028	0.0011	0.0006	0.0049	0.0032	0.0011	0.0011	0.0053
α_{24}	0.0000	0.0008	-0.0016	0.0016	0.0008	0.0008	-0.0007	0.0024
α_{33}	-0.0038	0.0004	-0.0047	-0.0030	-0.0038	0.0004	-0.0047	-0.0029
α_{34}	-0.0008	0.0003	-0.0015	-0.0002	-0.0005	0.0003	-0.0011	0.0000
α_{44}	-0.0017	0.0004	-0.0025	-0.0009	-0.0016	0.0004	-0.0023	-0.0009
β_{11}(Input interactions)	0.0427	0.0120	0.0193	0.0661	0.0752	0.0099	0.0556	0.0944
β_{12}	-0.0011	0.0085	-0.0180	0.0155	-0.0199	0.0068	-0.0327	-0.0067
β_{13}	-0.0119	0.0089	-0.0292	0.0061	-0.0177	0.0083	-0.0336	-0.0009
β_{14}	-0.0402	0.0109	-0.0617	-0.0191	-0.0419	0.0111	-0.0653	-0.0219
β_{15}	0.0105	0.0041	0.0024	0.0185	0.0043	0.0032	-0.0022	0.0104
β_{22}	0.0580	0.0110	0.0361	0.0790	0.0605	0.0108	0.0398	0.0810
β_{23}	-0.0383	0.0086	-0.0550	-0.0216	-0.0353	0.0079	-0.0511	-0.0208
β_{24}	-0.0089	0.0109	-0.0297	0.0127	0.0000	0.0095	-0.0183	0.0178
β_{25}	-0.0097	0.0038	-0.0172	-0.0023	-0.0052	0.0033	-0.0120	0.0008
β_{33}	0.0783	0.0113	0.0562	0.1007	0.0784	0.0113	0.0559	0.0995
β_{34}	-0.0256	0.0107	-0.0475	-0.0051	-0.0238	0.0098	-0.0445	-0.0011
β_{35}	-0.0025	0.0044	-0.0110	0.0059	-0.0016	0.0036	-0.0082	0.0051
β_{44}	0.0810	0.0156	0.0516	0.1128	0.0697	0.0146	0.0419	0.1001
β_{45}	-0.0063	0.0048	-0.0158	0.0030	-0.0041	0.0044	-0.0127	0.0047
β_{55}	0.0079	0.0017	0.0046	0.0112	0.0067	0.0016	0.0035	0.0100
γ_{11} (Outp-inp. interact.)	0.0648	0.0059	0.0533	0.0768	0.0598	0.0056	0.0489	0.0707
γ_{12}	-0.0509	0.0059	-0.0623	-0.0390	-0.0499	0.0062	-0.0620	-0.0378
γ_{13}	-0.0211	0.0057	-0.0321	-0.0102	-0.0216	0.0056	-0.0319	-0.0107
γ_{14}	0.0099	0.0070	-0.0036	0.0240	0.0131	0.0066	-0.0002	0.0250
γ_{15}	-0.0027	0.0029	-0.0081	0.0030	-0.0013	0.0028	-0.0067	0.0041
γ_{21}	-0.0117	0.0043	-0.0200	-0.0034	-0.0173	0.0040	-0.0252	-0.0095
γ_{22}	0.0253	0.0046	0.0166	0.0343	0.0307	0.0044	0.0218	0.0393
γ_{23}	0.0128	0.0047	0.0035	0.0220	0.0138	0.0048	0.0043	0.0233
γ_{24}	-0.0273	0.0054	-0.0378	-0.0164	-0.0289	0.0054	-0.0401	-0.0194

(continued on next page)

Table 3-6. *(continued)*

	Unrestricted Model				Restricted Model			
	Posterior mean	St. Dev.	95 % CrI		Posterior mean	St. Dev.	95 % CrI	
γ_{25}	0.0009	0.0024	-0.0039	0.0054	0.0017	0.0023	-0.0030	0.0060
γ_{31}	0.0009	0.0017	-0.0026	0.0043	-0.0004	0.0016	-0.0036	0.0027
γ_{32}	0.0007	0.0018	-0.0029	0.0043	0.0021	0.0017	-0.0012	0.0053
γ_{33}	-0.0033	0.0020	-0.0072	0.0006	-0.0035	0.0020	-0.0076	0.0003
γ_{34}	0.0024	0.0024	-0.0022	0.0072	0.0027	0.0023	-0.0018	0.0075
γ_{35}	-0.0007	0.0011	-0.0028	0.0014	-0.0009	0.0010	-0.0028	0.0010
γ_{41}	0.0008	0.0012	-0.0016	0.0033	-0.0006	0.0012	-0.0030	0.0018
γ_{42}	-0.0010	0.0014	-0.0038	0.0018	0.0019	0.0013	-0.0006	0.0044
γ_{43}	-0.0005	0.0015	-0.0034	0.0023	-0.0010	0.0014	-0.0038	0.0018
γ_{44}	0.0016	0.0018	-0.0020	0.0049	0.0007	0.0017	-0.0025	0.0041
γ_{45}	-0.0009	0.0008	-0.0024	0.0007	-0.0010	0.0008	-0.0025	0.0005
ζ_1 (Age of farmer)	-0.0007	0.0001	-0.0008	-0.0005	-0.0006	0.0001	-0.0008	-0.0005
ζ_2 (1 if farmer holds higher education degree)	-0.0019	0.0034	-0.0084	0.0047	-0.0004	0.0036	-0.0075	0.0065
ζ_3 (1 if farm is operated full-time)	-0.1593	0.0054	-0.1700	-0.1482	-0.1566	0.0054	-0.1681	-0.1471
ζ_4 (Region 1)	0.0192	0.0333	-0.0554	0.0675	0.0595	0.0141	0.0343	0.0865
ζ_5 (Region 2)	0.0376	0.0306	-0.0274	0.0834	0.0768	0.0113	0.0538	0.0986
ζ_6 (Region 3)	0.0158	0.0314	-0.0497	0.0663	0.0525	0.0135	0.0255	0.0781
ζ_7 (Region 4)	-0.0169	0.0312	-0.0830	0.0347	0.0228	0.0123	0.0003	0.0472
ζ_8 (Region 5)	0.1712	0.0327	0.1039	0.2261	0.2132	0.0184	0.1789	0.2499
ζ_9 (Region 6)	-0.0218	0.0449	-0.1067	0.0709	0.0281	0.0516	-0.0479	0.1313
ζ_{10} (Region 7)	-0.0969	0.0308	-0.1590	-0.0501	-0.0592	0.0131	-0.0822	-0.0331
ζ_{11} (Region 8)	-0.0491	0.0317	-0.1177	-0.0004	-0.0108	0.0135	-0.0343	0.0198
ζ_{12} (Region 9)	-0.0463	0.0324	-0.1100	0.0062	-0.0101	0.0153	-0.0412	0.0189
ζ_{13} (Region 10)	-0.0030	0.0314	-0.0691	0.0468	0.0376	0.0129	0.0137	0.0630
ζ_{14} (Region 11)	-0.0919	0.0321	-0.1598	-0.0401	-0.0523	0.0203	-0.0918	-0.0137
δ_{2001} (Year dummies)	0.0183	0.0027	0.0131	0.0236	0.0186	0.0026	0.0135	0.0235
δ_{2002}	0.0813	0.0027	0.0759	0.0867	0.0818	0.0027	0.0765	0.0871
δ_{2003}	0.0679	0.0028	0.0625	0.0733	0.0684	0.0027	0.0632	0.0736
δ_{2004}	0.0520	0.0028	0.0463	0.0574	0.0525	0.0027	0.0474	0.0579
δ_{2005}	0.1121	0.0030	0.1061	0.1179	0.1128	0.0028	0.1075	0.1183
δ_{2006}	0.1054	0.0030	0.0993	0.1112	0.1063	0.0028	0.1009	0.1115
δ_{2007}	0.0071	0.0031	0.0007	0.0132	0.0077	0.0028	0.0022	0.0132
δ_{2008}	0.2300	0.0036	0.2228	0.2370	0.2312	0.0033	0.2249	0.2378
δ_{2009}	0.1379	0.0036	0.1306	0.1449	0.1394	0.0032	0.1333	0.1459
δ_{2010}	0.0125	0.0037	0.0048	0.0195	0.0136	0.0032	0.0075	0.0199
δ_{2011}	0.0934	0.0040	0.0851	0.1008	0.0949	0.0035	0.0882	0.1019
δ_{2012}	0.1413	0.0042	0.1328	0.1493	0.1431	0.0037	0.1360	0.1506
δ_{2013}	0.0369	0.0045	0.0278	0.0452	0.0388	0.0040	0.0310	0.0467
δ_{2014}	0.2094	0.0050	0.1994	0.2188	0.2115	0.0044	0.2033	0.2205
η	0.0161	0.0009	0.0144	0.0178	0.0164	0.0008	0.0149	0.0180
λ	3.0001	0.0912	2.8298	3.1825	2.9776	0.0880	2.8140	3.1549
σ^2	0.0036	0.0000	0.0035	0.0036	0.0036	0.0000	0.0035	0.0036
Returns to scale $= -1/\sum_{m=1}^{4} \alpha_m$	1.8047	0.0139	1.7787	1.8335	1.8070	0.0143	1.7784	1.8341
Mean of TE	0.7505				0.7474			

Note: CrI is credibility interval, calculated based on 10,000 successive draws from the posterior distribution after a burn-in period of 5,000 draws

Table 4-7. Bayesian estimates for the unrestricted IDF with endogeneity

Parameter	Posterior mean	St. Dev.	95 % CrI	
α_0 (Constant)	0.5018	0.0284	0.4584	0.5453
(Dummy for $Y3 = 0$)	0.0134	0.0020	0.0093	0.0175
(Dummy for $Y4 = 0$)	0.0072	0.0015	0.0042	0.0102
α_1 (Milk output)	-0.4835	0.0037	-0.4905	-0.4761
α_2 (Livestock output)	-0.0405	0.0021	-0.0447	-0.0363
α_3 (Crop output)	-0.0129	0.0010	-0.0148	-0.0109
α_4 (Other output)	-0.0040	0.0007	-0.0054	-0.0026
β_1 (Land)	0.2161	0.0048	0.2066	0.2255
β_2 (Labour)	0.1685	0.0034	0.1616	0.1753
β_3 (Intermediate inputs)	0.1894	0.0040	0.1818	0.1974
β_4 (Cows)	0.4106	0.0051	0.4007	0.4204
β_5 (Capital)	0.0155	0.0022	0.0114	0.0198
α_{11}(Output interactions)	-0.1157	0.0042	-0.1236	-0.1072
α_{12}	0.0288	0.0031	0.0229	0.0350
α_{13}	0.0021	0.0014	-0.0005	0.0048
α_{14}	0.0024	0.0010	0.0003	0.0044
α_{22}	-0.0277	0.0031	-0.0337	-0.0216
α_{23}	0.0024	0.0011	0.0003	0.0045
α_{24}	0.0001	0.0008	-0.0014	0.0017
α_{33}	-0.0035	0.0004	-0.0043	-0.0027
α_{34}	-0.0008	0.0003	-0.0015	-0.0002
α_{44}	-0.0018	0.0004	-0.0026	-0.0010
β_{11}(Input interactions)	0.0375	0.0118	0.0141	0.0607
β_{12}	-0.0036	0.0080	-0.0195	0.0119
β_{13}	-0.0081	0.0087	-0.0248	0.0093
β_{14}	-0.0324	0.0105	-0.0528	-0.0118
β_{15}	0.0066	0.0041	-0.0016	0.0147
β_{22}	0.0491	0.0109	0.0278	0.0703
β_{23}	-0.0342	0.0085	-0.0511	-0.0179
β_{24}	-0.0074	0.0109	-0.0289	0.0138
β_{25}	-0.0040	0.0039	-0.0115	0.0038
β_{33}	0.0768	0.0106	0.0566	0.0974
β_{34}	-0.0314	0.0103	-0.0512	-0.0113
β_{35}	-0.0032	0.0044	-0.0118	0.0051
β_{44}	0.0794	0.0159	0.0472	0.1103
β_{45}	-0.0083	0.0053	-0.0186	0.0019
β_{55}	0.0089	0.0016	0.0057	0.0121
γ_{11}(Outp-inp. interact.)	0.0547	0.0055	0.0438	0.0654
γ_{12}	-0.0525	0.0058	-0.0639	-0.0411
γ_{13}	-0.0182	0.0055	-0.0285	-0.0070

(continued on next page)

Table 3-7. *(continued)*

Parameter	Posterior mean	St. Dev.	95 % CrI	Parameter
γ_{14}	0.0188	0.0066	0.0061	0.0319
γ_{15}	-0.0028	0.0030	-0.0086	0.0030
γ_{21}	-0.0159	0.0042	-0.0241	-0.0075
γ_{22}	0.0237	0.0045	0.0148	0.0329
γ_{23}	0.0142	0.0046	0.0051	0.0230
γ_{24}	-0.0217	0.0051	-0.0316	-0.0118
γ_{25}	-0.0003	0.0023	-0.0046	0.0042
γ_{31}	0.0003	0.0017	-0.0031	0.0036
γ_{32}	0.0011	0.0018	-0.0024	0.0047
γ_{33}	-0.0051	0.0020	-0.0089	-0.0013
γ_{34}	0.0049	0.0024	0.0003	0.0096
γ_{35}	-0.0011	0.0010	-0.0032	0.0009
γ_{41}	0.0011	0.0012	-0.0012	0.0035
γ_{42}	-0.0009	0.0014	-0.0037	0.0020
γ_{43}	-0.0009	0.0015	-0.0038	0.0019
γ_{44}	0.0015	0.0017	-0.0019	0.0049
γ_{45}	-0.0008	0.0008	-0.0023	0.0007
ζ_1 (Age of farmer)	-0.0007	0.0001	-0.0008	-0.0005
ζ_2 (1 if farmer holds higher education degree)	-0.0041	0.0034	-0.0106	0.0027
ζ_3 (1 if farm is operated full-time)	-0.1380	0.0056	-0.1498	-0.1275
Regional dummies		*(not reported)*		
Year dummies		*(not reported)*		
η	0.0183	0.0009	0.0166	0.0199
λ	1.9962	0.0038	1.9862	1.9999
σ^2	0.0034	0.0000	0.0033	0.0035
ρ_0	-0.7104	0.0241	-0.7558	-0.6621
ρ_{q_1}	-0.0347	0.0477	-0.1250	0.0608
ρ_{q_2}	0.0187	0.0368	-0.0541	0.0907
ρ_{q_3}	0.0087	0.0168	-0.0248	0.0415
ρ_{q_4}	0.0074	0.0135	-0.0188	0.0334
$\rho_{\tilde{x}_2}$	-0.0322	0.0620	-0.1523	0.0864
$\rho_{\tilde{x}_3}$	-0.0040	0.0598	-0.1195	0.1120
$\rho_{\tilde{x}_4}$	0.0624	0.0797	-0.0923	0.2204
$\rho_{\tilde{x}_5}$	0.0223	0.0343	-0.0454	0.0897

Note: CrI is credibility interval, calculated based on 10,000 successive draws from the posterior distribution after a burn-in period of 5,000 draws

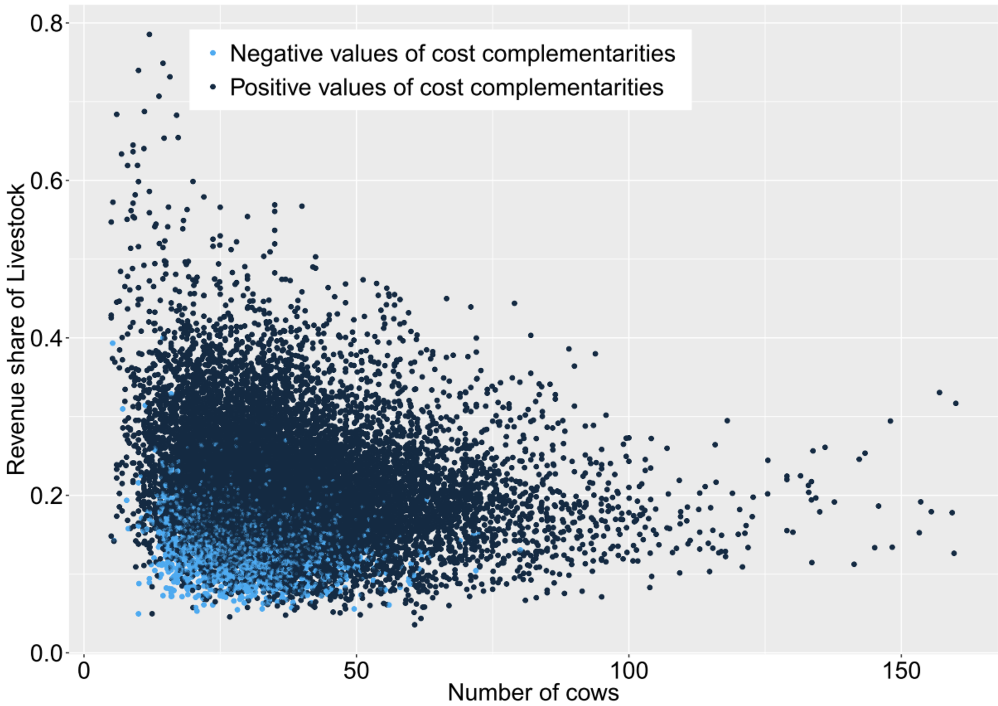

Figure 4-2. Cost complementarities between milk and livestock

Note: Negative (positive) values of cost complementarities indicate that marginal costs of producing one good decrease (increase) in response to increasing the production level of another good.

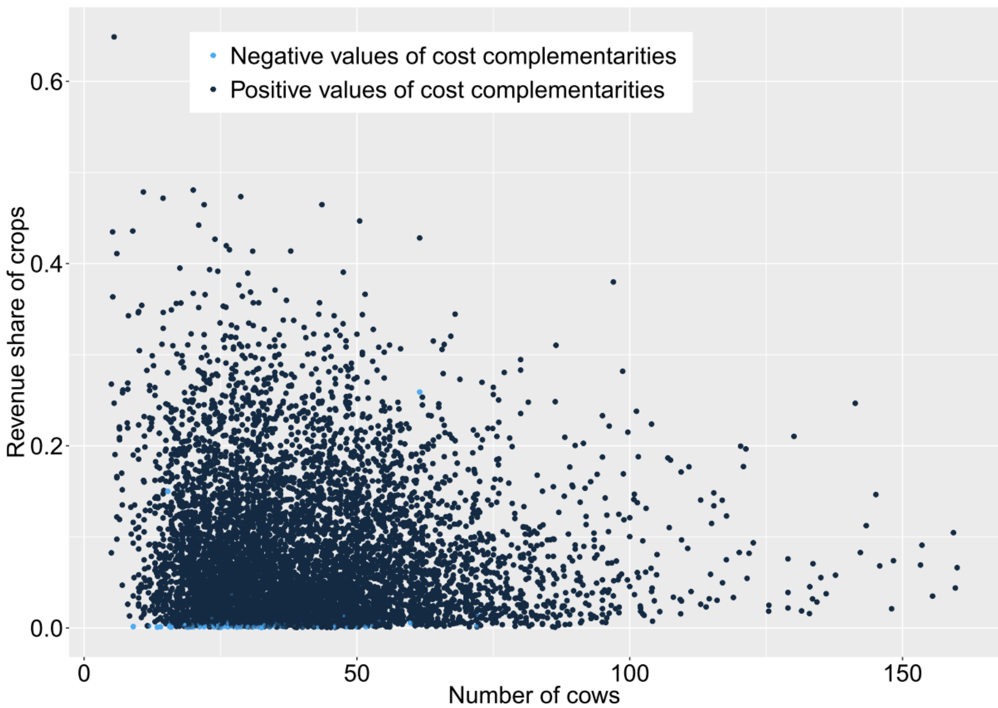

Figure 4-3. Cost complementarities between between milk and crops

Note: Negative (positive) values of cost complementarities indicate that marginal costs of producing one good decrease (increase) in response to increasing the production level of another good.

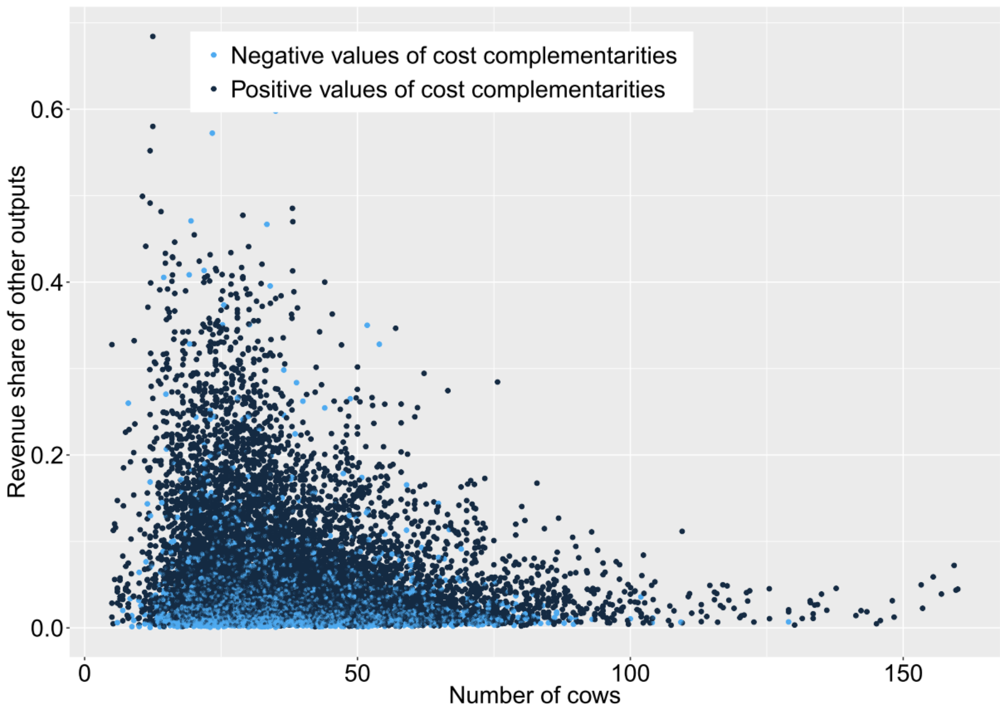

Figure 4-4. Cost complementarities between milk and other outputs

Note: Negative (positive) values of cost complementarities indicate that marginal costs of producing one good decrease (increase) in response to increasing the production level of another good.

5

Credit Access and Farm Productivity: Evidence from a Field Experiment in Rural China*

Abstract. Credit constraints have been one of the main obstacles for poor rural households to escape poverty in developing countries. The literature shows that access to credit improves smallholder farm performance in terms of yield or other partial productivity measures. The implications may be misleading since partial productivity measures do not account for changes in all inputs. Using a unique randomised controlled trial of agricultural microcredits in rural China over four years (2010–2014), we estimate total factor productivity (TFP) based on an endogeneity-robust production function approach. In addition, we decompose TFP growth into its components of technical efficiency change, technical change and scale efficiency change with a production frontier approach. The results show that improved credit access causes higher agricultural outputs and productivity gains over a wide range of measures. These effects are homogeneous across socio-demographic variables and initial resource endowments. The productivity gains are driven by increasing technical efficiency and technical changes. The effect on technical change is shown to increase four years after the intervention.

Keywords: Microfinance, randomised control trial, smallholder credit access, stochastic production frontier, total factor productivity

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5.1 Introduction

Lack of credit access has long been recognised as a barrier for smallholder farmers to increase welfare (Carter, 1989; Feder et al., 1990). In their household models, Singh, Squire and Strauss (1986) show that consumption and production decisions are independent if liquidity is available at a given price. Liquidity is crucial in agricultural production because of the time lag between input expenses and cash income. However, as well known from Stiglitz and Weiss, A. (1981), credit rationing arises from asymmetric information and adverse selection, which is often observed in credit markets. If the credit constraints are binding, smallholder farms use less than optimal levels of inputs in order to smooth consumption, which reduces agricultural output. The relationship between credit access and yield – or output per unit of land – has been studied by a large body of literature (e.g. Carter, 1989; Feder et al., 1990; Guirkinger and Boucher, 2008; Dong, Lu, J. and Featherstone, 2012; Hossain, M. et al., 2019), while faced with two main challenges.

First, partial productivity measures (e.g. land productivity or labour productivity) are incomplete, because they are affected by the use of the excluded inputs (Syverson, 2011). For example, yield can be increased by intensifying the use of materials (e.g. seed, fertiliser), labour or capital assets. By contrast, total factor productivity (TFP) considers changes in all inputs used in the production process and hence reflects unit costs of production more closely (Fuglie, 2015). Hence, to understand the welfare impact of improved credit access, it is important to evaluate TFP in addition to partial productivity measures. Moreover, changes in TFP can be decomposed into technical efficiency changes (TEC), technical change (TC), and scale change (SEC), which allows to identify sources of productivity changes and hence design and target policy measures more effectively.

Second, studies concerned with the effects of credit constraints often face econometric challenges to identify the causal effect of credit access rather than correlations. As noted by Feder et al. (1990), the effect of credit for liquidity-constrained households is expected to be different from their unconstrained counterparts. Moreover, more productive farms may be more likely to receive credits than less productive ones, for example if they can present more collaterals to potential lenders. Therefore, causal inference is complicated by the fact that credit is not randomly assigned among farm operators but farmers with credit access may systematically differ from farmers who face credit constraints. To overcome this problem, studies mostly exploit the between-variations as their identification strategy based on cross sectional data, and use of switching regression models, the Heckman (1979) selection model, semi-parametric matching models or random trend models. This strand of the literature finds that credit access increases production (Briggeman, Towe and Morehart, 2009; Feder et al., 1990; Foltz, 2004; Petrick, 2004), investment (Berhane and Gardebroek, 2011; Carter and Olinto, 2003; Foltz, 2004), partial productivity (Ciaian, Fałkowski and Kancs, 2012; Dong, Lu, J. and Featherstone, 2012; Guirkinger and Boucher, 2008; Reyes et al., 2012) and household consumption (Berhane and

Gardebroek, 2011), and promotes technology adoption (Abate et al., 2016; Theriault, Smale and Haider, 2017) and increases crop specialisation (Mulwa and Visser, 2020). The existing findings could be biased if the household's or farm's unobservable characteristics (or time-varying unobserved heterogeneity in the case of panel data) confound the relationship between credit access and productivity.

Another strand of the literature investigates correlations between credit access (or credit uptake) and technical efficiency in a production frontier framework. The results in these studies, however, are ambiguous: in various developing countries, Battese and Broca (1997) find a negative relation between credit constraints and technical efficiency, Liu, Y. and Myers (2009), Hazarika and Alwang (2003), and Nguyen et al. (2018) find no correlation, and Shrestha, R. B. et al. (2016) find a positive association. Owing to data constraints, these studies are not able to identify the causal link between credit access and productivity, which may explain the divergence of the results.

The purpose of the present study is to examine the causal impact of access to agricultural microcredit on total factor productivity (TFP) of smallholder farms. Our article makes two contributions to the literature on the impact of relaxing credit constraints on smallholder farms' productivity by integrating the two lines of research summarised above. First, we estimate TFP using both the Solow residual approach and a Malmquist TFP index consisting of technical efficiency changes, technical change and scale change. To facilitate comparisons to previous studies in the field, we also report the effects on partial productivity measures. Estimating and decomposing TFP into its components allows us to identify the causal effect of improved credit access on each component. Identifying the sources of productivity is important for policymakers to tailor public spending to the regional needs. We are not aware of a previous study that has done so in assessment of the productivity effects of credit constraints. Second, we examine the dynamic causal relationship between improved credit access and TFP (and its components). The data comes from a field experiment in five provinces in the People's Republic of China (hereafter "China") that has been implemented from 2010–2014. We use a difference-In-Difference (DID) strategy to estimate the Intent-To-Treat (ITT) effect of the microcredit programme, which has been introduced in randomly selected villages, on TFP and its components. To the best of our knowledge, Jimi et al. (2019) are the only authors that use data from a randomised controlled trial to estimate the causal effect of credit access on productivity and efficiency. Using data from 3,292 households surveyed in 2012 and one follow-up in 2014, they find that the microcredit programme improved productivity through both technological changes and increases in technical efficiency. Our analysis deviates as our data stem from a randomised controlled trial with two follow-ups over four years and therefore allow us to differentiate between short and long-term productivity or efficiency gains of improved credit access. Moreover, we use a more flexible form for the production function to allow for non-linearities in inputs and to test for scale efficiency changes, and we account for endogenous input usage. Finally, combined with our decomposed TFP, our analysis shows how different components of TFP would respond to credit access differently over time.

Our article also speaks to the estimates for productivity growth among smallholder farms and adds new evidence to developing countries. Owing to data availability, most agricultural TFP studies have focused on high-income countries (Fuglie, 2015). Using regional data provided by the FAO, Fuglie estimates in a series of papers (e.g. 2008, 2012, 2015) that TFP growth in developing countries accelerated in recent decades, primarily driven by Brazil and China. However, since these data do not include cost shares or production elasticities, they must be imputed from other country-level studies to measure changes in TFP. Maue, Burke and Emerick (2020), by contrast, use household-level data to estimate productivity dispersion and persistence for smallholder farms in four countries in Sub-Saharan Africa. We add to this literature by providing TFP estimates for smallholder farms in rural China based on a detailed household-level data set that allows us to identify the sources of productivity change over time.

We find that technical change was the primary source of productivity growth in our sample of Chinese smallholder farms over the period 2010–2014. Relaxing the credit constraint significantly improved both partial productivity and TFP of farm households in the treated villages and the results are robust across a wide range of production function specifications. Using the Levinsohn-Petrin (2003) estimator, we find that output elasticities differ when accounting for endogenous input choice, while derived productivity measures were only slightly affected. Finally, the results suggest that improved credit access positively contributed to TFP growth via gains in technical efficiency and technical change, and that the positive effect on technical change accumulates over time.

The remainder of the article is organised as follows. In Section 5.2, we describe the Village Fund, a microcredit programme for smallholders in rural China that provides the data for our study. Section 5.3 presents the data and descriptive sample statistics including baseline balance tests. The empirical estimation and the identification strategy are outlined in Section 5.4, before the results are presented and discussed in Section 5.5. Section 5.6 concludes and offers policy implications.

5.2 Programme background and experimental design

Like in other developing countries, access to formal loans has long been limited and insufficient for rural households in China.[27] By 2006, there were 3,302 out of 34,461 towns (9.6 %) having not set up any formal financial branch, and 8,231 towns (23.9 %) had only set up one branch. At the village level, there had been about 520,000 out of 585,451 administrative villages accessing formal financial services by 2014, leaving 11.2 % of villages without accessing formal credits. The China Financial Service Report 2008 published by the People's Bank of China suggests that only 78 million out of 230 million rural households (33.2 %) obtained formal loans in 2007, despite half of rural households being in demand of credits; the average loan size was 2,673 *yuan* per borrowing rural household (equivalent to 907 *yuan* per rural household).[28]

The presented numbers indicate that formal loans are not sufficient to meet the household demand. Despite increasing average loans borrowed by rural households, more than half of loans were borrowed from relatives or friends that are usually free from interests and more convenient to have compared with formal credits, as indicated by Figure 5-4 in the Appendix. The Figure also shows that 38–54 % of total loans were used for production purposes between 1995 and 2009. Moreover, 10–14 % of production costs relied on loans regardless of the loan sources.

Formal financial services are particularly limited in poor rural areas. As shown in Figure 5-4, the size of household loans in poor counties (denoted by the grey dash line) was only two thirds of that of an average rural household (denoted by the total length of the bar) in 2002. This proportion dropped continuously to one third in 2009. Even though the government introduced the poverty-alleviation loans in 1986 particularly for poor rural population, according to the Ministry of Finance, only 0.72 % of about 40,000 sample households in the official Poverty Monitoring Household Survey obtained poverty-alleviation loans in 2001 with an average size of 17.03 *yuan* per household.[29] Only 0.60 % of poor households whose income was lower than the national poverty line obtained the loans with an average size of 8.77 *yuan*. The loans received by poor households accounted for merely 9.67 % of the total poverty-alleviation loans. Production costs were 318.33 *yuan* per capita among poor households, of which 116.84 *yuan* per capita (36.7 %) were loans from any source. Assuming 1.66 *yuan* (=17.03 *yuan* / 9.67 %) as an average poor household's poverty-alleviation loans, it is

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[27] The figures in this paragraph are authors' compilation and computation of official data in China Statistical Yearbooks published by the National Bureau of Statistics, the Distribution of China Rural Financial Services released by the China Banking and Insurance Regulatory Commission in 2007, and the China Financial Service Report (2008, 2010, 2012 and 2014) published by the People's Bank of China (i.e., the central bank of China).

[28] 1 *yuan* = 0.148 USD on average in 2010

[29] The figures in this and the next two sentences are from the report of the Ministry of Finance, available in Chinese at http://nys.mof.gov.cn/zhengfuxinxi/bgtDiaoCheYan-Jiu_1_1_1_1_2/200806/t20080619_47086.html [accessed January 30, 2020]

obvious that formal microcredits in form of poverty-alleviation loans only counted 1.42 % (=1.66/116.84) of per capita borrowed production costs and 0.52 % (=1.66/318.33) of per capita total production costs.

To improve rural finance especially for 128,000 poor villages listed by different levels of government, the State Council piloted the Village Fund (one for each administrative village) in 2006 in 140 administrative villages across 14 out of 23 Chinese provinces. By the end of 2009 (before we conducted the experiment in 2010), the Village Fund had been set up in 9,003 administrative villages. This number is equivalent to a coverage rate of 6 % among listed administrative villages by the State Council. The coverage rate rose to 15 % of listed poor villages in 2014 when our experiment ended.

The central government's fiscal budget of poverty alleviation invests 150,000 *yuan* to each Village Fund. Villagers vote for members of the Village Fund Committee who determine the participation fees to the Fund and terms of loans (e.g., the interest rate, the length and amount of lending, repayment methods, and penalties for defaults) and manage the lending. The Fund committee sets up village-specific terms under the guidelines of the State Council. That is: (i) households have to pay participation fees (100–500 *yuan* per household to be determined by the Fund Committee) to join the Village Fund, but the fees are waived for poor households whose annual net income per capita is lower than the national poverty line; (ii) a loan should not be larger than 5,000 *yuan* with the length being no longer than 12 months; (iii) loans can only be used in income-generating activities, typically agricultural production given the local context, without negative influences on the village environment; (iv) lending is made on a rotating basis within a borrowing group including five to seven participating households; (v) lending is made on group liability without collaterals; (vi) poor and female participants are endowed with priority to loan allocation. After the Committee sets up village-specific terms, households pay the participation fees, join the Village Fund, and form their own borrowing group on the voluntary basis. In this sense, the Village Fund is most likely to be a rotating credit association.

To evaluate the impact of the Village Fund for poor areas, we collaborated with the State Council Leading Group Office of Poverty Alleviation and Development (CPAD) and conducted an experiment starting in 2010. To this end, we selected five sample provinces covering coastal, central and western regions (see Figure 5-5 in the Appendix), which include 5 out of 11 ultra-poor clusters designated by the State Council. Two poor counties in each province and five poor villages in each county were selected according to households' net income per capita and other socioeconomic indicators. In each sample county, we assigned treatment to three villages randomly, while two villages for control. 30 households, representing both the poor and affluence in the village, were randomly selected within each village according to the equal distance in a name list of all households ordered by family wealth. After the baseline interview at the household and village levels in August 2010, the CPAD of the State Council immediately set up and injected 150,000 *yuan* into the Village Fund in each of the 30 treatment villages during September–October 2010, while the 20 control villages did not receive any intervention. By comparison, according to the official Poverty Monitoring Household Survey, the village average size of the poverty-alleviation loans was only 38,000 *yuan* in 2009. The experiment provided treatment villages formal credits exogenously and substantially. We conducted two follow-up surveys in July 2012 and August 2014, respectively. After July 2012, 10 original control villages became treated, while 2 treatment villages withdrew the Fund. Therefore, in the end-line survey in 2014, there were 12 control villages (of which 10 were always part of the control group over the period 2010–2014) and 38 treatment villages (of which 28 were always part of the treatment group). The CPAD together with provincial and county governments helped treatment villages establish the Village Fund Committee and trained the committee members for the guidelines of the Village Fund and necessary financial and accounting knowledge and skills. The Fund Committee set up specific regulations and terms and submitted them to the county governments that would archive and approve those documents. The Fund Committee members attended regular trainings and meetings held by provincial governments and uploaded every transaction to the fund system managed and monitored by the CPAD. Throughout the four-year project period, the central and provincial officials closely monitored and checked the operation and management of the Village Fund to avoid local corruption or collusion.

Among treatment villages, the average size of the Village Fund was 182,700 *yuan*, of which the State Council's fiscal injection counted 86.8 %. The remaining 12.39 % came from households' contributions in terms of participation fees and 0.81 % were other contributions from the society. The average participation fee was 286 *yuan* per household. The annual interest rates ranged between 6–11 %. In the meanwhile, the People's Bank of China set the benchmark interest rate of 6 to 12-month loans at 5.56 % on 20 October 2010; and the Rural Credit Cooperatives – the main source of formal credits to an average rural households – were allowed to set up their own interest rates between 0.9 and 2.3 times as low/high as this benchmark level. Thus, the Village Fund was not more costly, but rather more accessible than the prevailing formal credits at the time of experiment. Each Fund Committees specified their own loan size between 1,000 and 5,000 *yuan* in their respective Village Fund regulations. For an average household in the listed poor counties in 2009, a 12-month loan of 5,000 *yuan* could cover its annual productive costs including purchases of productive assets.[30]

[30] As seen in the last row of Table A 1, 4,698 yuan per household ≈ (1,013.10 yuan per capita of productive costs + 105.47 yuan per capita of purchases of productive assets) x 4.2 family members as an average household size

5.3 Data and descriptive statistics

In the baseline interview in 2010, 1,500 households were interviewed, of whom 900 households resided in 30 treatment villages. 1,351 (90 %) households were repeatedly interviewed in 2012 and 1,323 (88 %) again in 2014. Hence, the annualised attrition rate is 5.2 %, which is lower than that in many other longitudinal surveys in developing countries (e.g. 7 % in Brazil, 6 % in South Africa and an average of 10 % in developing countries according to Barrientos and Mase (2012) and Dercon and Shapiro, J. S. (2007))[31]. To ensure consistent estimates of the production function, we dismissed households that reported negative or zero values for agricultural production in at least one year, households that reported an unrealistically high number of production value[32], and households for which only one observation was available. The final sample used for our analysis consists of 1,256 households with a total of 3,569 observations over three survey waves, which is 86 % of the original sample size. In 2010, 755 households were in the treatment villages, while 501 households were in the controlled villages. In 2012, after the second treatment wave, 1,020 households were treated and 236 were controls. Thus, the ratios of households in treatment over control villages (1.5 in 2010 and 4 in 2012) are maintained after the data cleaning.

To check if there are systematic differences between the control and the treatment group in the remaining sample, we regress all covariates on a dummy variable that indicates the treatment status after the baseline survey in 2010, standard errors being clustered at the village level. Because the number of clusters (50) is relatively small, we bootstrap standard errors following the suggestion by Cameron, Gelbach and Miller (2008). Table 5-1 shows the means and standard deviations of the collected data in columns 1 and 2, respectively, and the regression coefficients and p-values in columns 3 and 4, respectively. If treatment was truly random across villages, there should be no significant differences between the treated and control households. All p-values are above 0.10, providing support for the hypothesis that randomisation was successful. The descriptive statistics show that the majority of households are headed by males (93 %) at an average age of 52. Furthermore, household heads have on average 5.94 years of education. The relatively low share of household consumption for food indicates that the majority of households in the sample rely on subsistence farming. Agricultural production value and input expenses (the definitions are explained in detail below) are also equally balanced between the treatment and control group. Finally, 20 % of households report in 2010 that they have no access to credit. 77 % indicate that they have access to informal loans, and only 35 % report that they have access to formal loans. Nevertheless, outstanding debts and total loans are relatively high, compared to yearly household consumption.

[31] We used a probit specification to regress whether the household disappeared in any follow-ups on various household characteristics, village traits and the county dummies. The estimators are insignificantly different from zero, both individually and jointly. Thus, we trust that attrition is broadly random.
[32] In particular, we removed 87 observations that indicated revenues above the 99th percentile

Table 5-1. Baseline balance

	Control Group		Treatment-Control	
	Mean	SD	Coeff.	p-value
	(1)	(2)	(3)	(4)
Household demographics				
Household head is female (1 if yes, 0 otherwise)	0.07	0.26	-0.02	0.17
Age of household head	52.13	11.35	0.86	0.53
Household size	4.33	1.54	-0.15	0.47
Education of household head	5.94	3.74	-0.40	0.31
Income and consumption				
Household income (CN¥)	13,333.79	16,242.45	-1,767.25	0.35
Household food consumption (CN¥)	276.61	241.65	-17.71	0.47
Household total consumption (CN¥)	6,395.64	14,956.61	-634.42	0.56
Agricultural outputs and inputs				
Crop production value (CN¥)	3,785.52	3,684.67	517.57	0.45
Livestock production value (CN¥)	1,819.63	3,234.67	-39.60	0.92
Agricultural land (mu)	6.12	7.99	0.38	0.80
Labour input (index)	24.85	11.17	-1.01	0.30
Crop-specific inputs (CN¥)	1,330.29	1,282.02	250.27	0.47
Animal-specific inputs (CN¥)	1,378.27	3,141.92	-209.88	0.46
Productive assets (CN¥)	3,073.88	17,488.78	-320.05	0.80
Credit access				
Access to any type of loan (1 if yes, 0 otherwise)	0.80	0.40	-0.01	0.83
Access to informal loan (1 if yes, 0 otherwise)	0.77	0.42	0.00	0.92
Access to formal loan (1 if yes, 0 otherwise)	0.35	0.48	-0.08	0.11
Total loans (CN¥)	10,734.41	43,075.43	-3,188.79	0.21

Note: 501 households are in the control group, 755 households in the treatment group. Coefficients and p-values in columns (3) and (4) are from a regression of the respective variable on a dummy variable that indicates treatment (1 if yes, 0 otherwise). Standard errors are clustered at the village level and bootstrapped with 400 repetitions. The respondents reported their annual income in 2009 as the baseline took place in mid of 2010, while other variables were asked for their values in 2010. The asterisks ***, **, and * indicate significance levels at 0.01, 0.05, and 0.10, respectively.

To facilitate estimation of the production technology, we aggregate crop production value and livestock production value to one output variable. We divide monetary values by provincial input price indices obtained from the National Development and Reform Commission of China to convert revenues to implicit quantities. The data contains quantities and prices for 38 crop categories.[33] Most households report prices even if the entire output is consumed within the households. For those that do not report prices, we calculate the village or town average prices. The individual crop value is then computed as the product of quantities produced (both for home consumption and sale) multiplied with the price. As for animal production, the production values are calculated as the sum of sales, self-consumption, stolen animals, and inventory changes net of animal purchases for pigs, poultry, sheep, big livestock (e.g. cattle), and other livestock. We further add the production value of wool, cashmere, milk, eggs, and other livestock output, which is again calculated physical output multiplied with market prices. In our sample, most farm households produce crop and livestock simultaneously. For 33 % of observations, the value share of crop production exceeds 95 %. We use a binary variable for farm type in our production function estimation to account for potential differences in the production technology.

The inputs considered are cultivated land, family labour, material usage (both for crops and animal production) and capital. Land use is measured in mu.[34] If the reported land use is zero or missing (4 % of observations), we replace it with the household's average land use in other years. Unfortunately, the data does not directly report labour devoted to agricultural production. Hence, we calculate a labour index based on the number of months each household member stays at home and the reported frequency in productive activities. We trust that this index adequately reflects the amount of agricultural family labour, since family members typically help with family agriculture when staying at home, including those returning from migration or school. Material inputs consist of both crop-specific inputs (seed, fertiliser, pesticides, and hired labour and machinery) and animal-specific inputs (fodder, medical costs, and hired labour). Finally, capital summarises productive assets such as tractors, farm implements, handcarts, or threshing machines. Crop-specific, animal-specific, and capital inputs are all reported in value terms and converted to implicit quantities by using corresponding provincial price indices. The descriptive statistics for the output and input variables used to estimate the production technology for our sample of smallholder farms in rural China are reported in Table 5-2.

[33] By land shares, the most important crops are corn, wheat, and rice.
[34] 1 mu = 0.07 hectares

Table 5-2. Descriptive statistics for variables used in the production function

	Mean	Std. dev.	Min.	Max.
Aggregated output (cCN¥)	7,059.90	6,640.35	5.86	62,076.70
Agricultural land (mu)	6.23	6.73	0.10	107.00
Labour input (index)	23.29	10.19	0.50	100.00
Materials (cCN¥)	2,934.95	3051.96	0.00	59,981.61
Capital (cCN¥)	3,544.78	19,994.41	0.00	452,328.94

Note: cCN¥ denotes constant *Yuan*. Descriptive statistics are based on 3,569 observations from 1,256 households in the years 2010, 2012 and 2014.

5.4 Empirical framework

5.4.1 Measuring productivity

Total factor productivity is defined as the ratio of output to aggregate inputs. One way to aggregate quantities is based on value terms by using appropriate price indices, so that the productivity measure is independent of price differences. Another way is to weigh inputs by their output elasticities. With K production inputs X_{kit} and output Q_{it}, TFP is then defined as (e.g. Syverson, 2011)

$$TFP_{it} = A_{it} = \frac{Q_{it}}{X_{1it}^{\alpha_1} + X_{2it}^{\alpha_2} + \cdots + X_{Kit}^{\alpha_K}} \quad , \tag{5-1}$$

where α_k denotes the k-th input's output elasticity, A_{it} is a technology shift factor that contains technical efficiency and technical change (Frick and Sauer, 2018), and i and t are subscripts for household units and time. As discussed by Syverson (2011) there are two approaches to measure output elasticities. The first one is non-parametric and relies on the assumption of cost-minimising behaviour of firms. Under this assumption, elasticities can be constructed as the product of the input's cost share and the scale elasticity, which has to be either estimated or assumed (see Foster, Haltiwanger and Syverson (2008) for an application in the manufacturing sector). The second approach – which we will follow in our analysis – is to estimate the production function and measure firm-level productivity as the Solow residual (see Maue, Burke and Emerick, 2020 for a recent application of this approach to measure TFP in smallholder farming). In this way, we avoid relying on the assumption of cost minimisation, which is unlikely given the importance of subsistence farming in our sample. Specifically, we estimate the production function in the form

$$\ln q_{it} = \beta_0 + x_{it}'\beta + \beta_t trend_t + farmtype_{it} + household_i + \epsilon_{it} \quad , \tag{5-2}$$

where the row vector x_{it}' contains either only linear (Cobb-Douglas functional form) or linear, interaction and squared terms (translog functional form) of production inputs. The Cobb-Douglas functional form is employed in similar contexts (e.g. Jimi et al., 2019; Maue, Burke and Emerick, 2020). In addition to the Cobb-Douglas production function, we estimate the more flexible translog form to capture non-linearities between input factors. A trend variable ($trend_t$) is included so that the production function can shift over time, representing technical change.[35] Household fixed effects ($household_i$) are included to account for unobserved heterogeneity across households such as geographical factors and ability. Controlling for these factors in the production function estimation helps mitigating endogeneity problems stemming from omitted variable bias. Finally, we include a dummy variable to account for technological heterogeneity between crop farming and crop-livestock mixed farming ($farmtype_{it}$). After estimating (5-2), we compute estimated productivity levels as variation in output that is not attributable to differences in input levels (see, e.g. Frick and Sauer, 2018):

$$\ln TFP_{it} = \hat{\beta}_0 + \hat{\beta}_t + farmtype_{it} + household_i + \hat{\epsilon}_{it} = \ln q_{it} - x'_{it}\beta \qquad (5\text{-}3)$$

While the TFP measure in equation (5-3) represents output differences that cannot be explained by differences in input levels, they can be caused by household fixed effects which contain both geographical factors (e.g. soil quality) and farmers' abilities. To isolate the effect of improved credit access on productivity, we therefore account for these confounding factors in the DID design specified below.

5.4.2 Accounting for endogenous input choice

Despite accounting for unobserved heterogeneity in the model specification (5-2), endogeneity may arise owing to unobserved productivity shocks that are time-varying and entail a change in input use. In other words, endogeneity problems arise when the inputs in the production function are not exogenous but determined by the individual farmers' choices who respond to productivity shocks that are not observable to the econometrician (Griliches and Mairesse, 1999). To account for potential endogeneity of input choice, we employ the proxy-variable approach by Levinsohn and Petrin (2003) (LP hereafter). The technique proposed by LP is a modification of the Olley and Pakes (1996) control function approach that uses investment to proxy unobserved productivity shocks. LP argue that this approach is problematic if adjustment of capital is costly so that the investment response to productivity shocks is not smoothly. From a practical perspective, high adjustment costs result in a substantial amount of observations reporting zero investments. As a remedy, LP propose to proxy productivity shocks with intermediate inputs. In particular, the productivity process is described as a first-order Markov process, assuming that capital stock is a state variable that cannot be immediately adjusted as a response to sudden productivity shocks. Under this assumption, the identification strategy is based on the observation that material use can be represented as a function of a firm's productivity and its capital endowment. We follow this procedure to estimate the production function in (5-2) in the Cobb-Douglas form. Unfortunately, the control function approaches by Olley and Pakes

[35] We also estimate a model with county-year fixed effects ($county$ - $year_{it}$) instead of a time trend to verify that the results are not driven by regional-specific shocks such as weather events.

(1996) and LP cannot accommodate the translog functional form. This is because it is not clear how to incorporate the interactions between the state variable capital and the freely variable inputs. An alternative endogeneity-robust estimation technique, which may be better suited to the translog functional form, is the Wooldridge-Levinsohn-Petrin GMM estimator described in Wooldridge (2009). However, this estimation technique requires several-period lags of variables as instruments. Since we only observe three periods per household at maximum, we abstain from this approach.[36] Nevertheless, comparing the productivity levels obtained from the LP Cobb-Douglas function to the ones obtained from the fixed effects estimation allows us to assess whether endogeneity problems affect the results. In particular, we will estimate the effect of improved credit access on the Solow residual obtained from the fixed effects translog model (FE-TL), the fixed effects Cobb Douglas model (FE-CD), and the LP Cobb Douglas (LP-CD) model. If the results are robust across all our specifications, we can be confident that our main results are not sensitive to input endogeneity.

5.4.3 Decomposition of productivity growth

The residual approach discussed above measures differences in output while holding inputs constant. As such, it does not measure productivity changes that are due to scale efficiency effects. Stochastic frontier analysis, as proposed by Aigner, Lovell and Schmidt, P. (1977) and Meeusen and van Den Broeck (1977), provides a tool to decompose productivity growth into technical efficiency change, technical change and scale change (Orea, 2002). The resulting productivity index is called generalised Malmquist TFP index. To derive this TFP index, output is estimated as a function of inputs while allowing for inefficient input use. In this framework, we estimate a translog functional form only, so that scale elasticity can vary across farm observations. With four production inputs, the equation to be estimated takes the following form:

$$\begin{aligned}\ln q_{it} = \beta_0 &+ \sum_{j=1}^{4} \beta_j \ln x_{jit} + 0.5 \sum_{j=1}^{4} \sum_{k=1}^{4} \beta_{jk} \ln x_{jit} \ln x_{kit} + \beta_t trend \\ &+ \beta_{tt} trend^2 + \sum_{j=1}^{4} \beta_{jt} \ln x_{jit}\, trend + farmtype_{it} + household_i \\ &- \eta_i - u_{it} + v_{it} \quad ,\end{aligned} \tag{5-4}$$

where the variables are defined as above. The error term consists of four components as proposed by Kumbhakar, Lien and Hardaker (2014). The first component, $household_i$, captures time-invariant farm effects as in (5-2); second, $\eta_i > 0$ and $u_{it} > 0$ are persistent and time-varying inefficiency, respectively; finally, v_{it} is a symmetric error term accounting for random noise, omitted variables and functional form errors. This model is an extension of models that have widely been adopted in the literature. Perhaps the most popular is the Battese and Coelli (1992) time decay model where

[36] Frick and Sauer (2018) applied the Wooldridge-Levinsohn-Petrin GMM estimator to a large panel of dairy farms. They report that the resulting estimates were very sensitive to the specification of the control function, possibly owing to multicollinearity between input variables, and thus proceeded with the Cobb Douglas form.

inefficiency is modelled as a function of time. However, it imposes the restriction that the inefficiency change is monotonically increasing or decreasing for all production units. Moreover, it does not distinguish between technical inefficiency and firm heterogeneity. We follow Kumbhakar, Lien and Hardaker (2014) and estimate equation (5-4) in three steps. First, we define $\alpha_0 = \beta_0 - E(\eta_i) - E(u_{it})$, $\alpha_i = household_i - \eta_i + E(\eta_i)$, and $\epsilon_{it} = v_{it} - u_{it} + E(u_{it})$, so that equation (5-4) can be written as

$$y_{it} = \alpha_0 + f(x_{it}; \beta) + \alpha_i + \epsilon_{it} \ . \tag{5-5}$$

Since α_i and ϵ_{it} have zero means and constant variances, this equation can be estimated as standard fixed effect panel regression. This multi-step procedure implies that the estimates for the slope parameters of the production frontier are equal to those from the production function in (5-2) with the translog functional form. In steps 2 and 3, time-varying technical efficiency, $\exp(\hat{u}_{it})$, is estimated from $\hat{\epsilon}_{it}$, and persistent technical efficiency, $\exp(\hat{\eta}_i)$, is estimated from $\hat{\alpha}_i$ using stochastic frontier estimators. Following Kumbhakar and Lovell (2000), we then compute TFP growth as the difference between output change and an input change index where output elasticities are used as weights:

$$T\dot{F}P_{it} = \ln \dot{q}_{it} - \sum_{j=1}^{4} \sigma_j \ln \dot{x}_{jit} \ \ , \tag{5-6}$$

where σ_j represents the output elasticity of input j and the dot over a variable indicates growth rate. The output growth can be expressed as the derivative of equation (5-4) with respect to time:

$$\begin{aligned} \dot{q}_{it} = \sum_{j=1}^{4} \beta_j \ln \dot{x}_{jit} + 0.5 \sum_{j=1}^{4} \sum_{k=1}^{4} \beta_{jk} \ln \dot{x}_{jit} \ln \dot{x}_{kit} + \sum_{j=1}^{4} \beta_{jt} \ln \dot{x}_{jit}\, trend \\ + \sum_{j=1}^{4} \beta_{jt} \ln x_{jit} + \Delta\lambda_t - \Delta u_{it} \end{aligned} \tag{5-7}$$

We can now insert equation (5-7) into equation (5-6) and rearrange to obtain a parametric measure of TFP growth (see Alvarez and del Corral, 2010):

$$T\dot{F}P_{it} = \frac{\partial \ln f(.)}{\partial t} + \left(-\frac{\partial u}{\partial t}\right) + (RTS - 1) \sum_{j=1}^{4} \sigma_j \ln \dot{x}_{jit} \ \ , \tag{5-8}$$

where RTS denotes returns to scale, defined as the sum of output elasticities. The first term in (5-8) measures technical change, the second one represents technical efficiency change, and the last one denotes scale efficiency change. This decomposition allows us to estimate treatment effects both on TFP growth and on its individual components (see, e.g. Mennig and Sauer, 2020; Baráth, Fertő and Bojnec, 2020).

5.4.4 *Identification of treatment effects*

To provide empirical evidence on the causal effect of credit access on agricultural TFP growth, we estimate the ITT effect (see also Hossain, M. et al., 2019). The ITT measures the difference in outcomes between the treatment and the control group. Thus, it provides an estimate for the effect of implementing the credit programme, irrespective of households' actual participation. The ITT is a widely applied measure for the treatment effect in the evaluation of credit programmes (among previously mentioned studies, see Hossain, M. et al., 2019 and Jimi et al., 2016) or other financial programmes (e.g. Haushofer and Shapiro, J., 2016). As discussed above, participation in the Village Fund was voluntary and the village committee decided whether households were eligible to receive a credit or not. In 2012 (2014), 57 % (54 %) of farm households residing in treated villages joined the Village Fund, of whom 47 % (52 %) borrowed from the Fund. Overall, 29 % (31 %) of eligible households acquired loans from the Village Fund. This rate is higher than the one reported by Hossain, M. et al. (2019), who find that 20 % of eligible households acquired loans from a microcredit programme in Bangladesh. Table 5-11 in the Appendix shows that there are no systematic differences except household income between farm households taking part in the village fund programme and those that are not. Moreover, Table 5-12 shows that most characteristics are successfully balanced between the farms who actually took up credit from the village fund programme and those that did not. Exceptions are gender, household size, and land (all statistically significant at the 10 % significance level) and household income (1 % significance level). Agricultural outputs and labour, material and capital inputs are largely balanced between borrowers and non-borrowers.

We can therefore rely on the exogenous access to the Village Fund to identify the causal impact of relaxing farm households' credit constraints on their agricultural productivity and other outcome variables. We use a DID approach with two-way fixed effects to estimate the treatment effect:[37]

$$y_{ivt} = \alpha + \gamma D_{vt} + \delta X_{ivt} + \omega_{vt} + \rho_t + v_i + \epsilon_{ivt} \quad , \tag{5-9}$$

where y_{ivt} is the outcome variable (e.g., components of productivity growth) by household i in village v in year t. D_{vt} takes the value of 1 for the village if treated in year t and the value 0 otherwise;[38] and X_{ivt} are covariates at either the household level (gender, age, education of household head, and household size) or the village level (distance to town, investment into farmland). Although they are not systematically related to the treatment assignment, they may have explanatory power for the outcome variables and thus increase estimation efficiency. Furthermore, we include interaction terms of county dummies and a time trend ω_{vt} to control for unobserved, county-specific time-varying influences, such as different factors and output markets across counties regarding agriculture or the

[37] Note that this is precisely the intent-to-treat (ITT) effect.
[38] Recall that treatment occurred either in September 2010 after the baseline survey or after July 2012.

widening differences across prefectures brought about by unequal socioeconomic development during the long-time horizon of our study. Year fixed effects ρ_t further pick up changes over time that affect all households similarly (e.g., changes of national policy). Finally, υ_i are household-level fixed effects to account for the fact that assignment was random across villages but not within villages, and ϵ_{ivt} is the error term. The parameter of main interest is γ, which reflects the change in the outcome variable in response to being offered credit access through the Village Fund programme, i.e., the ITT effect of the programme.

5.5 Results and discussion

In this section, we first present and discuss the results from the estimation of the production technology and the derived productivity measures. We then compare productivity measures across treatment and control group and present the DID-estimates that reveal the ITT effect of improved credit access.

5.5.1 Production technology

We report the full parameter estimates of the Cobb-Douglas and Translog production functions in Table 5-13 in the Appendix.[39] The corresponding output elasticities are presented in Table 5-3. The output elasticities show the expected sign for all specifications as they satisfy the monotonicity requirement at the sample mean. For all specifications, material inputs exhibit the highest elasticity. For example, with the conventional Cobb-Douglas production function, a one per cent-increase in material use is associated with a 0.56 % increase in output. The results obtained using the LP (2003) estimation technique reveal that the output elasticity of materials tend to be upwards biased when endogeneity in input use is not accounted for. This result is consistent with the theory that unobserved productivity shocks (e.g. weather conditions) are positively correlated with variable input usage. Overall, the obtained elasticities are in similar ranges for the three models. Labour and capital show the far lowest elasticity values in all specifications, and land and material show the highest elasticities. This result is consistent with the subsample of farm households in the Southwest of China presented in Chen, Z., Huffman and Rozelle (2009). With an average area of 6.47 mu, this subsample is similar to our sample in terms of farm size. Furthermore, we find that average RTS – calculated as the sum of individual input elasticities – varies between 0.79 for the Levinsohn-Petrin Cobb Douglas specification and 0.86 for the fixed effects Cobb-Douglas specification, implying that the production technology is characterised by decreasing RTS. Again, this result is in line with Chen, Z., Huffman and Rozelle (2009), who find RTS equal to 0.78. Although decreasing RTS are remarkable considering the small scale of the sample farms, this finding is consistent with the inverse size-productivity

[39] A likelihood ratio test indicated that the Cobb-Douglas production function is rejected in favour of the Translog production function at p = 8.54e-24. Nevertheless, we report results obtained from both Cobb-Douglas and Translog functional form for the sake of comparisons with related studies and to assess the robustness of the results.

relationship documented in the literature (e.g. Sheng, Ding and Huang, J., 2019 for partial productivity, Muyanga and Jayne, 2019 for TFP) and possibly reflects the state of production technology used. Figure 5-6 in the Appendix displays the frequency distribution of technical efficiency scores obtained from the Kumbhakar, Lien and Hardaker (2014) stochastic frontier model. The efficiency scores vary between 0.10 and 0.87 with an average of 0.59. Thus, the average household in our sample could improve agricultural output by 41 % without changing the amount of inputs used, according to our estimates.

Table 5-3. Output elasticities obtained from main production function specifications

	FE-CD	LP-CD	FE-TL	FE-TL (ii)
	(1)	(2)	(3)	(4)
Land	0.204***	0.199***	0.232***	0.284***
	(0.025)	(0.031)	(0.038)	(0.036)
Labour	0.058**	0.062**	0.053	0.060
	(0.028)	(0.028)	(0.042)	(0.040)
Material	0.564***	0.491***	0.507***	0.480***
	(0.019)	(0.027)	(0.028)	(0.028)
Capital	0.030***	0.035	0.024*	0.022*
	(0.009)	(0.023)	(0.064)	(0.012)
Returns to Scale	0.856	0.787	0.853	0.853
Min	-	-	0.156	0.188
Max	-	-	1.149	1.115
Standard Deviation	-	-	0.069	0.060

Note: Number of observations is 3,569. ***, **, and * indicate significance levels at 0.01, 0.05, and 0.10, respectively. Standard errors are in parentheses. FE-CD is the standard Cobb-Douglas production function, LP-CD is the Cobb-Douglas function estimated with the Levinsohn-Petrin (2003) technique. FE-TL is the translog production function and frontier. FE-TL (ii) contains county-year fixed effects instead of a time trend. Elasticities for the TL specifications vary across household observations and are evaluated at the sample mean using the delta method.

Elasticities based on the flexible translog specifications (columns 3 and 4) vary across household observations. Hence, we check curvature conditions at every data point. Table 5-14 in the Appendix shows that the estimated production functions are monotonically increasing in inputs at the majority of data points. Use of labour is the input with the highest share of monotonicity violations (5.18 % for the specification with a time trend and 13.9 % for the specification with county-year fixed effects). A possible explanation might be that family labour input is proxied by an index rather than actual working hours, leaving the possibility of measurement errors. Another potential reason might be that within-household variation of labour use is rather limited, and thus part of the labour contribution towards output may be captured by the household fixed effect. Finally, we assess concavity of the production function by evaluating the Hessian matrix of first and second derivatives. We find that the Hessian matrix is negative semi-definite for 75.7 % (67.2 %) of observations for the specification with a time trend (county-year fixed effects), implying that the concavity condition is satisfied at the majority of data points. The specification with the time trend results in fewer regularity violations with respect to both monotonicity and curvature conditions than the specification with county-year fixed effects. Deviations from the concave part of the production function indicate non-profit maximising behaviour, which seems reasonable in the case of smallholder farming with limited access to resources. Overall, the consistency of our estimated parameters to economic theory makes us confident that the production function specifications are reliable approximation to the underlying technology.

5.5.2 Productivity measures

As discussed above, we employ two strategies to estimate household-level productivity: The Solow residual to measure TPF in levels and the Malmquist index to measure changes in TFP. The Solow residual is estimated based on four different production function specifications: The conventional Cobb-Douglas function; the LP (2003) Cobb-Douglas function; and two translog production functions either with a time trend or with county-year fixed effects. Although there are differences in the estimated parameters and elasticities between different model specifications, the Solow residual is highly robust across these specifications as indicated by correlation coefficients above 95 %. Our preferred model is the Cobb-Douglas specification estimated with the LP (2003) technique, as it is robust to endogenous input choice. However, we also present treatment effects on other specifications in the following as robustness checks. For the Malmquist index, we focus on the production frontier with the time trend, as it allows decomposing productivity change into technical change, technical efficiency change, and scale change. It also results in fewer regularity violations than the frontier with county-year fixed effects.

The Malmquist productivity index shows that TFP increased by 7.7 % per period, on average. Because data are collected every two years, this amounts to an annual average rate of 3.9 %. This estimate lies between the estimates by Cao and Birchenall (2013) for the years 1991 to 2009 (6.5 %), and the estimates by Jin et al. (2010) for Chinese crop farms for the years 1990 – 2004 (2 %). Furthermore, our estimates suggest that the overall technical efficiency change over the sample period was slightly negative. This result is driven by the negative efficiency change in the control group (- 1.3 %). Technical efficiency in the treatment group, by contrast, is slightly positive on average (+ 0.02 %). Finally, the scale effect is negative both in the control group and in the treatment group. The largest driver of TFP growth appears to be technical change, with 10.6 % on average.

Table 5-4. Components of productivity growth

Variable	Mean	Std. dev.	Min.	Max.
Entire sample				
TFP change	0.077	0.239	-1.254	1.082
Technical efficiency change	-0.001	0.211	-1.314	1.189
Scale change	-0.028	0.087	-0.613	0.296
Technical change	0.106	0.090	-0.081	0.252
Households in control villages (n=428)				
TFP change	0.038	0.273	-1.093	1.038
Technical efficiency change	-0.013	0.252	-1.123	1.189
Scale change	-0.040	0.094	-0.518	0.179
Technical change	0.092	0.088	-0.070	0.228
Households in treated villages (n=1885)				
TFP change	0.086	0.229	-1.254	1.082
Technical efficiency change	0.002	0.200	-1.314	0.994
Scale change	-0.025	0.085	-0.613	0.296
Technical change	0.109	0.091	-0.081	0.252

Note: Number of observations is 2,313. The first sample appearance is omitted because variables are measured in changes.

Figure 5-1 displays Kernel density plots of the Solow residual and of the Malmquist TFP index obtained from our preferred models, separated by the treatment status, in the end-line survey in 2014. Descriptively, both plots suggest higher productivity for farms in treated villages, i.e. those with improved credit access. The descriptive comparison, however, does not allow to make statistical inference on the effect of the improved credit access, which will be done in the following section.

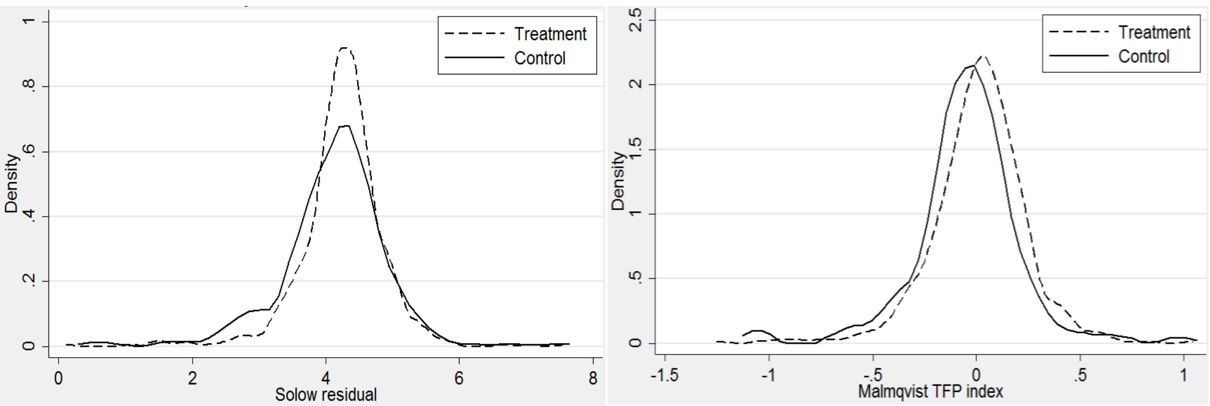

Figure 5-1. Kernel density plots for Solow residual (left) and Malmquist TFP index (right) with and without credit access (2014).

Note: The Solow residual is derived from the Levinsohn-Petrin (2003) estimation of the Cobb-Douglas production function. The Malmquist index is derived from a translog production frontier.

5.5.3 *Treatment effects of credit access*

This section presents the DID-estimates for the ITT-effect of the Village Fund programme obtained from equation (5-9). Standard errors in this section are clustered at the household level as the panel unit, as we expect serial correlation within the household. Autocorrelation in the time dimension is accounted for by including year fixed effects. First of all, we assess whether access to the Village Fund programme has improved credit access. The dependent variables are "access to formal loans" (1 if household stated that it has access to formal loans, 0 otherwise), "access to informal loans" (1 if household stated that it has access to informal loans, 0 otherwise), and total current loans measured in CNY. As Table 5-5 shows, implementation of the Village Fund increased access to formal loans but – as expected – not access to informal loans. In monetary terms, access to the Village Fund increases a household's total loan by about 2,995 CNY. This value is comparable to the average value of material use in the sample as indicated by the descriptive statistics (see Table 5-2).

Table 5-5. Impact of the Village Fund on credit access

	Access to Formal loans	Access to informal loans	Total loans
Treatment effect	0.090***	0.008	2994.891*
(Robust SE)	(0.033)	(0.028)	(1721.761)
P-value	0.006	0.769	0.082
Baseline mean	0.298	0.768	8817.58
(Std. dev.)	(0.458)	(0.422)	(29753.92)

Note: Estimation is based on 3,559 observations. ***, **, and * indicate significance levels at 0.01, 0.05, and 0.10, respectively. Standard errors are clustered at the household levels as the panel units, while controlling for year fixed effects and interactions between a time trend and county dummies. Further control variables include household and village characteristics.

Next, Table 5-6 presents the impact of the Village Fund programme on agricultural output and input usage. As described above, we distinguish between four inputs: land, labour, material inputs (including crop- and animal-specific inputs) and capital input. Table 5-6 shows that the estimated coefficients for the treatment effect are all positive except for labour. However, only the effect on output is statistically significant. As the amount of land allocated to a household is often determined by nutrition needs, i.e. family size, the non-significant effect on land use is expected. Indeed, the correlation coefficient between household size and agricultural land is +0.24 in our sample. Contrary to expectations, we find no overall significant ITT effect on material or capital use. Although the treatment effect of improved credit access on these two inputs are both economically significant, they are associated with high standard errors and hence statistically not significant. To explore this further, we estimate the treatment effect of individual material components. The estimated coefficients are displayed in Figure 5-7 in the Appendix. This figure reveals that the ITT effect on seed is significantly positive (p-value: 0.056), implying that farm households with improved credit access may be able to afford more seed or seed with higher quality.

Table 5-6. Impact of credit access on agricultural output and inputs

	Output	Land	Labour	Material	Capital
Treatment effect	997.560***	0.121	-0.078	172.340	1681.140
(Robust SE)	(317.505)	(0.194)	(0.552)	(154.730)	(1262.013)
P-value	0.002	0.533	0.888	0.266	0.183
Baseline mean	4935.443	6.346	24.239	2452.860	2881.492
(Std. dev.)	(4451.785)	(7.232)	(10.488)	(2739.582)	(14924.170)

Note: Estimation is based on 3,559 observations. ***, **, and * indicate significance levels at 0.01, 0.05, and 0.10, respectively. Standard errors are clustered at the household levels as the panel units, while controlling for year fixed effects and interactions between a time trend and county dummies. Further control variables include household and village characteristics.

Table 5-7 reports the effect of the Village Fund on gross and net value per unit of land (i.e., two measures for land productivity), as well as the effect on TFP levels obtained from various production function specifications. Consistent with previous findings in the literature (Ciaian, Fałkowski and Kancs, 2012; Dong, Lu, J. and Featherstone, 2012; Guirkinger and Boucher, 2008; Reyes et al., 2012), our results suggest that improved credit access positively contributes to land productivity. Partial productivity gains are not necessarily associated with a positive overall productivity effect (Baráth, Fertő and Bojnec, 2020). In our empirical case, however, we find that the positive effect on partial productivity also translates to a positive effect on TFP. The DID estimator suggests that the implementation of the Village Fund causes an increase in TFP level by more than 9 %. As Table 5-7 shows, this finding is robust across the production function specifications considered in our analysis, including the endogeneity-robust estimation of the Cobb-Douglas production function using the Levinson-Petrin (2003) estimator.

Table 5-7. Impact of credit access on agricultural productivity

	Gross value per mu	Net value per mu	log(TFP) (Solow residual)		
			FE-CD	LP-CD	FE-TL
	(1)	(2)	(3)	(4)	(5)
Treatment effect	808.506**	516.919**	0.098***	0.092**	0.091**
(Robust SE)	(350.600)	(223.486)	(0.036)	(0.039)	(0.035)
P-value	0.021	0.021	0.006	0.020	0.010
Baseline mean	1520.838	707.954	3.336	3.854	-0.248
(Std. dev.)	(2832.960)	(1863.840)	(0.512)	(0.539)	(0.514)

Note: Estimation is based on 3,559 observations and 1256 clusters. ***, **, and * indicate significance levels at 0.01, 0.05, and 0.10, respectively. Standard errors are clustered at the household level as the panel units, while controlling for year fixed effects and interactions between county dummies. Further control variables include household and village characteristics. FE-CD is the standard Cobb-Douglas production function, LP-CD is the Cobb-Douglas function estimated with the Levinsohn-Petrin (2003) technique. FE-TL is the translog production function.

Finally, in Table 5-8, we report the effect of the Village Fund on the Malmquist TFP index and its components. These variables are measured in changes with respect to the previous period, and thus are missing for the first year. To keep all observations for the estimation, we translate the index to a chain index, so that it takes the value 1 in the first period, which serves as the base for the second and third periods. The results in Table 5-8 show that the treatment effect on technical efficiency change is positive and statistically significant. The gains in technical efficiency in response to improved credit access are in line with the positive treatment effect on output but only small effects on input usage, as reported in Table 5-6. For example, higher technical efficiency may be achieved by improved timing of input applications. No statistically significant effect on scale efficiency change is observed. Again, this is consistent with only marginal responses in input usage, which implies that the (input-related) scale of farming remains constant. Finally, we observe a small but statistically significant effect of credit access on technical change. Thus, our results are generally in line with the findings by Jimi et al. (2019), who found a significantly positive of a microcredit programme in Bangladesh on both technical efficiency and technical change by directly including credit access as a dummy variable in the production function. We refrained from this approach because we define technical change as new technologies or innovations that cause an outwards-shift of the production functions for all farms in the same way. Thus, in our interpretation, differences in technical change between the control and treatment group only arise from differences in input levels, i.e. non-neutral technical change. Taken together, the overall effect of improved credit access on the Malmquist productivity index (i.e., the sum of technical efficiency change, scale efficiency change, and technical change) is positive and statistically insignificant (column 1 in Table 5-8).

Table 5-8. Impact of credit access on agricultural productivity growth

	Malmquist TFP index	Technical efficiency change	Scale efficiency change	Technical change
	(1)	(2)	(3)	(4)
Treatment effect	0.033***	0.023**	0.002	0.006***
(Robust SE)	(0.011)	(0.009)	(0.003)	(0.002)
P-value	0.002	0.014	0.670	0.001

Note: Estimation is based on 3,559 observations and 1256 clusters. ***, **, and * indicate significance levels at 0.01, 0.05, and 0.10, respectively. Standard errors are clustered at the household levels as the panel units, while controlling for year fixed effects and interactions between county dummies. Further control variables include household and village characteristics.

5.5.4 Heterogeneous and dynamic treatment effects

Heterogeneous treatment effects on agricultural output, the Solow residual, the Malmquist productivity index as well as technical efficiency change are explored in Table 5-15 in the Appendix. To identify potential treatment heterogeneity, we estimate equation (5-9) for subsamples, separated by the following baseline characteristics: age cohorts, gender, initial poverty, credit availability, initial asset holdings and initial material usage. Standard errors of differences between the estimators are obtained by bootstrapping with 400 iterations. The initial poverty status is defined as whether the household's per capita net income in 2009 was below the national poverty line of 2300 yuan. The initial credit availability status is defined as whether the household's total available credits (the sum of outstanding loans and potentially available credits) in 2010 (before the intervention began in September) are below the sample median. The asset holdings are defined as whether the value of machines held by the household in 2010 was below the sample median. Material usage is defined in the identical way. The results in Table 5-15 indicate that there is only limited treatment heterogeneity across farm households with different baseline characteristics. We do not find any heterogeneous treatment effects of improved credit access on agricultural output (column 1) and TFP measured with the Solow residual (column 2) in our preferred specification. The effect on the Malmquist index and technical efficiency, by contrast, seems to be more pronounced for households that indicated higher credit availability in the beginning. While this finding seems counterintuitive, we emphasize that the total availability of credits does not indicate whether a household is credit constrained or not. By and large, the heterogeneous treatment analysis shows that the defined subsamples respond similarly to improved credit access.

Finally, to explore treatment effects over time, we estimate a modification of equation (5-9) as follows:

$$y_{ivt} = \alpha + \gamma_1 D_{vt} + \gamma_2 D_{v,t-1} + \beta X_{ivt} + \omega_{vt} + \rho_t + v_i + \epsilon_{ivt} \tag{5-10}$$

In equation (5-10), $D_{v,t-1}$ is the lagged value of the treatment variable. While γ_1 still captures the effect of improved credit access, γ_2 indicates the lasting or accumulating effect of the treatment after four years (e.g., in year 2014 if the treatment took place after the baseline survey in 2010), and all other variables are defined as above. The results of the estimation for our productivity measures are presented in Figure 5-2. The plots show that the effects of improved credit access on our overall TFP measures as well as on technical efficiency change are realised within two years (coefficients for D_{vt}). Moreover, a small positive effect on technical change is realised within two years and this effect accumulates over time (coefficient for $D_{v,t-1}$). In particular, the DID-estimate of receiving treatment after the baseline survey in 2010 on technical change is more than three times as high in the follow-up survey in 2014 than in the first follow-up survey in 2012. This finding suggests that there is a long-term and accumulating effect of improved credit access on technical change.

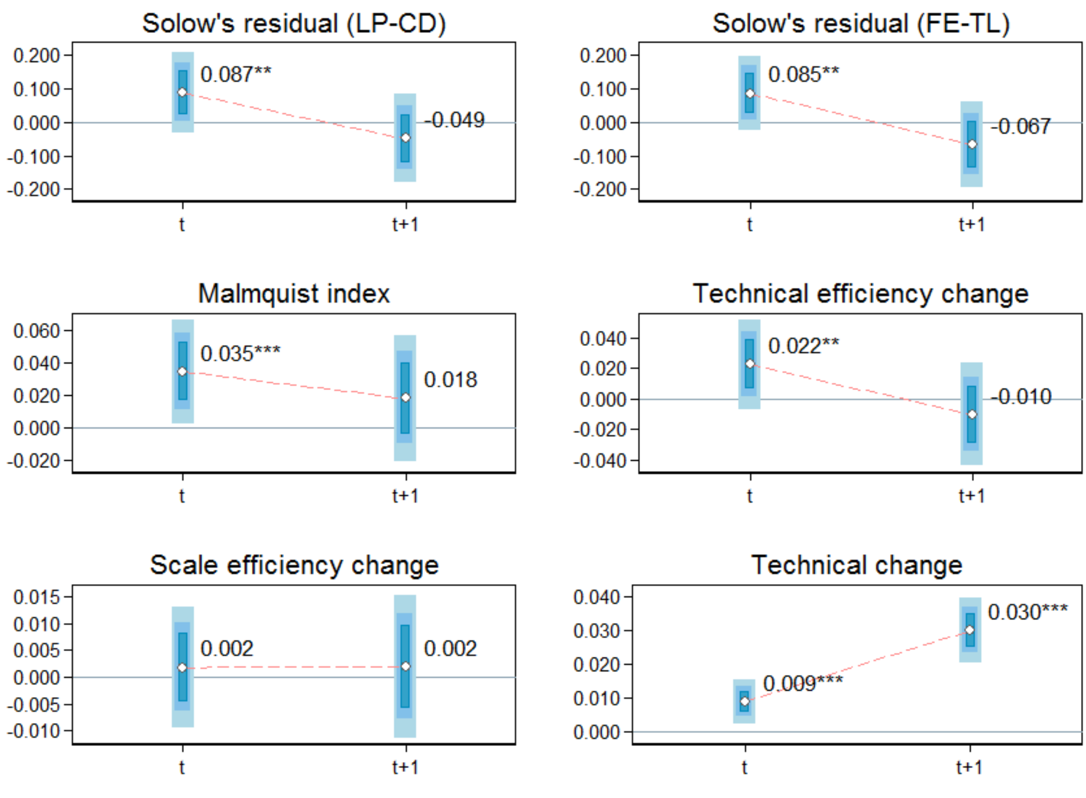

Figure 5-2. Dynamic treatment effects of improved credit access on productivity and components.
Note: Blue bars represent 90 %, 95 % and 99 % confidence intervals. LP-CD is the Cobb-Douglas function estimated with the Levinsohn-Petrin (2003) technique. FE-TL is the translog production function.

5.5.5 Robustness checks

In this section, we present three placebo tests to assess the robustness of our results with respect to TFP and its components: First, we evaluate whether the results are statistical artefacts driven by the research design. Second, we test whether the results are driven by changes in the treated group rather than concurrent changes in the control group. Third, we test whether initial differences between the treated and controlled groups are accountable for the results.

For the first purpose, we conduct a randomisation inference test for which we randomly re-assign treatment at the level of actual treatment assignment (villages) 1,000 times. For each of the 1,000 iterations, we re-estimate equation and store the coefficient $\hat{\gamma}$, representing the placebo estimate. The null hypothesis of this randomisation inference test is that there is no effect of credit access on the outcome variables. The p-value of this test is given by the share of estimated coefficients that are closer to zero than our actual estimates. In Figure 5-3, we plot histograms of the placebo estimates for the effect of credit access on our productivity measures. The actual estimates are indicated with dashed lines in these plots. The results support our original results: only in very rare cases, the placebo effect exceeds the estimated effects in the actual model, as indicated by the p-values of the tests that are all below zero. The only exception is scale efficiency change, for which the estimated effect has already been statistically insignificant using the actual research design.

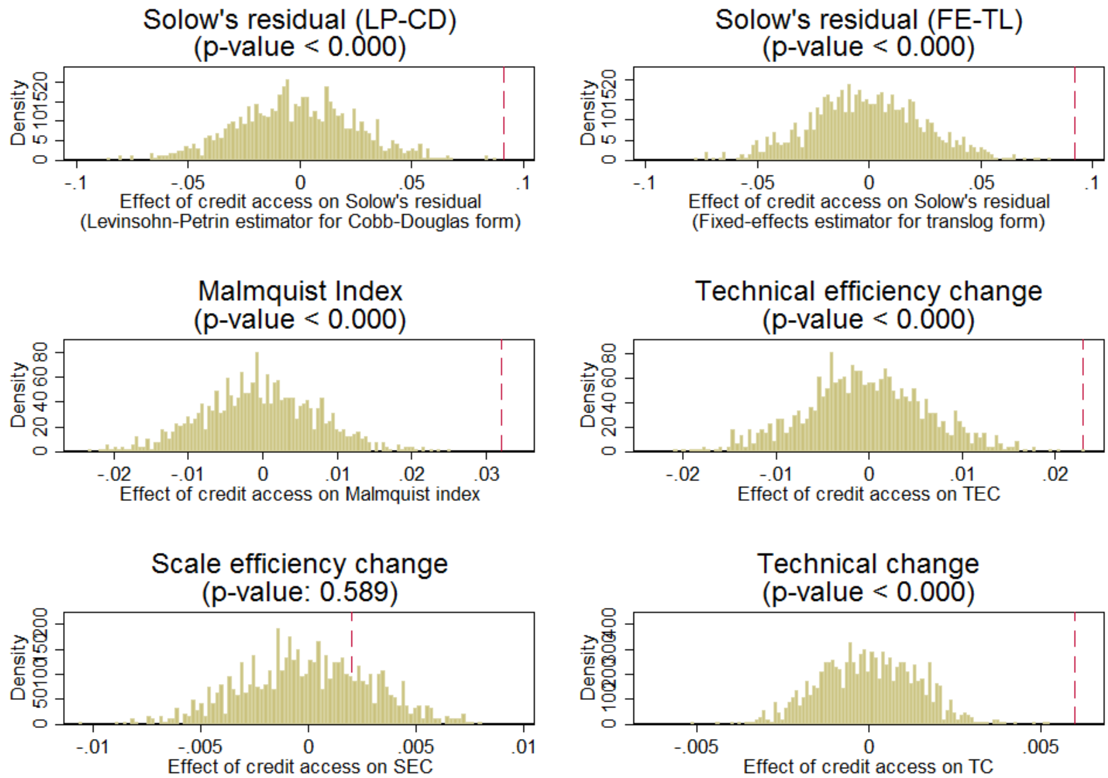

Figure 5-3. Randomisation inference test for estimated effects of credit access on productivity

For the second purpose, to test whether the results are driven by changes in the treated group rather than concurrent changes in the control group, we repeat this exercise but restrict the sample to the controlled villages. This allows us to assess the likelihood of changes in our outcome variables in the controlled group. If the “artificial” effects are statistically non-significant, we can conclude that our treatment effects are not driven by a deterioration of outcomes in the control group. The corresponding plots showing the histograms of the simulated effects are displayed in Figure 5-8 in the Appendix. Large p-values for all outcome variables except scale efficiency change indicate that the "artificial" effects are statistically not different from zero. The significant estimate for scale efficiency changes suggests that there are changes in scale efficiency among the control group. However, since these changes are positive, and our actual treatment effect on scale efficiency is not significant, we do not have to be concerned that these changes in the control group drive any of our results.

Finally, for the third purpose, we assume that the intervention began in 2010 and re-estimate (5-9) with the baseline wave only. Since productivity *changes* are not available for the first period, this robustness check can only be carried out for the productivity measures in levels, i.e. the Solow residuals. The results in Table 5-9 show that the placebo effects on the Solow residuals from our three different production function specifications are statistically insignificant. Therefore, we conclude that the estimated positive effects of improved credit access on TFP are not driven by initial differences in TFP between the treated and controlled groups.

Table 5-9. Placebo tests on credit access using the baseline data only

	Solow residual (LP-CD)	Solow residual (FE-CD)	Solow residual (FE-TL)
Treatment	0.031	0.034	0.028
(Robust SE)	(0.045)	(0.039)	(0.474)
P-value	0.491	0.400	0.474

Note: Estimation is based on 1,252 observations. ***, **, and * indicate significance levels at 0.01, 0.05, and 0.10, respectively. Standard errors are in parentheses and clustered at the village level. FE-CD is the standard Cobb-Douglas production function, LP-CD is the Cobb-Douglas function estimated with the Levinsohn-Petrin (2003) technique. FE-TL is the translog production function.

5.6 Conclusion

Market failures constitute a major challenge for smallholder farmers in developing countries. In particular, limited access to credits as a result of few collaterals prevent farm households from using the optimal amount of agricultural inputs. A large body of empirical work demonstrated that relaxing credit constraints result in more investments, higher agricultural output and higher land and labour productivity. In this article, we investigated whether improving credit access for smallholder farmers also results in *total* factor productivity gains. To this end, we used data from a randomized controlled trial in rural China. The data comes from household interviews conducted in 2010, 2012 and 2014. After the baseline interview in 2010, a Village Fund was introduced in 30 out of 50 randomly selected villages across five sample provinces. After the first follow-up interview in 2012, 10 more villages received treatment. More than 50 % of households in treated villages applied for credit from the Village Fund and approximately 30 % of eligible households received loans by 2014.

We find that improved credit access had a significantly positive effect not only on land productivity – as documented in the literature – but also on TFP. This finding is robust across a wide range of production function specifications. Decomposing TFP change into various components, we find that gains in TFP were driven by technical efficiency gains and technical change, consistent with the findings in Jimi et al. (2019). The availability of three survey rounds allowed us to assess effects of credit access beyond two years. We find that most effects are realised within two years and that the effect on technical change accumulates over time. Improved credit access may allow farm households to invest in better technologies that affect agricultural productivity not only immediately, but lead to further improvements in the future, for example because investment takes time or by dissemination of new technologies at the farm level across multiple plots (e.g. reproduction of improved seed varieties).

A limitation of our study is that poor and female participants are prioritised in loan allocation in our experiment. Indeed, the baseline test reveals that households with higher incomes were less likely to participate and borrow from the Village Fund. While this result could also imply that poorer households show the highest demand for credits, this qualification must kept in mind when interpreting the ITT effect in our study. Another limitation is that our sample is restricted to particularly poor counties. The external validity of the study could therefore be improved by extending the experiment to more representative rural areas in China and to other regions in developing countries. Although we did not find treatment heterogeneity across initial poverty status in our sample, theory suggests that wealthier households are less credit constrained (e.g., owing to more collaterals), and therefore would respond less to microcredit programmes. This effect may become visible if data were taken from a more heterogeneous sample population.

Despite these limitations, the study provides important implications for policy. First and foremost, supporting poor smallholder farms with microcredit programmes is shown to successfully increase agricultural output and productivity, and hence household welfare. The treatment effect of the credit programme on agricultural output amounts to approximately one third of the treatment effect on total loans, suggesting an effective turnaround of the credits into economic output. The results also suggest that there are even higher gains evolving years after the implementation of the microcredit programme via long-term effects on technical change. Second, the results suggest that output gains were primarily achieved by higher technical efficiency and technical change, while no strong effects on total input use were found. Anecdotally, some households reported that enlarging the production would require large lump-sum investments for which the loan size was not sufficient. In addition, some households may also not only be restricted by liquidity but also by a limitation of investment opportunities, as already discussed by Taylor, Drummond and Gomes (1986). Thus, policymakers may potentially adjust the loan size to regional needs and support market access to improved inputs for smallholder farmers. Since changes in total input usage in response to improved credit access were only marginal, it is not surprising that no significant effects on scale efficiency were found. As the technology is found to be characterized by decreasing returns-to-scale, increasing the overall scale of the production would likely come at the cost of overall productivity. This is in line with Sheng, Ding and Huang, J. (2019), who conclude that land rental subsidies without technology adaptations would result in resource misallocation towards larger farms that use less-efficient labour-intensive technologies.

Several avenues for further research exist. Besides improving the external validity of the study with replications in other regions, evaluating the long-term effects of improved credit access on efficiency and productivity is important to comprehensively evaluate credit programmes. As Shoji et al. (2012) show, households facing credit constraints reduce investments in social capital. Thus, a long-term benefit of credit-access on agricultural productivity may occur through the channel of improved education, which is unlikely to be captured in our data period, although the data allowed us to investigate dynamic effects over four years. Future work should also evaluate how financial instruments can be tailored to enhance the adaption of modern technologies that offer economies of scale rather than diseconomies of scale for smallholder farms.

Appendix

Table 5-10. Household per capita expenditures in production (nationally designated poor counties, 2002-2009)

Year	Productive costs	Of productive costs				Purchase of productive assets
		(i) Cropping	(ii) Forestry	(iii) Husbandry	(iv) Fishery	
2002	575.250	298.254	8.324	207.587	2.433	49.816
2003	625.936	304.775	9.453	250.072	2.017	77.265
2004	701.422	350.831	7.697	283.359	2.045	83.468
2005	779.175	402.238	11.415	293.970	3.884	82.495
2006	818.095	437.222	14.841	291.597	4.522	84.407
2007	890.254	465.973	16.720	330.339	4.730	82.832
2008	1,009.445	520.681	17.559	389.607	5.164	99.984
2009	1,013.104	530.225	15.851	377.933	6.423	105.465

Note: The unit is *yuan* per capita. All figures are in the 2010 constant prices.
Source: Authors' calculations based on costs in the China Rural Poverty Monitoring Report (2010) published by the CPAD based on the official Poverty Monitory Household Survey, and the rural CPI in the China Statistical Yearbooks published by the NBS

Table 5-11. Baseline balance, Village Fund participation vs. non-participation

	Not participate in 2012		Participate in 2012		
	Mean	SD	Coeff.	p-value	
	(1)	(2)	(3)	(4)	
Household demographics in 2010					
Household head is female (1 if yes, 0 otherwise)	0.06	0.25	-0.02	0.13	
Age of household head	52.14	11.37	1.46	0.22	
Household size	4.32	1.55	-0.24	0.14	
Education of household head	5.76	3.73	-0.20	0.53	
Income and consumption					
Household income (CN¥)	13,238.32	16,288.69	-2,811.00	0.04	**
Household food consumption (CN¥)	269.19	216.60	-9.39	0.66	
Household total consumption (CN¥)	6,276.87	12,771.91	-763.44	0.43	
Agricultural outputs and inputs					
Crop production value (CN¥)	4,129.10	3,968.21	-94.37	0.84	
Livestock production value (CN¥)	1,708.91	2851.49	252.68	0.39	
Agricultural land (mu)	6.82	7.71	-1.39	0.15	
Labour input (index)	24.32	10.51	-0.25	0.78	
Crop-specific inputs (CN¥)	1,558.85	1,904.20	-227.11	0.17	
Animal-specific inputs (CN¥)	1,233.91	2,618.33	52.90	0.81	
Productive assets (CN¥)	2991.44	16,041.08	-319.67	0.77	
Credit access in 2010					
Access to any type of loan (1 if yes, 0 otherwise)	0.79	0.40	0.00	0.90	
Access to informal loan (1 if yes, 0 otherwise)	0.77	0.42	0.01	0.81	
Access to formal loan (1 if yes, 0 otherwise)	0.30	0.46	0.01	0.80	
Total loans (CN¥)	9,151.66	34,711.34	-971.30	0.63	

Note: 842 households do not participate in 2012, 432 households participate. Coefficients and p-values in columns (3) and (4) are from a regression of the respective variable on a dummy variable that indicates treatment (1 if yes, 0 otherwise). Standard errors are clustered at the village level and bootstrapped with 400 repetitions. The respondents reported their annual income in 2009 as the baseline took place in mid of 2010, while other variables were asked for their values in 2010. The asterisks ***, **, and * indicate significance levels at 0.01, 0.05, and 0.10, respectively.

Table 5-12. Baseline balance, borrowing from Village Fund vs. non-borrowing

	Not borrow in 2012		Borrow in 2012		
	Mean	SD	Coeff.	p-value	
	(1)	(2)	(3)	(4)	
Household demographics in 2010					
Household head is female (1 if yes, 0 otherwise)	0.06	0.24	-0.03	0.09	*
Age of household head	52.39	11.45	1.53	0.21	
Household size	4.29	1.59	-0.29	0.09	*
Education of household head	5.72	3.72	-0.17	0.55	
Income and consumption in 2009					
Household income (CN¥)	13,018.46	16,199.38	-4,510.62	0.00	***
Household food consumption (CN¥)	271.80	216.40	-35.24	0.12	
Household total consumption (CN¥)	6,140.49	11,967.54	-762.10	0.52	
Agricultural outputs and inputs in 2010					
Crop production value (CN¥)	4,069.98	3,785.72	160.98	0.80	
Livestock production value (CN¥)	1,798.36	2,812.10	-15.32	0.96	
Agricultural land (mu)	6.64	7.34	-1.76	0.07	*
Labour input (index)	24.21	10.52	0.19	0.87	
Crop-specific inputs (CN¥)	1,516.41	1,781.31	-215.41	0.17	
Animal-specific inputs (CN¥)	1,254.03	2,426.00	-11.60	0.97	
Productive assets (CN¥)	2,945.87	15,165.63	-388.77	0.78	
Credit access in 2010					
Access to any type of loan (1 if yes, 0 otherwise)	0.80	0.40	0.00	0.92	
Access to informal loan (1 if yes, 0 otherwise)	0.77	0.42	0.00	0.90	
Access to formal loan (1 if yes, 0 otherwise)	0.30	0.46	-0.02	0.53	
Total loans (CN¥)	8,612.42	31,395.91	1,238.86	0.55	

Note: 1,048 households do not borrow in 2012, 208 households borrow. Coefficients and p-values in columns (3) and (4) are from a regression of the respective variable on a dummy variable that indicates treatment (1 if yes, 0 otherwise). Standard errors are clustered at the village level and bootstrapped with 400 repetitions. The respondents reported their annual income in 2009 as the baseline took place in mid of 2010, while other variables were asked for their values in 2010. The asterisks ***, **, and * indicate significance levels at 0.01, 0.05, and 0.10, respectively.

Table 5-13. Parameter estimates for production function specifications

	FE-CD	LP-CD	FE-TL	FE-TL (ii)
	(1)	(2)	(3)	(4)
Land	0.204***	0.199***	0.232***	0.284***
	(0.025)	(0.031)	(0.038)	(0.036)
Labour	0.058**	0.062**	0.053*	0.060
	(0.028)	(0.028)	(0.042)	(0.040)
Material	0.564***	0.491***	0.507***	0.480***
	(0.019)	(0.072)	(0.028)	(0.028)
Capital	0.030***	0.035	0.024*	0.022*
	(0.009)	(0.023)	(0.013)	(0.012)
Land × Land			0.056*	0.057**
			(0.029)	(0.028)
Land × Labour			0.023	0.027
			(0.033)	(0.032)
Land × Material			-0.056***	-0.033*
			(0.020)	(0.020)
Land × Capital			-0.007	-0.005
			(0.010)	(0.009)
Labour × Labour			0.021	0.010
			(0.048)	(0.046)
Labour × Material			-0.042	-0.056**
			(0.029)	(0.028)
Labour × Capital			0.002	0.012
			(0.015)	(0.014)
Material × Material			0.053***	0.036*
			(0.020)	(0.019)
Material × Capital			-0.007	-0.004
			(0.008)	(0.008)
Capital × Capital			-0.005	-0.007
			(0.006)	(0.006)
Trend	0.182***	0.178***	0.208***	
	(0.012)	(0.013)	(0.019)	
Trend × Trend			-0.175***	
			(0.020)	

(continued on next page)

Table 5-15. *(continued)*

	FE-CD	LP-CD	FE-TL	FE-TL (ii)
	(1)	(2)	(3)	(4)
Trend × Land			0.021	
			(0.017)	
Trend × Labour			0.006	
			(0.030)	
Trend × Material			0.004	
			(0.017)	
Trend × Capital			0.000	
			(0.009)	
Dummy for $x3 = 0$		-1.382	-2.584	-2.557
		(2.509)	(0.193)	(0.187)
Dummy for $x4 = 0$		-0.009	-0.275	-0.257
		(0.234)	(0.060)	(0.059)
Dummy for $farmtype$	0.176***	0.174***	0.201***	0.230***
	(0.036)	(0.047)	(0.036)	(0.035)
Constant term	2.517***	-0.105***	-0.758**	0.382
	(0.350)	0.025	(0.316)	(0.380)
Household fixed effects		*yes*		
County-year fixed effects	*no*	*no*	*no*	*yes*

Note: Number of observations is 3,569. Standard errors are in parentheses. *, ** and *** indicate statistical significance at the 0.10, 0.5 and 0.01 significance level. All variables except the time trend and binary variables are in logarithms. FE-CD is the standard Cobb-Douglas production function, LP-CD is the Cobb-Douglas function estimated with the Levinsohn-Petrin (2003) technique. FE-TL is the translog production function and frontier. FE-TL (ii) contains county-year fixed effects instead of a time trend.

Table 5-14. Violations of regularity conditions in translog specification

	FE-TL		FE-TL (ii)	
	Number of violations	% of violations	Number of violations	% of violations
Monotonicity				
Land	2	0.06 %	0	0.00 %
Labour	185	5.18 %	496	13.9 %
Material	0	0.00 %	0	0.00 %
Capital	32	0.95 %	48	1.42 %
Concavity	869	24.3 %	1171	32.8 %

Note: Number of observations is 3,569. Percentage values relate to the number of observations without zero values in corresponding inputs. FE-TL is the translog production function with time trends and FE-TL (ii) is the translog production function with county-year fixed effects.

Table 5-15. Heterogeneous treatment effects on output and productivity

	Ag. output	TFP (LP-CD)	Malmquist Index	TEC (SFA)
	(1)	(2)	(3)	
Panel A: Heterogeneity by age cohorts				
(1) Age < 50	815.190	0.068	0.036*	0.018
	(535.828)	(0.066)	(0.018)	(0.016)
(2) Age ≥ 50	1,112.983***	0.106**	0.031**	0.027**
	(387.694)	(0.047)	(0.013)	(0.012)
Difference: (2)-(1)	297.794	0.039	-0.004	0.008
(p-value)	(0.285)	(0.295)	(0.438)	(0.315)
Panel B: Heterogeneity by gender				
(1) Female	1521.049	0.261**	0.057	0.058*
	(989.07)	(0.039)	(0.039)	(0.034)
(2) Male	958.589***	0.080*	0.032***	0.022**
	(342.254)	(0.042)	(0.011)	(0.010)
Difference: (2)-(1)	-562.460	-0.182	-0.024	-0.036
(p-value)	(0.375)	(0.225)	(0.403)	(0.255)
Panel C: Heterogeneity by initial poverty status				
(1) Poor households	1,214.703***	0.094*	0.039**	0.029**
	(458.854)	(0.057)	(0.016)	(0.014)
(2) Less poor households	441.722	0.099*	0.024	0.018
	(435.691)	(0.055)	(0.015)	(0.013)
Difference: (2)-(1)	-772.982	0.006	-0.015	-0.011
(p-value)	(0.120)	(0.453)	(0.258)	(0.297)
Panel D: Heterogeneity by initial credit availability				
(1) Low credit availability	784.753*	0.045	0.007	0.006
	(432.289)	(0.058)	(0.016)	(0.013)
(2) Higher credit availability	1,136.613**	0.127**	0.055**	0.037***
	(458.538)	(0.053)	(0.015)	(0.013)
Difference: (2)-(1)	351.861	0.081	0.048***	0.031**
(p-value)	(0.295)	(0.115)	(0.007)	(0.048)

(continued on next page)

Table 5-17. *(continued)*

	Ag. output (1)	TFP (LP-CD) (2)	Malmquist Index (3)	TEC (SFA)
Panel E: Heterogeneity by initial asset holdings				
(1) Holding fewer machines than the median	1,121.065*** (406.116)	0.110* (0.060)	0.039** (0.016)	0.031** (0.015)
(2) Holding more machines than the median	834.886 (532.394)	0.092** (0.048)	0.024* (0.024)	0.018 (0.011)
Difference: (2)-(1)	-286.179	-0.017	-0.015	-0.012
(p-value)	(0.350)	(0.415)	(0.255)	(0.258)
Panel F: Heterogeneity by initial material use				
(1) Using less initial material than the median	926.895** (366.732)	0.086 (0.064)	0.028 (0.017)	0.023 (0.016)
(2) Using more initial material than the median	1,186.189** (536.415)	0.135*** (0.002)	0.031** (0.013)	0.026** (0.010)
Difference: (2)-(1) (p-value)	259.294 (0.347)	0.048 (0.273)	0.003 (0.412)	0.003 (0.427)

Note: ***, **, and * indicate significance levels at 0.01, 0.05, and 0.10, respectively. Standard errors are in parentheses and clustered at the household level as the panel unit. The standard errors of the differences between estimators are obtained by 400 times of bootstrapping. Further control variables include household and village characteristics. The initial poverty status is defined as whether the household's per capita net income in 2009 was below the national poverty line of 2300 yuan. The initial credit availability is defined as whether the household's total available credits in 2010 (before the intervention began in September) were below the sample median. The asset holdings and material usage are defined as whether the value of machines held and materials used by the household in 2010 (before the intervention began in September) was below the sample median.

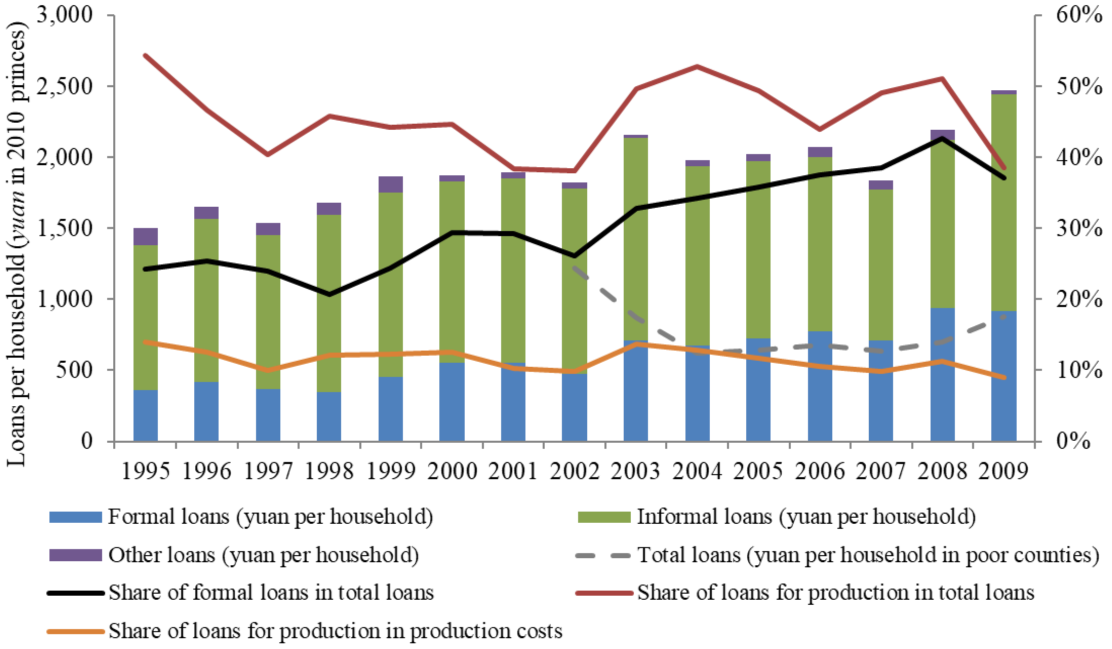

Figure 5-4. Composition of rural household loans

Source: All indicators except "total loans (yuan per household in poor counties)" are authors' calculation based on the Fixed Point Rural Household Survey. The total loans (yuan per household in poor counties) are from Poverty Monitoring Report of Rural China 2010 that is based on the Poverty Monitoring Household Survey and is published by the National Bureau of Statistics.

Note: The Fixed-Point Rural Household Survey has been conducted annually by the Research Center for Rural Economy at the Ministry of Agriculture since 1986. It is nationally representative, including about 23 thousand rural households in 360 villages out of 357 counties, 31 provinces. The Poverty Monitoring Household Survey is representative for poor areas in rural China. It is a panel with annual waves that is conducted by the National Bureau of Statistics. Each wave covers 40 thousand to 54 thousand rural households in 5,400 administrative villages out of 592 poor counties that were designated by the State Council in 2002.

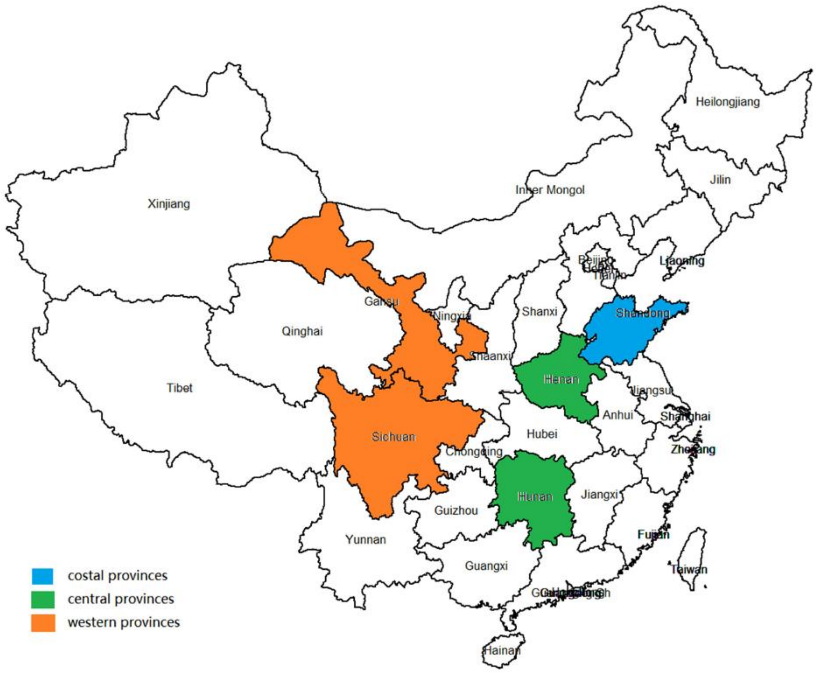

Figure 5-5. Experimental provinces

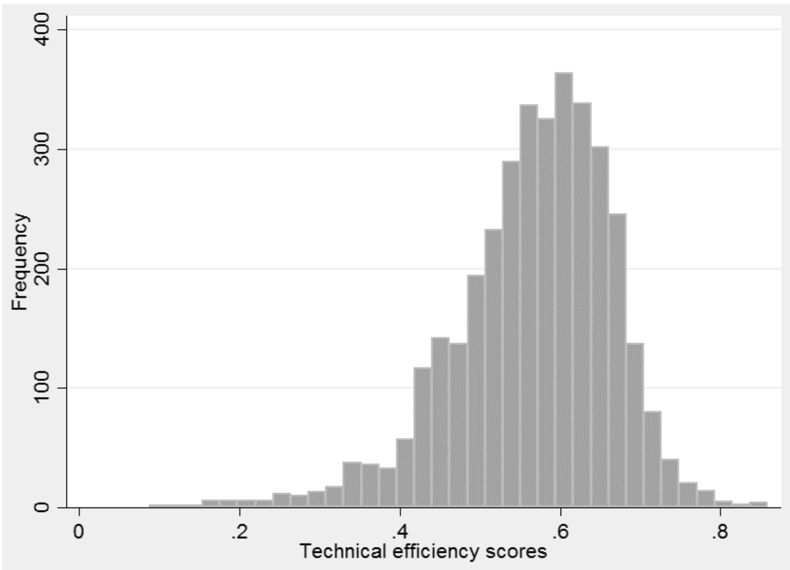

Figure 5-6. Frequency distribution of technical efficiency scores

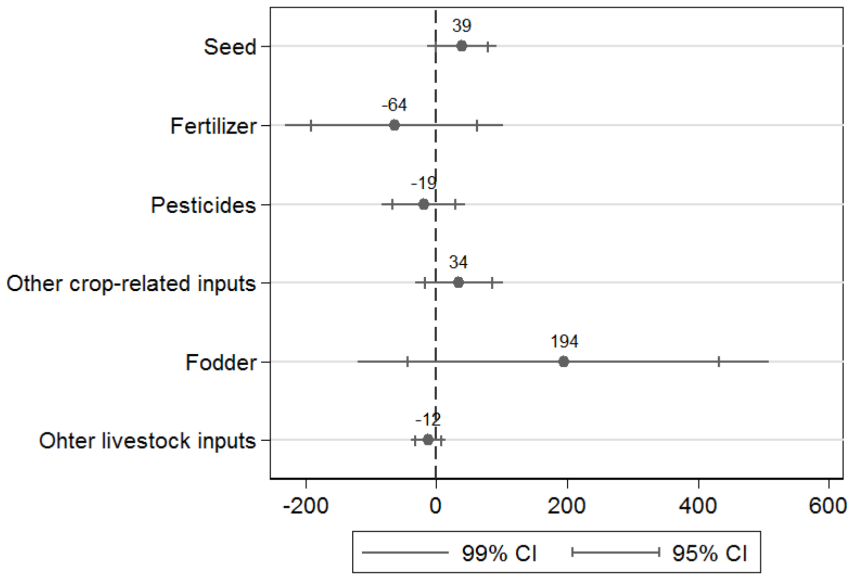

Figure 5-7. Effect of improved credit access on individual material components

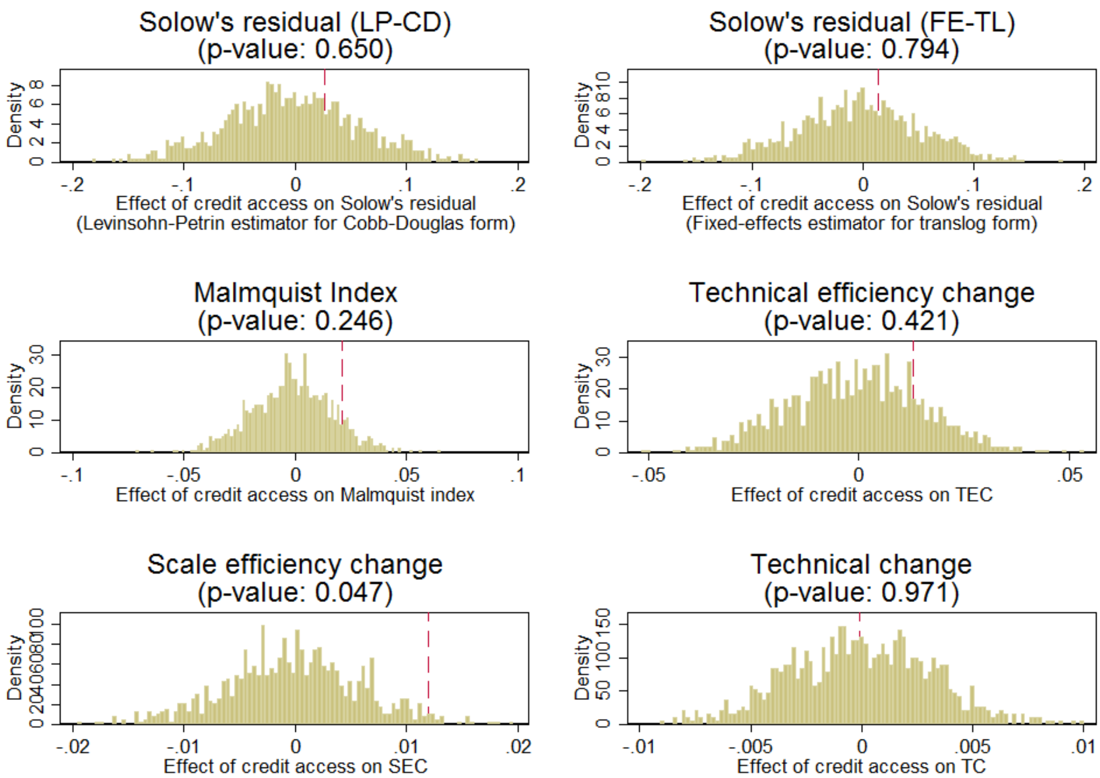

Figure 5-8. Results of the randomisation inference test for controlled villages only

6

Green Policies and Farm Production Decisions in Selected EU Member States*

Abstract. The EU has implemented various mandatory and voluntary measures to increase the environmental sustainability of farming. Using farm-level accountancy data from France, Germany, and the United Kingdom, we investigate how the EU set-aside programme and voluntary agri-environmental schemes affect farmers' land and production choices. For each country, we estimate two multi-output profit functions: One for the period with crop-specific area payments (1995–2004) and one for the period after (2005–2016). The resulting parameters are used to derive price and subsidy elasticities of output supply, input demand, and land allocation. To ensure that the estimated profit system is consistent to economic theory, we impose convexity using the Cholesky factorisation technique. Overall, we find that green policies reduce cereal production in favour of protein production and have a negative effect on fertiliser use. Our results also show that farmers' responses to green policies vary considerably across countries. Differences between the unrestricted and restricted models confirm that econometric results require a careful theoretical interpretation, in order to support evidence-based policymaking.

Keywords. Agri-environmental schemes, agricultural policy, land allocation, profit function, theoretical consistency

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* This article is based on joint work with Johannes Sauer. Johannes Sauer developed the research question. Stefan Wimmer worked out the empirical framework, conducted the econometric analysis and wrote the manuscript. Johannes Sauer contributed with the interpretation of the results and reviewing and editing of the manuscript. Target journal: American Journal of Agricultural Economics

6.1 Introduction

Reducing negative externalities of agricultural production is a central concern in ongoing political debates, both globally and in the European Union (EU). Amongst the most urgent pressures are the loss of biodiversity (e.g. Pilling, Bélanger and Hoffmann, 2020), soil degradation (e.g. Robinson, D. A. et al., 2017), water pollution (e.g. Mateo-Sagasta, Marjani and Turral, 2018) and the emission of greenhouse gases (e.g. Vermeulen, Campbell and Ingram, 2012). The Common Agricultural Policy (CAP) is the EU's main instrument to steer agricultural practices. In the past decades, it has undergone several major reforms to align with changing societal demands (Pe'er et al., 2017). When the CAP was introduced in 1962, environmental considerations were less pronounced. Instead, promoting food security and providing a stable income to farmers were the primary goals. Specifically, high support prices were in place, providing an incentive for farmers to expand production. However, the policy distorted the markets and led to an overproduction of agricultural commodities (Zobbe, 2001). In the 1980s, mandatory set-aside areas were introduced to reduce the amount of food produced and to increase the environmental sustainability of the farming sector. Farmers were compensated for leaving arable land fallow with set-aside premiums. Additionally, agri-environmental schemes (AES) are in place since the 1980s. Participating in these schemes is voluntary and farmers can choose from a wide range of programmes, which are designed at the regional level. In most cases, AES measures impose restrictions on agricultural practices, for example concerning the use of chemical inputs or farmers' choices of how to cultivate the agricultural land (e.g. Mennig and Sauer, 2020). In 1992, through the MacSharry reform, support prices were reduced and replaced by direct payments. These direct payments were crop-specific and based on the amount of land devoted to individual crops, hence not fully decoupled to production. Finally, in 2005, direct payments were replaced by single area payments, which are uncoupled from production in the sense that they do not depend on land allocation between crops.

The ongoing change of the CAP raises the question how effective different green policies are. The overall effectiveness of the agri-environmental policies depends on how farmers respond to the provided economic incentives. Therefore, the goal of this article is to estimate the impact of the EU's green agricultural policies on production decisions. In particular, we examine the impact of set-aside and AES programmes on farmers' optimal land use decision and input use over the period 1995–2016. Using farm accountancy data on crop farms in France, Germany, and the United Kingdom (UK), we estimate short-run profit functions with fixed allocable inputs as introduced by Chambers and Just (1989). From the estimated parameters, we derive subsidy elasticities of output supply, input demand, and land allocation between distinct crop categories. Our empirical framework for deriving land allocation equations extends the ones by Lacroix and Thomas (2011) and Laukkanen and Nauges (2014).

The literature on agri-environmental subsidies and farm production can be divided into two strands. The first one comprises treatment studies that assess the causal impact of subsidy payment on farm performance using reduced-form models, combining matching methods and difference-in-difference (DID) estimators. Pufahl and Weiss, C. R. (2009) estimate the average treatment effect of AES payments in Germany between 2000 and 2005. Their results show that scheme participation increases land growth rates and reduces chemicals purchases. Chabé-Ferret and Subervie (2013) estimate windfall effects of AES programmes in France in the same period, finding that in particular those programmes that only require small changes in the farm production plan are not cost-effective. Arata and Sckokai (2016) examine the impact of AES on farm production choices in Spain for the years 2003–2006. They find, for instance, that AES participation reduces expenses for fertiliser and pesticide per hectare land and increases the number of crops planted. Mennig and Sauer (2020) decompose farm productivity growth of German farms (2006–2011) into the components of technical change, technical efficiency change and scale effects, and estimate the causal effect of AES participation on each component. They find that AES participation reduces farm productivity of dairy farms, but no significant effect was found for crop farms. Employing similar methods, Baráth, Fertő and Bojnec (2020) find that agri-environmental subsidies have no effect on TFP in Slovenian agriculture in the years 2006–2013. The second strand of the literature evaluating the effect of agri-environmental on production decisions uses structural models to derive estimates for production elasticities. Based on a profit function approach, Lacroix and Thomas (2011) evaluate elasticities of land, output and input with respect to prices and subsidy rates in a sample of French farmers for the years 1995–2001. For example, they find that set-aside subsidies reduce land allocated to cereals but have no statistical significant effect on fertiliser usage. Laukkanen and Nauges (2014) follow the same approach but extend the model by including special AES programmes in Finland, using data from 1996 to 2005. Consistent with Lacroix and Thomas (2011), they find that set-aside subsidies have a negative impact on the amount of land devoted to grain production. Additionally, they find that higher subsidy rates also decrease optimal fertiliser levels. Moreover, special AES subsidies are shown to have a positive effect on grain area, but a negative effect on fertiliser use. The effect of area subsidies on land allocation has also been studied by Serra et al. (2009) for U.S. agriculture.

In this article, we opt for the structural model approach to quantify the effect of agri-environmental policies and subsidies on production decisions. In contrast to reduced-form models using matching methods and DID estimators, this approach allows us to recover the fundamental parameters that describe farms' production choices (Laukkanen and Nauges, 2014) and is therefore more suitable to model and simulate farmers' behaviour. The article contributes to the literature in three ways. First, we provide farm-level price and subsidy elasticities for agri-environmental measures for both the period with coupled subsidies (prior to 2005) and the period without coupled subsidies (post-2005). Prior studies employing the structural approach to model production choices with respect to agri-environmental payments in the EU exclusively focus on the pre-2005 period. Thus, we provide recent estimates that allow assessing whether AES subsidy rates have changed over time, in particular after the discontinuation of the set-aside programme. Second, we offer a comparative analysis of the structural model across different EU countries (France, Germany, UK). To the best of our knowledge, Arata and Sckokai (2016) provide the only cross-country study on the effects of EU agri-environmental policies, but using the reduced-form approach. Evaluating subsidy elasticities across countries offers insights into the heterogeneous responses to policies and hence supports the design of policies tailored to the regional needs. Third, in contrast to Laukkanen and Nauges (2014), we evaluate the effect of AES programmes on multiple crop categories, rather than an aggregate. It can be expected that green policies do not only affect overall output and input use, but also land allocation between crops (e.g. Arata and Sckokai, 2016). For example, it can be expected that farms with more engagement in AES programmes substitute cereal production in favour of protein crops because arable land schemes often involve the implementation of diversified crop rotations and planting of cover crops (e.g. Mennig and Sauer, 2020). Methodologically, we compare the results of an unrestricted profit function to a model where convexity is imposed. As emphasised by Sauer (2006), theoretically well-founded estimates are essential for the robustness of policy suggestions. Therefore, we check whether our estimates of main interest – subsidy elasticities of output supply, input demand, and land allocation – are sensible to the econometric imposition of regularity conditions derived from economic theory.

The article proceeds as follows. In Section 6.2, we introduce the conceptual framework that describes the profit-maximising problem of farmers in the presence of agri-environmental subsidies. In Section 6.3, we describe the data and provide descriptive statistics for the sample in the three countries. We then present the empirical strategy, including the procedure to impose curvature on the profit function, in Section 6.4. Following that, we present and discuss the results in Section 6.5. Section 6.6 concludes by offering policy implications.

6.2 Conceptual framework

We use a dual profit function approach to evaluate farm production decisions in response to agri-environmental subsidies. The conceptual framework closely follows the ones in Lacroix and Thomas (2011) and Laukkanen and Nauges (2014). We assume that farmers maximise profit given input and output prices, subsidy rates, and allocable land (L) and other quasi-fixed inputs (k). Thus, the farmers' profit maximisation problem is given by

$$\pi(p, w, s; L, k) = \max_{q, x, l_c, l_{sa}} \left\{ \sum_{c=1}^{C} l_c (p_c \times y_c + s_c) + l_{sa} s_{sa} - \sum_{n=1}^{N} w_n x_n + l_{aes} \times s_{aes} \right\} , \qquad (6\text{-}1)$$

where π denotes farm profit; p and y are output price and yield (i.e., $q = py$ is output); w and x are price and quantity of variable inputs x; l_c and l_{sa} denote land areas allocated to crop c and set-aside, respectively; s_c is the subsidy rate for land devoted to crop production; and s_{sa} is the subsidy rate for set-aside. Finally, l_{aes} denotes the area devoted to AES and s_{aes} is the corresponding subsidy rate.[40] Unfortunately, our data does not report the amount of land devoted to AES programmes, nor corresponding subsidy rates. Instead, we observe the total AES payments received (i.e., $l_{aes} \times s_{aes}$). Since AES participation is commonly based on five-year contracts, whether to participate is not an annual decision made by farmers (see Laukkanen and Nauges, 2014). It is therefore reasonable to assume that farmers choose output supply, input demand, and land allocation between crop production and set-aside to maximise farm profit, given quasi-fixed inputs and the level of AES participation. For this reason, we include AES revenues on the right-hand side of the profit function.

By standard results, the profit function is non-negative, non-decreasing in p, non-increasing in w and convex and positively linearly homogeneous in (p, w) (Chambers, 1988). We estimate the profit functions separately for the periods 1995–2004 and 2005–2016, since the former period includes area-related direct payments. The inclusion of land allocation decisions requires the following land adding-up condition in addition to the regularity conditions (e.g. Lacroix and Thomas, 2011):

$$\sum_{c=1}^{C} l_c + l_{sa} = L \Leftrightarrow \sum_{c=1}^{C} \frac{\partial l_c}{\partial p_{c'}} + \frac{\partial l_{sa}}{\partial p_{c'}} = \sum_{c=1}^{C} \frac{\partial l_c}{\partial s_{j'}} + \frac{\partial l_{sa}}{\partial s_{j'}} = \sum_{c=1}^{C} \frac{\partial l_c}{\partial w_n} + \frac{\partial l_{sa}}{\partial w_n}$$
$$= \sum_{c=1}^{C} \frac{\partial l_c}{\partial k_m} + \frac{\partial l_{sa}}{\partial k_m} = 0 \quad \forall c', \forall k \ \ and \ \ \sum_{c=1}^{C} \frac{\partial l_c}{\partial L} + \frac{\partial l_{sa}}{\partial L} = 1 \tag{6-2}$$

By Hotelling's (1932) Lemma, the partial derivatives of the profit function with respect to output prices are the output supply functions. Similarly, the partial derivatives with respect to input prices are the negative input demand functions. For the period prior to 2005, we can also take the partial derivative with respect to land-related subsidy rates, providing the land allocation functions (Lacroix and Thomas, 2011). Thus, we obtain the following system of output supply, input demand, and land allocation equations:

$$q_c(p, w, s; L, k) = \frac{\partial \pi(p, w, s, z)}{\partial p_c} \tag{6-3}$$

$$x_n(p, w, s; L, k) = -\frac{\partial \pi(p, w, s, z)}{\partial w_n} \tag{6-4}$$

$$l_i(p, w, s; L, k) = \frac{\partial \pi(p, w, s, z)}{\partial s_i} \tag{6-5}$$

[40]Most arable land schemes are compensated on a hectare basis, but measures with different reference units exist.

Given the properties of the profit function explained above, the output supply (input demand) functions are non-negative, symmetric, homogeneous of degree zero, and non-decreasing in p (non-increasing in w). In our analysis, we are primarily interested in changes of output supply, input usage, and land allocation in response to prices and green policies (AES subsidies and set-aside premiums). We quantify these changes by estimating elasticities based on equations (6-3) – (6-5). Subsidy and price elasticities of output supply, input demand, and land allocation are calculated by multiplying the corresponding parameter in equations (6-3) – (6-5) by the ratio of the price over the level of output, input, or land allocation. For example, the set-aside subsidy elasticity of land devoted to cereal production is given by:

$$\varepsilon_{l_{cereal}, s_{sa}} = \frac{\partial^2 \pi}{\partial l_{cereal} \partial s_{sa}} \times \frac{s_{sa}}{l_{cereal}} \tag{6-6}$$

Similarly, the relationship between AES participation and fertiliser use is derived as

$$\varepsilon_{x_{fertiliser}, r_{AES}} = \frac{\partial^2 \pi}{\partial x_{fertiliser} \partial r_{AES}} \times \frac{r_{AES}}{x_{fertiliser}} \quad . \tag{6-7}$$

6.3 Data and sample description

For the empirical analysis, we use farm-level accountancy data from the European Farm Accountancy Data Network (FADN). The FADN is a harmonised survey carried out by each member state of the EU, which is representative for commercial agricultural holdings due to stratification according to region, type of specialisation and economic size. Our sample consists of crop farms in France, Germany, and the UK for the years 1995–2016.

Figures 6-1 – 6-3 present yearly averages of land-related subsidies for the three countries from 1989 to 2016. It can be seen that area-based payments and single farm payments are the most important subsidies in terms of revenue. In France, area payments were gradually phased out after 2005 while they were abolished after 2004 in Germany and the UK. Set-aside premiums were discontinued in Germany and the UK in the same year, and one year later in France.[41]

Due to this policy change, we estimate two empirical models for each country: the first model (1995–2004) considers AES payments and area-related subsidies including set-aside premiums, whereas the second model (2005–2016) considers AES payments as only agri-environmental policy.

[41] With the decoupling of payments in 2005, farmers could still claim set-aside payments according to their historical entitlements until 2008. However, these payments are not separately recorded in the data.

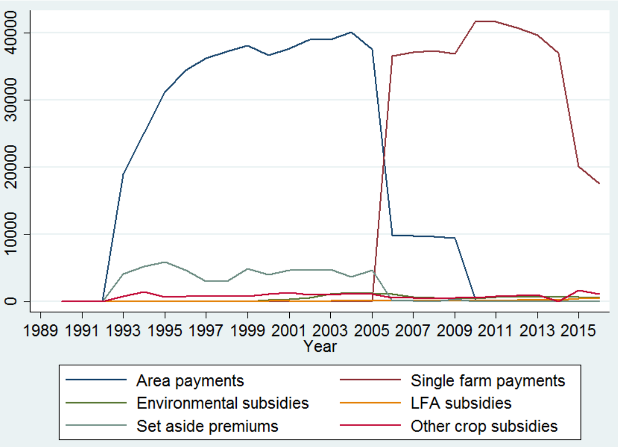

Figure 6-1. Yearly averages of land-related subsidies, FADN crop farms in France

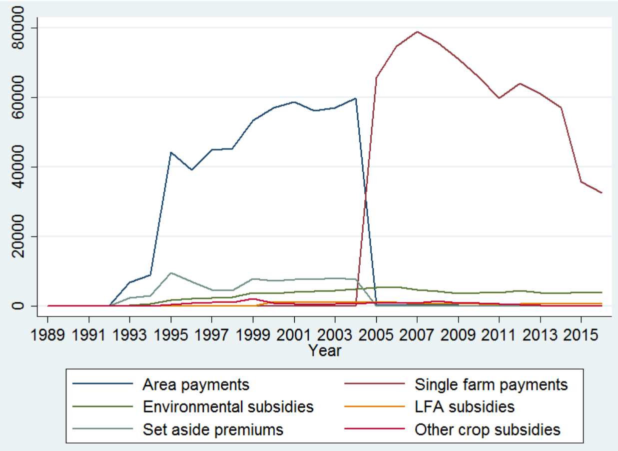

Figure 6-2. Yearly averages of land-related subsidies, FADN crop farms in Germany

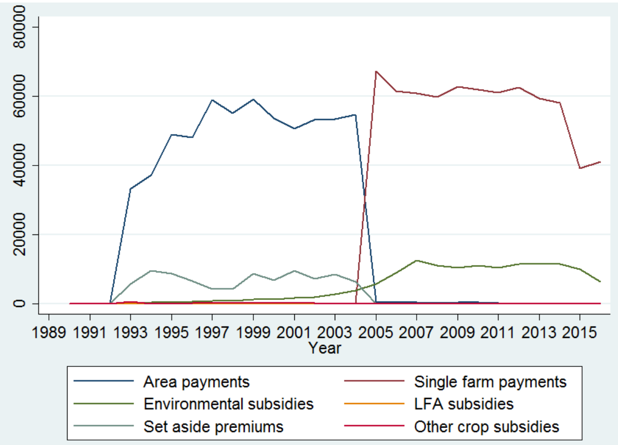

Figure 6-3. Yearly averages of land-related subsidies, FADN crop farms in the UK

We aggregate outputs into five crop categories: cereals (e.g. wheat, barley and rye), grain maize, protein crops (peas, lentils, other protein crops), oilseed crops (e.g. oilseed rape, sunflower, soybean), and root crops (sugar beet and potatoes). Output prices for the individual categories are district-level weighted averages of unit crop prices. To this end, we use the unit value approach and divide individual crop revenues by its quantities. For the empirical estimation, we use lagged values of output prices, assuming that output and land allocation decisions are made in the beginning of the accounting year, while realised prices reflect prices received in the end of the growing season after harvesting. Thus, we assume that farmers solve their maximisation problem based on expected prices, and that expected prices are the mean of current prices.

As for inputs, we consider two variable inputs (fertiliser, other variable inputs) and three quasi-fixed inputs (land, labour, capital). Land is measured in hectare, labour in annual working units, and capital is proxied by depreciation costs as, for example, in Sauer and Latacz-Lohmann (2015). Following Lacroix and Thomas (2011), we distinguish only two variable inputs, because quantities are required for estimating the input demand equations. Fertiliser quantities can be retained from expenses using district-level average application rates and regional-level nitrogen fertiliser unit prices.[42] Other variable inputs include seed, pesticides, material, energy, contract services and water use. The price for other variable inputs is calculated as a Stone price index at the regional (nuts2) level:

$$\log(w_t) = \sum_{i=1}^{n} \sigma_{it} \log(w_{it}), \tag{6-8}$$

where n denotes the number of items in the input category and σ_{it} is the cost share of the i-th item and t denotes time. This price index for other variable inputs is used as numeraire in the empirical estimation of the profit function, so that estimating the demand equation is not required.

Land-related subsidy unit prices apply to cereals, maize, protein crops and oilseed crops, as well as to set-aside land. We construct these unit prices from the data set by dividing area-based subsidies by the corresponding amount of land. Like output prices, the subsidy rates are computed at the regional (nuts-2) level[43]. For the land allocation equation, we only consider voluntary set-aside, because the amount of mandatory set-aside is not driven by price or subsidy incentives. To determine voluntary and mandatory set-aside, we closely follow the suggestion by Lacroix and Thomas (2011): set-aside land exceeding the mandatory rate is assumed voluntary set-aside. If observed set-aside land is below the mandatory rate, we assume that the farm is exempt from mandatory set-aside, and thus the entire set-aside land must be voluntary. Finally, if observed set-aside area is zero, and if

[42] Average application rates and fertiliser unit prices are only available for Germany. For France and the UK, we used implicit quantities as dependent variable in the fertiliser demand equation.
[43] While we compute subsidy unit rates directly from the observed data, the desirable approach is to use official data from individual regions. However, they are not publicly available for all years for most regions.

observed set-aside are equal to the mandatory area, we assume that voluntary set-aside is zero. The profit variable is computed from the data by subtracting variable costs from total crop revenue and area-related subsidies if applicable. As discussed above, AES revenues are included as independent variable in the profit function. Tables 6-1 and 6-2 present the mean values of variables used in the analysis for the three countries, separated by each sample period. Detailed descriptive statistics are reported separately for each country in Tables 6-6 – 6-11 in the Appendix.

Table 6-1. Descriptive statistics for the years 1995–2004

Variable	Unit	France	Germany	United Kingdom
Number of observations	#	19,912	12,632	7,086
Cereals output	1,000 kg	420.67	720.54	864.56
Maize output	1,000 kg	119.06	19.77	-
Protein output	1,000 kg	29.97	12.15	21.55
Oilseed output	1,000 kg	61.24	86.95	64.34
Root crops output	1,000 kg	427.79	685.99	666.95
Fertiliser use	kg | const. € [a]	158.91	63.75	508.32
Cereals area	ha	58.96	114.87	115.49
Maize area	ha	12.93	2.65	-
Protein area	ha	6.15	4.19	5.75
Oilseed area	ha	20.09	28.45	21.29
Root crops area	ha	6.81	14.38	14.18
Voluntary set-aside	ha	4.08	6.93	8.74
Cereals price	€/1,000 kg	119.00	120.82	122.27
Maize price	€/1,000 kg	119.20	120.29	-
Protein crops price	€/1,000 kg	136.08	120.06	163.81
Oilseed crops price	€/1,000 kg	202.81	310.13	223.02
Root crops price	€/1,000 kg	106.86	64.29	101.35
Fertiliser price	€/1,000 kg	102.06	298.15	42.80
Cereals subsidy rate	€/ha	364.01	331.68	353.75
Maize subsidy rate	€/ha	-	320.85	-
Protein subsidy rate	€/ha	492.54	419.62	465.69
Oilseed subsidy rate	€/ha	454.12	448.58	499.10
Set-aside subsidy rate	€/ha	478.31	374.24	433.90
AES	€	383.07	3,510.22	1,569.08
Profit	€	81,275.61	98,479.53	126,051.50

Note: Profits are computed by subtracting variable costs from total crop revenue and area-related subsidies. [a]Fertiliser use is measured in kg in the German sample, but in implicit quantity in the French and UK samples.

Table 6-2. Descriptive statistics for the years 2005–2016

Variable	Unit	France	Germany	United Kingdom
Number of observations	#	20,760	21,619	6,852
Cereals output	1,000 kg	468.76	791.29	988.83
Maize output	1,000 kg	129.24	31.26	1.50
Protein output	1,000 kg	13.43	9.50	34.40
Oilseed output	1,000 kg	72.91	140.54	100.58
Root crops output	1,000 kg	548.36	782.38	782.81
Fertiliser use	kg | const. € [a]	297.36	79.99	425.95
Cereals price	€/1,000 kg	156.52	161.53	157.38
Maize price	€/1,000 kg	146.76	147.41	151.06
Protein crops price	€/1,000 kg	231.53	242.97	228.55
Oilseed crops price	€/1,000 kg	323.35	338.13	332.96
Root crops price	€/1,000 kg	166.69	77.14	137.24
Fertiliser price	€/kg	92.92	464.75	98.22
AES payments	€	722.45	4,247.44	10,078.87
Profit	€	69,233.49	101,661.90	117,082.80

Note: Profits are computed by subtracting variable costs from total crop revenue. [a]Fertiliser use is measured in kg in the German sample, but in implicit quantity in the French and UK samples.

For France, the number of observations is around 20,000 in both periods. Because no subsidy rates are reported for maize production in our French data set, land allocation equations are only estimated for cereals, protein, oilseed, and (voluntary) set-aside. The German data consists of approx. 12,600 observations in the first and 22,000 farm observations in the second period. Finally, about 7,000 farm observations are included in the UK data set in both periods. Grain maize is omitted in the first period of the UK data. However, it is part of the second period because some farms took up its production after 2003. The average production remains very low compared to other crop outputs such as other cereals, oilseed or root crops.

In comparison, the descriptive statistics show that cereals are the most widely planted crop category in all countries. The largest farms in terms of crop area are found in Germany, followed by the UK and France. In the first period (1995–2004), German farms received the highest amount of AES payments. In the second period (2005–2016), farms in the UK received more than double the amount of AES payments than farms in Germany.

6.4 Empirical strategy

We assume a normalised quadratic functional form for the profit function. As stated by Csajbok, Oude Lansink and Huirne (2005), for instance, the advantages of the normalised quadratic are its flexibility, simplicity, and computational ease. Homogeneity in input prices is imposed by using the price of other variable inputs (w_2) as numeraire for the profit, all prices and subsidy rates. Thus, the normalised quadratic profit function takes the following form:

$$
\begin{aligned}
\tilde{\pi} = \beta_0 &+ \sum_{c=1}^{C} \beta_c^p \tilde{p}_c + \sum_{j=1}^{J} \beta_j^s \tilde{s}_j + \sum_{n=1}^{N-1} \beta_n^w \widetilde{w}_n + \sum_{m=1}^{M} \beta_m^k k_m \\
&+ \sum_{c=1}^{C}\sum_{j=1}^{J} \beta_{cj}^{ps} \tilde{p}_c \tilde{s}_j + \sum_{c=1}^{C}\sum_{n=1}^{N-1} \beta_{cn}^{pw} \tilde{p}_c \widetilde{w}_n + \sum_{c=1}^{C}\sum_{m=1}^{M} \beta_{cm}^{pk} \tilde{p}_c k_m + \sum_{j=1}^{J}\sum_{n=1}^{N-1} \beta_{jn}^{sw} \tilde{s}_j w_n \\
&+ \sum_{j=1}^{J}\sum_{m=1}^{M} \beta_{jm}^{sk} \tilde{s}_j k_m + \sum_{n=1}^{N-1}\sum_{m=1}^{M} \beta_{nm}^{wk} \widetilde{w}_n k_m \\
&+ \frac{1}{2}\sum_{c=1}^{C}\sum_{c'=1}^{C} \beta_{cc'}^{pp} \tilde{p}_c \tilde{p}_{c'} + \frac{1}{2}\sum_{j=1}^{J}\sum_{j'=1}^{J} \beta_{jj'}^{ss} \tilde{s}_j \tilde{s}_{j'} + \frac{1}{2}\sum_{n=1}^{N-1}\sum_{n'=1}^{N-1} \beta_{nn'}^{ww} \widetilde{w}_n \widetilde{w}_{n'} \\
&+ \frac{1}{2}\sum_{m=1}^{M}\sum_{m'=1}^{M} \beta_{mm'}^{kk} k_m k_{m'} \\
&+ \sum_{c=1}^{C} \beta_c^{pL} \tilde{p}_c L + \sum_{j=1}^{J} \beta_j^{sL} \tilde{s}_j L + \sum_{n=1}^{N-1} \beta_n^{wL} \widetilde{w}_n L + \sum_{m=1}^{M} \beta_m^{kL} k_m L \\
&+ \beta_{aes} r_{aes} + \sum_{c=1}^{C} \beta_{caes}^{pr} \tilde{p}_c r_{aes} + \sum_{j=1}^{J} \beta_{jaes}^{sr} \tilde{s}_j r_{aes} + \sum_{n=1}^{N-1} \beta_{naes}^{wr} \widetilde{w}_n r_{aes} + \sum_{m=1}^{M} \beta_{maes}^{kr} k_m r_{aes} \\
&+ \beta_t trend + \beta_{tt} trend^2 + \epsilon \quad ,
\end{aligned} \tag{6-9}
$$

where $\tilde{\pi}$ is normalised profit; $\tilde{p}, \tilde{s}$, and $\widetilde{w}$ are normalised output prices, subsidy rates, and input prices; k denote quasi-fixed inputs; and L denotes total land use, also considered fixed in the short run. Furthermore, c and j are indices for crop categories and subsidy rates (either crop production or set-aside), respectively; r_{aes} represents revenue from AES, and $trend$ is a time variable to capture technology shifts over time. Finally, the βs are the unknown parameters that characterize the technlogy.

Using Hotelling's lemma, we derive the parametric forms of output supply, input demand, and land allocation equations by taking the first derivatives of the profit function with respect to output prices (see equation (6-3)) and input prices (see equation (6-4)) and land-related subsidy rates (see equation (6-5)):

$$q_c = \frac{\partial \tilde{\pi}}{\partial \tilde{p}_c} = \beta_c^p + \sum_{c'=1}^{C} \beta_{cc'}^{pp} \tilde{p}_{c'} + \sum_{j=1}^{J} \beta_{cj}^{ps} \tilde{p}_c \tilde{s}_j + \sum_{n=1}^{N-1} \beta_{cn}^{pw} \tilde{w}_n + \sum_{m=1}^{M} \beta_{cm}^{pk} k_m + \beta_c^{pL} L + \beta_{caes}^{pr} r_{aes} \tag{6-10}$$

$$-x_n = \frac{\partial \tilde{\pi}}{\partial \tilde{w}_k} = \beta_n^w + \sum_{n'=1}^{N-1} \beta_{nn'}^{ww} \tilde{w}_{n'} + \sum_{c=1}^{C} \beta_{cn}^{pw} \tilde{p}_c + \sum_{j=1}^{J} \beta_{jn}^{sw} \tilde{s}_j w_n + \sum_{m=1}^{M} \beta_{nm}^{wk} k_m + \beta_c^{wL} L + \beta_{naes}^{wr} r_{aes} \tag{6-11}$$

$$l_i = \frac{\partial \tilde{\pi}}{\partial \tilde{s}_j} = \beta_j^s + \sum_{j'=1}^{J} \beta_{jj'}^{ss} \tilde{s}_j \tilde{s}_{j'} + \sum_{j=1}^{J} \beta_{cj}^{ps} \tilde{p}_c \tilde{s}_j + \sum_{n=1}^{N-1} \beta_{jn}^{sw} \tilde{s}_j w_n + \sum_{m=1}^{M} \beta_{jm}^{sk} \tilde{s}_j k_m + \beta_j^{sL} L + \beta_{jaes}^{sr} \tilde{s}_j r_{aes} \tag{6-12}$$

In addition, we impose cross-equation parameter constraints in the estimation procedure (e.g., the parameter of the squared price variable of cereals equals the constant term in the supply function for cereals). In addition, the following additional parameter constraints are imposed to impose the land adding-up condition in (6-2):

$$\begin{gathered} \sum_{j'=1}^{J} \beta_{cj'}^{ps} = \sum_{j'=1}^{J} \beta_{jj'}^{ss} = \sum_{j'=1}^{J} \beta_{j'n}^{sw} = 0 \quad \forall c, \forall j, \forall n; \\ \sum_{j=1}^{J} \beta_j^s = 0; \sum_{j=1}^{J} \beta_j^{sL} = 1 \end{gathered} \tag{6-13}$$

For convexity, the matrix of second-order derivatives of the profit function with respect to output and input prices must be positive semidefinite. Curvature conditions can be imposed on flexible functional forms using ex-post procedures (e.g. Henningsen, 2019), constrained maximum likelihood methods (e.g. Bokusheva and Hockmann, 2006) or Bayesian MCMC techniques (see O'Donnell and Coelli, 2005 and an application to the agricultural sector in Wimmer and Sauer, 2020a). In this article, we use the fact that every positive semidefinite matrix has a Cholesky factorisation (Lau, 1978). Thus, convexity can be imposed by estimating the Cholesky factorisation of the Hessian matrix rather than the parameter matrix itself (see Diewert and Wales, 1987 and Featherstone and Moss, 1994 for applications of this approach to cost functions, and Arnade and Kelch, 2007 and Lambert et al., 2020 fort profit functions). For this purpose, we rewrite the positive semidefinite Hessian matrix of the profit function as $\boldsymbol{B} = \boldsymbol{CC'}$ where $\boldsymbol{C}$ is an $(n-1) \times (n-1)$ lower triangular matrix with elements γ_{ij}. Then, for the simple example of $n = 5$ (e.g. 2 outputs, 1 area-related subsidy, 2 inputs whereby the second input is used as numeraire), the parameters in $\boldsymbol{B}$ can be rewritten as:

$$\boldsymbol{B} = \boldsymbol{CC'} = \begin{bmatrix} \gamma_{11} & 0 & 0 & 0 \\ \gamma_{12} & \gamma_{22} & 0 & 0 \\ \gamma_{13} & \gamma_{23} & \gamma_{33} & 0 \\ \gamma_{14} & \gamma_{24} & \gamma_{34} & \gamma_{44} \end{bmatrix} \times \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} \\ 0 & \gamma_{22} & \gamma_{23} & \gamma_{24} \\ 0 & 0 & \gamma_{33} & \gamma_{34} \\ 0 & 0 & 0 & \gamma_{44} \end{bmatrix}$$

$$= \begin{bmatrix} \gamma_{11}^2 & \gamma_{11}\gamma_{12} & \gamma_{11}\gamma_{13} & \gamma_{11}\gamma_{14} \\ \gamma_{11}\gamma_{12} & (\gamma_{12}^2 + \gamma_{22}^2) & (\gamma_{12}\gamma_{13} + \gamma_{22}\gamma_{23}) & (\gamma_{12}\gamma_{14} + \gamma_{22}\gamma_{24}) \\ \gamma_{11}\gamma_{13} & (\gamma_{12}\gamma_{13} + \gamma_{22}\gamma_{23}) & (\gamma_{12}^2 + \gamma_{22}^2 + \gamma_{33}^2) & (\gamma_{13}\gamma_{14} + \gamma_{23}\gamma_{24} + \gamma_{33}\gamma_{34}) \\ \gamma_{11}\gamma_{14} & (\gamma_{12}\gamma_{14} + \gamma_{22}\gamma_{24}) & (\gamma_{13}\gamma_{14} + \gamma_{23}\gamma_{24} + \gamma_{33}\gamma_{34}) & (\gamma_{14}^2 + \gamma_{24}^2 + \gamma_{34}^2 + \gamma_{44}^2) \end{bmatrix} \tag{6-14}$$

It follows, that the supply function for output 1 for this simple example can be estimated as

$$\frac{\partial \tilde{\pi}}{\partial \tilde{p}_1} = \beta_1^p + \gamma_{11}^2 \times \tilde{p}_1 + (\gamma_{11}\gamma_{12}) \times \tilde{p}_2 + (\gamma_{11}\gamma_{13}) \times \tilde{s}_1 + (\gamma_{11}\gamma_{14}) \times \tilde{w}_1 + \sum_{m=1}^{M} \beta_{cm}^{pk} k_m + \beta_1^{pL} L + \beta_{1,aes}^{pr} r_{aes} \tag{6-15}$$

In our empirical application, the maximum number of prices (including subsidy rates) is $n = 12$, i.e. the Cholesky matrix takes the dimension (11×11). To achieve convergence for this complex and highly nonlinear system of equations, we applied the rank reduction technique suggested by Diewert and Wales (1988). This requires setting $\gamma_{ij} = 0$ for all $i > K$, where K is the desired rank of the matrix. As stated by Moschini (1998), convergence is likely to occur if the rank of the matrix does not exceed the number inconsistent eigenvalues of the unrestricted model. Thus, for each of our six models, we first evaluate the eigenvalues of the Hessian matrix of the unrestricted models and then estimate the Cholesky factorisation such that the rank of the matrix equals the amount of non-negative eigenvalues obtained by the unrestricted system.

To estimate the system of equations (6-10) – (6-12) simultaneously, we employ iterated feasible generalised nonlinear squares, which converges to the maximum likelihood estimator (Zellner, 1962). The estimation is carried out using STATA's *nlsur* command (StataCorp, 2015). Farm-level fixed effects are accounted for by subtracting farm-specific average values from each variable prior to estimation ('within-transformation').

6.5 Results

The parameter estimates of the profit systems for Germany (1995–2004) are reported in Table 6-12 (unrestricted model) and Table 6-13 (restricted model using Cholesky factorisation). The corresponding estimates for the second period and all other countries are available from the authors upon request. The full set of own and cross price elasticities estimated for the two periods and three countries are reported in the Appendix, both for the unrestricted and restricted models (Tables 6-14 – 6-25). In what follows, we present and compare estimated own-price elasticities across countries and models. Thereafter, we discuss elasticities with respect to subsidies in more detail. All elasticities are evaluated at the sample mean and corresponding standard errors are obtained using the Delta method.

6.5.1 Period 1995–2004

Table 6-3 presents own-price elasticities for the unrestricted and restricted profit systems for all three countries in the period 1995–2004. In France, the unrestricted profit model obtains significantly negative own-price elasticities for cereals and root crops, inconsistent to economic theory. Significantly positive own-price elasticities are obtained for maize, protein and oilseed crops. For example, a 1 per cent increase in the price of maize increases maize supply by 0.12 per cent. Land elasticities with respect to own-subsidy rates are significantly positive for cereals and oilseed: a 1 per cent increase in the subsidy rate for cereals increases the land devoted to cereals by 0.07 per cent, and a 1 per cent increase in the oilseed subsidy rate causes a 0.2 per cent increase in oilseed land. Land devoted to protein crops, however, is negatively related to the protein subsidy rate. The own-price elasticity of fertiliser use is also inconsistent with profit-maximising behaviour, as a 1 per cent-increase in fertiliser price by 1 per cent is associated with a 0.4 per cent-increase in fertiliser demand. In the restricted model, all own-price elasticity estimates are statistically significant positive at the 1 per cent significance level. The highest output price elasticity is observed for oilseed crops, followed by protein crops and maize. As can be seen from Table 6-15, most significant cross-price elasticities are negative. We note that the economically consistent curvature of the profit function has no implications on the sign of cross-parameter elasticities. For example, cross-price elasticities can be positive if there are synergies between individual crops.

For the German sample, own-price elasticities are significantly positive for cereals and protein crops in the unrestricted profit system. A 1 per cent-increase in the cereal price increases cereal supply by 0.55 per cent, whereas a 1 per cent-increase in the protein price increases protein supply by 0.09 per cent. All other output price elasticities are not statistically significant, when evaluated at the sample mean. Land allocated to maize is positively affected by its own subsidy unit rate (elasticity = 0.08). However, land allocated to protein, oilseed and set-aside seem to be negatively related their own subsidy rates. Finally, the own-price elasticity of fertiliser use is statistically negative and quite elastic: a 1 per cent-increase in fertiliser price leads to a 1.5 per cent-decline in fertiliser use for the average farm. In the restricted model, all own-price elasticities except for oilseed and root crops are statistically significant. For example, own-price elasticity of cereal crops is 0.6 per cent, hence in a similar range as in the unrestricted model. Likewise, the own-price elasticities of maize and fertiliser are similar to those from the unrestricted model, while the own-price elasticity of protein crops is of larger size in the restricted model.

Finally, in the UK, the unrestricted model yields significantly positive own-price elasticities for cereal and oilseed output as well as for oilseed area. The own-price elasticity for fertiliser input is significantly negative: a 1 per cent-increase in fertiliser price reduces fertiliser demand by 0.59 per cent at the sample mean. Own-price elasticities for protein output and protein area as well as for set-aside area are negative, hence inconsistent with economic theory. In the restricted model, all output supply and input demand elasticities are statistically significant at the 1 per cent level of significance, except for root crops output, for which the own-price elasticity is statistically significant at the 5 per cent level of significance.

Table 6-3. Own-price elasticities for unrestricted and restricted profit functions, 1995-2004

	France		Germany		United Kingdom	
	Unrestr.	Restr.	Unrestr.	Restr.	Unrestr.	Restr.
Cereals output	-0.060[c]	0.070[c]	0.547[c]	0.607[c]	0.186[c]	0.264[c]
	(0.018)	(0.012)	(0.041)	(0.041)	(0.027)	(0.025)
Maize output	0.116[c]	0.232[c]	-0.002	0.032[b]	–	
	(0.022)	(0.020)	(0.070)	(0.013)	–	
Protein output	0.203[c]	0.337[c]	0.093[a]	0.207[c]	-0.410[c]	0.561[c]
	(0.032)	(0.023)	(0.056)	(0.043)	(0.129)	(0.094)
Oilseed output	0.123[c]	0.354[c]	-0.003	0.003	0.593[c]	0.806[c]
	(0.031)	(0.030)	(0.006)	(0.005)	(0.077)	(0.075)
Root crops output	-0.008[a]	0.003[c]	0.013	0.004	-0.025	0.037[b]
	(0.004)	(0.001)	(0.015)	(0.006)	(0.016)	(0.015)
Cereals area	0.068[c]	0.081[c]	0.003	0.033[c]	-0.004	0.067[c]
	(0.005)	(0.005)	(0.009)	(0.006)	(0.010)	(0.008)
Maiz area	–	–	0.081[a]	0.127[c]	–	–
	–	–	(0.046)	(0.032)	–	–
Protein area	-0.084[a]	0.182[c]	-0.198[b]	0.421[c]	-1.313[c]	0.657[c]
	(0.044)	(0.037)	(0.454)	(0.122)	(0.263)	(0.085)
Oilseed area	0.202[c]	0.309[c]	-0.153[c]	0.137[c]	0.670[c]	0.798[c]
	(0.020)	(0.019)	(0.035)	(0.027)	(0.061)	(0.058)
Set-aside area	-0.223[c]	0.423[c]	-0.250[c]	0.306[c]	-0.171[a]	0.409[c]
	(0.031)	(0.023)	(0.049)	(0.037)	(0.102)	(0.086)
Fertiliser use	0.433[c]	-0.139[c]	-1.488[c]	-1.543[c]	-0.588[c]	-0.616[c]
	(0.056)	(0.029)	(0.100)	(0.100)	(0.065)	(0.065)

Note: Elasticities evaluated at the sample mean. Standard errors in parentheses, obtained with delta method.
[a], [b], [c] indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

6.5.2 Period 2005–2016

Table 6-4 reports elasticities of output, land allocation, and fertiliser use for the three countries in the period 1995–2004. As discussed above, we cannot estimate land allocation equations for this period because crop-specific subsidies do not exist. Thus, we restrict the analysis to output and price elasticities. In France, own-price elasticities for cereals, maize, and oilseed crop are significantly positive and the own-price elasticity of fertiliser is significantly negative in the unrestricted model. For example, a 1 per cent increase in the cereal price increases cereal supply by 0.24 per cent, and a 1 per cent increase in fertiliser price reduces the amount of fertiliser by 0.5 per cent. Inconsistent to economic theory, the own price elasticity for protein crops is significantly negative in the unrestricted model. In the restricted model, all own-price elasticities are statistically significant, except the one for root crops, which is nearly zero. Overall, the magnitudes of own-price elasticities are similar to their values in the unrestricted model for the ones that showed the correct sign in the unrestricted model, which the exception of fertiliser use. This value is unrealistically high in the restricted model, implying that a 1 per cent increase in fertiliser price would decrease its use by 11 per cent. Thus, this estimate has to be interpreted with caution when derived from the restricted model.

In the German sample, all cross-price elasticities carry the theoretically consistent sign in the unrestricted model: a 1 per cent increase in the price of cereal (maize, oilseed, root crops) implies a 0.31 (0.40, 0.35, 0.02) per cent increase in cereal (maize, oilseed, root crops) supply. The own-price elasticity of protein crops is positive but statistically insignificant. Even though own-price elasticities carry the expected sign, the profit system is not convex, as indicated by two (out of six) negative eigenvalues of the Hessian matrix. Nevertheless, the corresponding elasticities from the restricted model are very similar to the ones from the unrestricted model. Contrary to the unrestricted model, own-price elasticity for protein crops are significant, although at the 10 per cent level of significance only.

Like in the German sample, the signs of the statistically significant own-price elasticities derived from the unrestricted model for UK farms are all consistent with economic theory. For example, a 1 per cent increase in cereal price causes a 0.08 per cent increase in the profit-maximising cereal supply. Thus, the response to cereal price changes is less sensitive in the UK compared to France and Germany, when evaluated at the sample mean. While own-price elasticities for protein and root crops are not significant in the unrestricted model, they become statistically significant at the 5 per cent significance level in the restricted model.

Table 6-4. Own-price elasticities for unrestricted and restricted profit functions, 2005–2016

	France		Germany		United Kingdom	
	Unrestr.	Restr.	Unrestr.	Restr.	Unrestr.	Restr.
Cereals output	0.235[c]	0.260[c]	0.307[c]	0.312[c]	0.078[c]	0.094[c]
	(0.014)	(0.013)	(0.014)	(0.014)	(0.025)	(0.017)
Maize output	0.122[c]	0.241[c]	0.399[c]	0.500[c]	1.857[c]	2.353[c]
	(0.025)	(0.021)	(0.087)	(0.080)	(0.412)	(0.383)
Protein output	-0.072[c]	0.080[c]	0.006	0.066a	0.003	0.146[b]
	(0.026)	(0.012)	(0.041)	(0.034)	(0.099)	(0.058)
Oilseed output	0.228[c]	0.309[c]	0.345[c]	0.389[c]	0.203[c]	0.106[c]
	(0.024)	(0.021)	(0.036)	(0.033)	(0.062)	(0.026)
Root crops output	-0.006	0.000	0.022[c]	0.041[c]	-0.033	0.036[b]
	(0.005)	(0.000)	(0.011)	(0.008)	(0.029)	(0.017)
Fertiliser use	-0.501[c]	-11.357[c]	-0.717[c]	-0.773[c]	-0.694[c]	-0.694[c]
	(0.023)	(2.138)	(0.036)	(0.074)	(0.027)	(0.058)

Note: Elasticities evaluated at the sample mean. Standard errors in parentheses, obtained with delta method. [a], [b], [c] indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

6.5.3 Elasticities related to agri-environmental subsidies

This section reports elasticity estimates related to agri-environmental subsidies for the three countries and both periods. As described in the previous section, the unrestricted model resulted in several violations of theoretically required properties of the profit and associated supply and demand functions. Therefore, we focus on the estimates from the restricted model here to support robust policy recommendations. Table 6-5 shows that a 1 per cent increase in set-aside unit prices increases the set-aside area by 0.42, 0.31 and 0.41 per cent in France, Germany, and the UK, respectively. In France, increased set-aside area primarily substitutes areas devoted to cereal and oilseed production. Furthermore, it is also associated with an increase in the protein area. In the German sample, the increase in the set-aside area primarily substitutes land devoted to protein crops production: a 1 per cent increase in set-aside subsidy rate decreases protein area by 0.39 per cent and protein production by 0.29 per cent. This reduction in protein supply seems to favour total cereal output, even though cereal area remains relatively stable, which can be due to a shift of input factors (other than land) from protein to cereal production in response to higher set-aside subsidy rates. Similarly, set-aside area primarily substitutes protein production in the UK. We note that the total land change adds up to zero when measured in absolute (i.e., hectare) numbers, as imposed by the parameter constraints in equation (6-13). For example, in the French case, increasing the set-aside subsidy unit price by 1 € increases the set-aside area and protein crops area by 0.38 hectares and 0.12 hectares, respectively, while it reduces the area devoted to cereal and oilseed crops production by 0.32 and 0.17 hectares.[44]

Fertiliser use is reduced in response to both set-aside and AES subsidies, except for set-aside subsidies in the French sample in the period 1995–2004. For example, in Germany, a 1 per cent increase in the set-aside subsidy rate reduces the amount of fertiliser used by 0.11 per cent. In the UK, a 1 per cent increase in the set-aside subsidy rate decreases fertiliser use by 0.05 per cent. Farm-level production responses to AES subsidy seem to be much smaller. For instance, a 1 per cent increase in revenues from AES participation decreases fertiliser use in France by 0.002 per cent in the 1995–2004 period and by 0.004 per cent in the 2005–2016 period. The response in Germany is only marginally higher: a 1 per cent increase in revenues from AES participation decreases fertiliser use by 0.01 per cent in the 1995–2004 period and by 0.006 per cent in the 2005–2016 period. Finally, in the UK, 1 per cent increase in revenues from AES participation decreases fertiliser use by 0.01 per cent in the period 1995–2004 and by 0.02 per cent in the period 2005–2016.

Table 6-5 also shows that output elasticities with respect to AES programmes are highly consistent across the two periods in France and Germany. For example, a 1 per cent increase in revenue from AES participation relates to a decrease in cereal output by 0.001 per cent (1995–2004) and 0.003 per

[44] The remaining 0.01 hectare is due to rounding of the numbers.

cent (2005–2016) in Germany, and by 0.021 per cent (1995–2004) and 0.025 per cent (2005–2016) in France. In the UK, by contrast, there are some differences between the two periods. Most notably, protein output and AES involvement are positively related in the earlier period but negatively related in the later period. This could be due to a change in the programme design, which is regularly updated on a 5-year basis by the individual EU member countries.

Table 6-5. Elasticities related to agri-environmental subsidies (restricted models)

	France		Germany		United Kingdom	
	Sample 1995–2004	Sample 2005–2016	Sample 1995–2004	Sample 2005–2016	Sample 1995–2004	Sample 2005–2016
Elasticities with respect to subsidies for set-aside						
Cereals output	0.007[c]	–	0.607[c]	–	0.028[c]	–
Maize output	0.093[c]	–	0.023	–	–	–
Protein output	0.222[c]	–	-0.291[c]	–	-0.177[c]	–
Oilseed output	0.047[c]	–	-0.001	–	0.043[a]	–
Root crop output	0.000	–	0.001	–	0.013[c]	–
Cereals area	-0.027[c]	–	-0.017[c]	–	-0.009	–
Maize area	–	–	0.014	–	–	–
Protein area	0.095[c]	–	-0.390[c]	–	-0.244[c]	–
Oilseed area	-0.042[c]	–	0.050[c]	–	-0.051	–
Set-aside area	0.423[c]	–	0.306[c]	–	0.409[c]	–
Fertiliser use	0.048[c]	–	-0.108[c]	–	-0.045[a]	–
Elasticities with respect to AES programmes						
Cereals output	-0.001[b]	-0.003[c]	-0.021[c]	-0.025[c]	-0.003[c]	-0.010[b]
Maize output	-0.002[b]	-0.002[a]	-0.035[c]	-0.086[c]	–	-0.823[a]
Protein output	0.002	0.014[c]	0.143[c]	0.028[b]	0.090[c]	-0.137[c]
Oilseed output	-0.003[b]	-0.002[b]	0.004	-0.035[c]	0.024[c]	-0.006
Root crop output	-0.001	-0.001	-0.011[c]	-0.010[c]	-0.022[c]	-0.002
Cereals area	0.000	–	-0.006[c]	–	-0.006[c]	–
Maize area	–	–	0.196[c]	–	–	–
Protein area	0.008[c]	–	0.144[c]	–	0.099[c]	–
Oilseed area	-0.002[c]	–	-0.008[b]	–	0.011	–
Set-aside area	0.000	–	-0.029[c]	–	-0.005	–
Fertiliser use	-0.002[c]	-0.004[c]	-0.011[c]	-0.006[c]	-0.013[c]	-0.021

Note: Elasticities evaluated at the sample mean. Standard errors in parentheses, obtained with delta method. [a], [b], [c] indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively. Subsidies for set-aside and area elasticities only apply to the early period (1995 - 2004). The upper panel displays elasticities with respect to subsidies for set-aside (e.g., percentage-change in cereal output in response to a 1 per cent increase in the subsidy rate for set-aside). The lower panel displays elasticities with respect to AES programmes (e.g., percentage-change in cereal output in response to a 1 per cent increase in AES involvement).

6.6 Discussion and conclusion

Over the past decades, agricultural policies in the EU gradually shifted from market support to producer support. During this process, environmental aspects are increasingly addressed to improve the environmental sustainability of farming. The most important green policies in this regard are voluntary agri-environmental programmes and set-aside premiums that compensate farmers for leaving agricultural land out of production. To evaluate the effectiveness of these programmes, this paper empirically evaluates the production response of farmers to the economic incentives provided by these programmes. In particular, we estimate subsidy and price elasticities of output supply, input demand, and land allocation with a particular focus on agri-environmental subsidies in France, Germany, and the UK, using FADN data on crop farms from 1995–2016. Due to the decoupling of subsidy payments in 2005, we distinguish two periods and estimate the system of profit equations separately for each country and each period. The existence of area-related unit subsidies for cereals, maize, protein crops and oilseed crops (paid per hectare of corresponding land use) allows us to estimate land allocation equations for the period 1995–2004 using Hotelling's Lemma. In the subsequent period (2005–2016), we focus on output and input elasticities with respect to prices and AES programmes. Our estimates are based on a profit function approach. We compare the results from an unrestricted model to the results from a restricted model, where the theoretically consistent curvature is imposed on the profit function by making use of Cholesky factorisation.

The results reveal substantial differences in production responses to price and subsidy rate changes across countries. For example, in response to higher set-aside subsidy rates, French farmers tend to substitute areas devoted to cereals and oilseed production in favour of set-aside areas in France, while farmers in the UK and Germany substitute areas devoted to protein crop production. Moreover, we find that higher levels of AES participation are related to less cereal and maize production, less fertiliser use, and higher supply of protein crops in all countries. This finding is consistent to expectations, as arable land schemes often involve the implementation of diversified crop rotations and planting of cover crops (e.g. Mennig and Sauer, 2020). The response in root crop production to agri-environmental subsidies is less pronounced. A possible explanation is that sugar beet and potatoes are highly intensive and profitable crops, which require especially high subsidy premiums to be replaced. Finally, the results also show that fertiliser use is consistently reduced with an increase in set-aside subsidy rates and AES involvement. The only exception is the French data set in the period 1995–2004. Applying the structural model to the same country over the period 1995–2001, Lacroix and Thomas (2011) find no statistically significant effect of set-aside subsidy rates on fertiliser use. For a sample of Finnish farms, Laukkanen and Nauges (2014) find that the elasticity of fertiliser use with respect to subsidies for set-aside and with respect to AES programmes is -0.008 and -0.052, respectively. In contrast to that, we find that fertiliser use is more elastic to set-aside subsidies but less elastic to AES participation in our samples of French, UK, and German farmers.

The result that AES participation is related to less fertiliser use is consistent with the reduced-form estimates by Pufahl and Weiss, C. R. (2009) and Arata and Sckokai (2016). For example, Pufahl and Weiss, C. R. (2009) estimate that AES participation reduces expenditures for fertiliser by 9.4 per cent. Contrary to the identified treatment effects in the reduced-form literature, our structural parameters allow the simulation of farm responses to simultaneous changes in output and input prices and various policy changes. This is important as agricultural policies become increasingly complex and often formulate multiple and heterogeneous goals. Knowing the structural parameters that describe farmers' production decisions are therefore essential to predict farm-level outcomes under a range of different policy scenarios. Regarding immediate policy implications, our results demonstrate that production decisions in response to agri-environmental policies significantly vary across countries. This is the case not only for fertiliser usage but also for output decisions and land allocation. Therefore, we conclude that heterogeneity between regions must be considered to increase the effectiveness of green policies.

Methodologically, our results show that the unrestricted estimation of the profit system results in large violations of theoretically required properties, especially in the period former period (1995–2004). However, meaningful economic interpretation is only possible if estimation results are consistent to theory (Sauer, 2006). Hence, econometric techniques are needed to improve the theoretical consistency of the estimated model and support evidence-based policymaking.

The study offers significant scope for further research. In particular, we propose to collect subsidy rate data for individual AES programmes to evaluate their effects separately and uncover interdependencies between them. Unfortunately, FADN bookkeeping data only allows us to consider total AES payments, i.e. a mix of individual programmes. However, individual programmes are very diverse and may promote ecosystem services that are either complementary or supplementary to agricultural production (Sauer and Wossink, A., 2013). Thus, looking at aggregate revenues from individual programmes may hide effects on production responses if they point in opposite directions. Thus, more detailed data is needed to guide policymakers on effectively designing green agricultural policies according to the objective to make agriculture more sustainable while maintaining its competitiveness.

Appendix

Table 6-6. Descriptive statistics for France, period 1995–2004

Variable	Unit	Mean	Std. Dev.	Min.	Max.
Cereals output	1,000 kg	420.67	344.14	0.00	3,073.80
Maize output	1,000 kg	119.06	260.35	0.00	5,837.40
Protein output	1,000 kg	29.97	48.36	0.00	538.10
Oilseed output	1,000 kg	61.24	78.55	0.00	888.70
Root crops output	1,000 kg	427.79	865.98	0.00	12,220.00
Fertiliser use	const. €	158.91	103.26	0.00	1,088.66
Cereals area	ha	58.96	46.14	0.00	440.65
Maize area	ha	12.93	26.50	0.00	574.82
Protein area	ha	6.15	9.37	0.00	93.05
Oilseed area	ha	20.09	24.94	0.00	230.48
Root crops area	ha	6.81	14.17	0.00	216.00
Voluntary set-aside	ha	4.08	6.76	0.00	174.68
Cereals price	€/1,000kg	119.00	16.89	85.09	266.93
Maize price	€/1,000kg	119.20	35.37	74.29	616.35
Protein price	€/1,000kg	136.08	26.10	89.12	620.00
Oilseed price	€/1,000kg	202.81	24.39	79.16	305.09
Root crops price	€/1,000kg	106.86	114.28	24.92	656.16
Fertiliser price	index	102.06	5.66	95.20	112.40
Cereals subsidy rate	€/ha	364.01	41.81	251.01	553.33
Protein subsidy rate	€/ha	492.54	62.83	246.71	689.40
Oilseed subsidy rate	€/ha	454.12	75.27	274.34	596.46
Set-aside subsidy rate	€/ha	478.31	165.68	251.76	1,307.85
AES Payments	€	383.07	2,071.70	0.00	71,143.00
Profit	€	81,275.61	67,770.55	-345,171.00	1,093,222.00

n=19,912; number of farms: 3,918

Table 6-7. Descriptive statistics for France, period 2005–2016

Variable	Unit	Mean	Std. Dev.	Min	Max
Cereals output	1,000 kg	468.76	385.72	0.00	3,249.20
Maize output	1,000 kg	129.24	261.89	0.00	2,632.10
Protein output	1,000 kg	13.43	30.79	0.00	439.80
Oilseed output	1,000 kg	72.91	84.61	0.00	1,050.80
Root crops output	1,000 kg	548.36	1,139.78	0.00	14,233.80
Fertiliser use	const. €	297.36	210.53	0.00	2,322.04
Cereals price	€/1,000 kg	156.52	40.90	55.54	285.45
Maize price	€/1,000 kg	146.76	51.20	71.99	648.15
Protein crops price	€/1,000 kg	231.53	117.31	103.46	1,729.17
Oilseed crops price	€/1,000 kg	323.35	89.50	180.63	734.41
Root crops price	€/1,000 kg	166.69	192.58	14.24	1,010.94
Fertiliser price	index	92.92	15.04	67.00	116.70
AES payments	€	722.45	2,808.50	0.00	58,421.00
Profit	€	69,233.49	100,481.60	-149,496.00	2,924,784.00

n = 20,760; number of farms: 3,609

Table 6-8. Descriptive statistics for Germany, period 1995–2004

Variable	Unit	Mean	Std. Dev.	Min	Max
Cereals output	1,000 kg	720.54	1,461.71	0.00	25,167.10
Maize output	1,000 kg	19.77	112.46	0.00	2,908.00
Protein output	1,000 kg	12.15	58.48	0.00	1,236.00
Oilseed output	1,000 kg	86.95	261.08	0.00	17,162.30
Root crops output	1,000 kg	685.99	1,230.40	0.00	23,507.30
Fertiliser use	kg	63.75	117.88	0.00	1,752.54
Cereals area	ha	114.87	233.65	0.00	3,754.65
Maize area	ha	2.65	14.61	0.00	522.72
Protein area	ha	4.19	18.85	0.00	308.62
Oilseed area	ha	28.45	69.05	0.00	1,379.00
Root crops area	ha	14.38	26.74	0.00	572.00
Voluntary set-aside	ha	6.93	23.49	0.00	509.33
Cereals price	€/1,000 kg	120.82	13.27	87.29	222.64
Maize price	€/1,000 kg	120.29	38.80	67.54	396.50
Protein crops price	€/1,000 kg	120.06	64.00	0.00	403.40
Oilseed crops price	€/1,000 kg	310.13	637.06	80.77	8,736.22
Root crops price	€/1,000 kg	64.29	22.09	38.97	287.61
Fertiliser price	€/1,000 kg	298.15	19.39	266.28	327.91
Cereals subsidy rate	€/ha	331.68	39.72	210.88	429.07
Maize subsidy rate	€/ha	320.85	141.89	0.00	792.94
Protein subsidy rate	€/ha	419.62	50.43	300.97	567.22
Oilseed subsidy rate	€/ha	448.58	84.01	275.99	1,463.68
Set-aside subsidy rate	€/ha	374.24	132.89	124.84	1,294.28
AES	€	3,510.22	14,433.01	0.00	350,001.00
Profit	€	98,479.53	180,361.30	-1,438,091.00	3,260,773.00

n=12,632; number of farms: 3,361

Table 6-9. Descriptive statistics for Germany, period 2005–2016

Variable	Unit	Mean	Std. Dev.	Min	Max
Cereals output	1,000 kg	791.29	1,579.95	0.00	35,953.10
Maize output	1,000 kg	31.26	201.10	0.00	10,474.30
Protein output	1,000 kg	9.50	52.42	0.00	1,846.60
Oilseed output	1,000 kg	140.54	336.63	0.00	11,560.30
Root crops output	1,000 kg	782.38	1,621.45	0.00	40,212.20
Fertiliser use	kg	79.99	145.28	0.00	2,485.62
Cereals price	€/1,000 kg	161.53	39.03	92.58	321.91
Maize price	€/1,000 kg	147.41	53.61	28.42	441.07
Protein crops price	€/1,000 kg	242.97	127.07	31.46	1,528.04
Oilseed crops price	€/1,000 kg	338.13	80.26	142.39	583.78
Root crops price	€/1,000 kg	77.14	46.02	31.99	480.22
Fertiliser price	€/kg	464.75	57.85	348.37	537.13
AES payments	€	4,247.44	14,310.02	0.00	333,337.00
Profit	€	101,661.90	229,802.90	-2,275,018.00	5,642,586.00

n=21,619; number of farms: 4,511

Table 6-10. Descriptive statistics for the UK, period 1995–2004

Variable	Unit	Mean	Std. Dev.	Min	Max
Cereals output	1,000 kg	864.56	874.99	0.00	10,811.10
Protein output	1,000 kg	21.55	67.76	0.00	1,684.60
Oilseed output	1,000 kg	64.34	111.92	0.00	1,393.10
Root crops output	1,000 kg	666.95	1,630.40	0.00	25,902.00
Fertiliser use	const. €	508.32	517.86	0.00	14,822.63
Land for cereals	ha	115.49	109.75	0.00	1,449.72
Land for protein	ha	5.75	17.32	0.00	410.28
Land for oilseed	ha	21.29	34.45	0.00	357.22
Land for root crops	ha	14.18	33.47	0.00	491.79
Voluntary set-aside	ha	8.74	14.78	0.00	248.82
Cereals price	€/1,000kg	122.27	13.68	82.82	166.57
Protein price	€/1,000kg	163.81	35.70	96.17	366.70
Oilseed price	€/1,000kg	223.02	26.35	120.49	312.47
Root crops price	€/1,000kg	101.35	51.69	22.21	286.14
Fertiliser price	index	42.80	4.51	36.74	53.03
Cereals unit subsidy	€/ha	353.75	18.26	294.57	380.42
Protein unit subsidy	€/ha	465.69	52.44	316.63	544.21
Oilseed unit subsidy	€/ha	499.10	108.81	281.52	688.52
Set-aside unit subsidy	€/ha	433.90	102.84	256.67	1,363.77
AES revenue	€	1,569.08	7,290.29	0.00	229,278.70
Profit	€	126,051.50	173,096.20	-157,727.10	2,158,676.00

Note: n=7,086; number of farms: 1,673

Table 6-11. Descriptive statistics for the UK, period 2005–2016

Variable	Unit	Mean	Std. Dev.	Min	Max
Cereals output	1,000 kg	988.83	1,153.75	0.00	17,983.00
Maize output	1,000 kg	1.50	48.03	0.00	3,437.00
Protein output	1,000 kg	34.40	91.45	0.00	1,465.00
Oilseed output	1,000 kg	100.58	164.94	0.00	1,659.00
Root crops output	1,000 kg	782.81	2,880.81	0.00	90,897.00
Fertiliser use	const. €	425.95	495.59	0.00	7,338.68
Cereals price	€/1,000kg	157.38	38.95	92.77	255.07
Maize price	€/1,000kg	151.06	134.48	0.00	550.27
Protein crops price	€/1,000kg	228.55	77.23	98.76	721.50
Oilseed crops price	€/1,000kg	332.96	83.40	146.57	694.52
Root crops price	€/1,000kg	137.24	68.44	33.63	387.29
Fertiliser price	index	98.22	26.64	58.07	146.31
AES payments	€	10,078.87	20,646.56	0.00	335,106.30
Profit	€	117,082.80	260,382.40	-359,232.30	7,267,414.00

n=6,852; number of farms: 1,419

Table 6-12. Profit system estimates (unrestricted model), Germany 1995–2004

	Coeff.	Std. Err.		Coeff.	Std. Err.		Coeff.	Std.Err.
Matrix terms						*Fixed inputs and AES*		
B11	259.224	19.044	B66	0.466	0.252	D11	3.661	0.081
B12	1.887	2.804	B67	-0.080	0.070	D12	-0.004	0.001
B13	4.663	2.043	B68	0.856	0.170	D13	0.079	0.014
B14	0.983	0.285	B69	-0.209	0.179	D14	-0.004	0.000
B15	21.708	10.881	B610	-1.0327		D21	0.380	0.013
B16	8.105	1.305	B611	-3.397	0.470	D22	0.001	0.000
B17	-0.650	0.511	B77	0.037	0.037	D23	-0.012	0.002
B18	-2.830	0.843	B78	0.001	0.055	D24	0.000	0.000
B19	-6.140	1.196	B79	0.212	0.059	D31	0.279	0.010
B110	1.515	-	B710	-0.1692		D32	-0.003	0.000
B111	-12.625	2.651	B711	1.135	0.186	D33	-0.012	0.002
B22	0.137	0.906	B88	-0.156	0.208	D34	0.000	0.000
B23	0.516	0.456	B89	-0.068	0.118	D41	0.484	0.040
B24	-0.028	0.047	B810	-0.6326		D42	-0.010	0.001
B25	-1.388	2.103	B811	0.198	0.440	D43	0.038	0.007
B26	-0.166	0.298	B99	-0.715	0.182	D44	0.000	0.000
B27	-0.060	0.138	B910	0.7804		D51	2.233	0.074
B28	0.249	0.191	B911	0.184	0.387	D52	0.006	0.001
B29	0.243	0.269	B1010	1.054		D53	0.099	0.012
B210	-0.2661	-	B1011	1.879		D54	-0.002	0.000
B211	2.629	0.572	B1111	22.901	1.913	D61	0.602	0.005
B33	1.051	0.454				D62	0.000	0.000
B34	0.089	0.036				D63	0.001	0.001
B35	1.247	1.543				D64	0.000	0.000
B36	1.814	0.223				D71	0.044	0.002
B37	0.108	0.085				D72	0.000	0.000
B38	0.218	0.159				D73	-0.002	0.000
B39	-0.646	0.196				D74	0.000	0.000
B310	-1.49372	-				D81	0.082	0.003
B311	-2.742	0.416				D82	-0.001	0.000
B44	-0.068	0.141				D83	-0.002	0.001
B45	0.365	0.260				D84	0.000	0.000
B46	0.008	0.018				D91	0.217	0.005
B47	-0.007	0.008				D92	-0.001	0.000
B48	0.017	0.012				D93	-0.003	0.001
B49	0.012	0.017				D94	0.000	0.000
B410	-0.03111	-				D101	0.054	-
B411	-0.021	0.030				D102	0.002	-
B55	11.780	12.784				D103	0.006	-
B56	-0.060	0.835				D104	0.000	-
B57	-0.127	0.354				D111	-0.253	0.008
B58	-0.045	0.549				D112	0.001	0.000
B59	0.041	0.780				D113	-0.001	0.001
B510	0.191319	-				D114	0.000	0.000
B511	-1.905	1.449						

Note: The first six rows of the matrix represent output prices. Rows 7-10 represent subsidy rates. The terms of the last subsidy rate are recovered from land-use restrictions (see equation 13). The final row represents fertiliser price. The letter D represents fixed inputs (land, labour, capital) and AES payments.

Table 6-13. Profit system estimates with Cholesky factorisation, Germany 1995–2004

	Coeff.	Std.Err.		Coeff.	Std.Err.		Coeff.		Coeff.
Cholesky matrix terms			*Fixed inputs and AES*			*Original matrix terms*			
C11	16.858	0.564	D11	3.735	0.082	B11	284.203	B66	0.891
C12	0.074	0.163	D12	0.000	0.001	B12	1.251	B67	-0.121
C13	0.185	0.119	D13	0.085	0.014	B13	3.115	B68	0.351
C14	0.054	0.017	D14	-0.004	0.000	B14	0.905	B69	-0.715
C15	1.167	0.626	D21	0.385	0.013	B15	19.672	B610	-0.406
C16	0.498	0.069	D22	0.001	0.000	B16	8.395	B611	-3.002
C17	-0.077	0.026	D23	-0.011	0.002	B17	-1.294	B77	0.082
C18	-0.118	0.042	D24	0.000	0.000	B18	-1.982	B78	-0.023
C19	-0.454	0.065	D31	0.304	0.010	B19	-7.652	B79	0.054
C110	-	-	D32	-0.002	0.000	B110	2.533	B710	0.008
C111	-1.032	0.142	D33	-0.010	0.002	B111	-17.396	B711	1.192
C22	-0.636	0.131	D34	0.000	0.000	B22	0.410	B88	0.330
C23	0.252	0.404	D41	0.516	0.040	B23	-0.146	B89	-0.315
C24	0.040	0.072	D42	-0.008	0.001	B24	-0.021	B810	-0.343
C25	0.537	0.730	D43	0.043	0.007	B25	-0.255	B811	-0.819
C26	0.218	0.228	D44	0.000	0.000	B26	-0.102	B99	0.680
C27	-0.213	0.075	D51	2.222	0.074	B27	0.130	B910	0.296
C28	-0.001	0.162	D52	0.005	0.001	B28	-0.008	B911	1.183
C29	0.127	0.201	D53	0.095	0.012	B29	-0.115	B1010	0.445
C210	-	-	D54	-0.002	0.000	B210	0.095	B1011	1.446
C211	-4.553	0.606	D61	0.603	0.005	B211	2.818	B1111	25.938
C33	1.245	0.152	D62	0.001	0.000	B33	1.648		
C34	0.056	0.034	D63	0.002	0.001	B34	0.090		
C35	0.116	0.726	D64	0.000	0.000	B35	0.495		
C36	0.558	0.142	D71	0.039	0.002	B36	0.842		
C37	0.078	0.053	D72	0.000	0.000	B37	0.029		
C38	0.396	0.063	D73	-0.002	0.000	B38	0.472		
C39	-0.441	0.121	D74	0.000	0.000	B39	-0.601		
C310	-	-	D81	0.085	0.003	B310	-0.742		
C311	-1.088	1.440	D82	-0.001	0.000	B311	-2.691		
C44	0.244	0.220	D83	-0.001	0.001	B44	0.067		
C45	1.427	1.420	D84	0.000	0.000	B45	0.439		
C46	-0.243	0.218	D91	0.225	0.005	B46	0.007		
C47	0.022	0.056	D92	0.000	0.000	B47	-0.003		
C48	0.005	0.043	D93	-0.002	0.001	B48	0.017		
C49	0.163	0.154	D94	0.000	0.000	B49	-0.004		
C410	-	-	D101	0.048	-	B410	-0.017		
C411	1.131	1.575	D102	0.001	-	B411	-0.021		
C55	0.158	0.647	D103	0.003	-	B55	3.726		
C56	-0.475	0.265	D104	0.000	-	B56	0.341		
C57	0.157	0.092	D111	-0.260	0.008	B57	-0.139		
C58	-0.399	0.127	D112	0.001	0.000	B58	-0.148		
C59	0.487	0.169	D113	-0.001	0.001	B59	-0.203		
C510	-	-	D114	0.000	0.000	B510	0.149		
C511	1.295	1.801				B511	-1.956		

Note: The first six rows of the matrix represent output prices. Rows 7-10 represent subsidy rates. The terms of the last subsidy rate are recovered from land-use restrictions (see equation 13). The letter D represents fixed inputs (land, labour, capital) and AES payments.

Table 6-14. Elasticities of output, land, and fertiliser use for France, period 1995–2004 (unrestricted model)

	Price Cereals	Price Maize	Price Protein	Price Oilseed	Price Root Crops	Subsidy Cereals	Subsidy Protein	Subsidy Oilseed	Subsidy Set-aside	Price Fertiliser	AES
Output Cereals	-0.060^{c}	-0.033^{c}	0.035^{c}	-0.077^{c}	0.010^{c}	0.001	0.037^{c}	-0.065^{c}	0.031^{c}	-0.060	-0.001^{c}
	(0.018)	(0.008)	(0.005)	(0.008)	(0.002)	(0.005)	(0.004)	(0.005)	(0.003)	(0.007)	(0.000)
Output Maize	-0.115^{c}	0.116^{c}	0.054^{c}	-0.044^{c}	-0.022^{c}	-0.096^{c}	0.026^{c}	-0.049^{c}	0.154^{c}	0.029^{b}	-0.002^{c}
	(0.028)	(0.022)	(0.009)	(0.016)	(0.005)	(0.008)	(0.007)	(0.010)	(0.006)	(0.012)	(0.001)
Output Protein	0.416^{c}	0.179^{c}	0.203^{c}	-0.152^{c}	0.041^{c}	-0.144^{c}	0.083^{c}	-0.220^{c}	0.341^{c}	-0.155^{c}	0.002
	(0.061)	(0.032)	(0.032)	(0.038)	(0.008)	(0.022)	(0.023)	(0.025)	(0.016)	(0.035)	(0.001)
Output Oilseed	-0.313^{c}	-0.050^{c}	-0.052^{c}	0.123^{c}	-0.001	-0.173^{c}	-0.034^{c}	0.058^{c}	0.200^{c}	-0.112^{c}	-0.003^{c}
	(0.034)	(0.018)	(0.013)	(0.031)	(0.005)	(0.012)	(0.010)	(0.016)	(0.009)	(0.019)	(0.001)
Output Roots	0.011^{c}	-0.007^{c}	0.004^{c}	0.000	-0.008^{a}	0.001	0.003^{c}	-0.004^{c}	0.001^{c}	0.001	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Land Cereals	0.003	-0.064^{c}	-0.029^{c}	-0.099^{c}	0.001	0.068^{c}	0.005	-0.077^{c}	-0.014^{c}	0.100^{c}	0.000
	(0.011)	(0.005)	(0.004)	(0.007)	(0.001)	(0.005)	(0.004)	(0.006)	(0.003)	(0.009)	(0.000)
Land Protein	0.589^{c}	0.116^{c}	0.113^{c}	-0.131^{c}	0.039^{c}	0.033	-0.084^{a}	-0.078^{b}	0.120^{c}	0.268^{c}	0.008^{c}
	(0.063)	(0.031)	(0.031)	(0.040)	(0.008)	(0.030)	(0.044)	(0.033)	(0.017)	(0.079)	(0.001)
Land Oilseed	-0.355^{c}	-0.075^{c}	-0.102^{c}	0.077^{c}	-0.022^{c}	-0.179^{c}	-0.027^{b}	0.202^{c}	0.050^{c}	-0.210^{c}	-0.002^{c}
	(0.029)	(0.015)	(0.012)	(0.022)	(0.004)	(0.013)	(0.011)	(0.020)	(0.009)	(0.026)	(0.001)
Land Set-aside	0.748^{c}	1.044^{c}	0.695^{c}	1.184^{c}	0.029^{c}	-0.141^{c}	0.182^{c}	0.221^{c}	-0.223^{c}	-0.770^{c}	0.000
	(0.081)	(0.043)	(0.032)	(0.055)	(0.011)	(0.030)	(0.026)	(0.040)	(0.031)	(0.055)	(0.002)
Fertiliser Use	0.016	-0.025^{b}	0.040^{c}	0.083^{c}	-0.003	-0.129^{c}	-0.051^{c}	0.116^{c}	0.097^{c}	0.433^{c}	-0.002^{c}
	(0.020)	(0.010)	(0.009)	(0.014)	(0.002)	(0.012)	(0.015)	(0.015)	(0.007)	(0.056)	(0.000)

Note: Elasticities evaluated at the sample mean. Standard errors in parentheses, obtained with delta method. ^{a}, ^{b}, ^{c} indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 6-15. Elasticities of output, land, and fertiliser use for France, period 1995–2004 (restricted model)

	Price Cereals	Price Maize	Price Protein	Price Oilseed	Price Root Crops	Subsidy Cereals	Subsidy Protein	Subsidy Oilseed	Subsidy Set-aside	Price Fertiliser	AES
Output Cereals	0.070[c]	-0.012[a]	0.024[c]	-0.037[c]	0.011[c]	0.020[c]	0.017[c]	-0.047[c]	0.007[c]	0.070	-0.001[b]
	(0.012)	(0.007)	(0.003)	(0.008)	(0.002)	(0.004)	(0.003)	(0.005)	(0.002)	(0.004)	(0.000)
Output Maize	-0.042[a]	0.232[c]	0.079[c]	0.022	-0.022[c]	-0.073[c]	0.043[c]	-0.036[c]	0.093[c]	-0.039[c]	-0.002[b]
	(0.024)	(0.020)	(0.008)	(0.016)	(0.005)	(0.008)	(0.006)	(0.009)	(0.005)	(0.010)	(0.001)
Output Protein	0.286[c]	0.263[c]	0.337[c]	-0.001	0.038[c]	-0.155[c]	0.139[c]	-0.145[c]	0.222[c]	-0.250[c]	0.002
	(0.034)	(0.027)	(0.023)	(0.035)	(0.007)	(0.019)	(0.017)	(0.023)	(0.011)	(0.024)	(0.001)
Output Oilseed	-0.152[c]	0.026	0.000	0.354[c]	0.004	-0.145[c]	-0.038[c]	0.173[c]	0.047[c]	-0.112[c]	-0.003[c]
	(0.031)	(0.018)	(0.012)	(0.030)	(0.005)	(0.012)	(0.009)	(0.016)	(0.008)	(0.017)	(0.001)
Output Roots	0.012[c]	-0.007[c]	0.004[c]	0.001	0.003[c]	0.001[a]	0.002[c]	-0.004[c]	0.000	0.000	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Land Cereals	0.047[c]	-0.048[c]	-0.031[c]	-0.083[c]	0.002[a]	0.081[c]	-0.007[a]	-0.070[c]	-0.027[c]	0.064[c]	0.000
	(0.010)	(0.005)	(0.004)	(0.007)	(0.001)	(0.005)	(0.004)	(0.006)	(0.003)	(0.008)	(0.000)
Land Protein	0.269[c]	0.195[c]	0.188[c]	-0.149[c]	0.033[c]	-0.046[a]	0.182[c]	-0.201[c]	0.095[c]	0.056	0.008[c]
	(0.040)	(0.028)	(0.023)	(0.037)	(0.007)	(0.028)	(0.037)	(0.028)	(0.014)	(0.057)	(0.001)
Land Oilseed	-0.257[c]	-0.056[c]	-0.067[c]	0.232[c]	-0.019[c]	-0.164[c]	-0.069[c]	0.309[c]	-0.042[c]	-0.124[c]	-0.002[c]
	(0.027)	(0.015)	(0.011)	(0.021)	(0.004)	(0.013)	(0.010)	(0.019)	(0.008)	(0.020)	(0.001)
Land Set-aside	0.159[c]	0.630[c]	0.452[c]	0.275[c]	0.006	-0.277[c]	0.143[c]	-0.187[c]	0.423[c]	-0.382[c]	0.000
	(0.057)	(0.037)	(0.023)	(0.047)	(0.010)	(0.027)	(0.021)	(0.037)	(0.023)	(0.040)	(0.002)
Fertiliser Use	-0.019	0.033[c]	0.064[c]	0.083[c]	0.001	-0.083[c]	-0.011	0.069[c]	0.048[c]	-0.139[c]	-0.002[c]
	(0.013)	(0.008)	(0.006)	(0.013)	(0.002)	(0.010)	(0.011)	(0.011)	(0.005)	(0.029)	(0.000)

Note: Elasticities evaluated at the sample mean. Standard errors in parentheses, obtained with delta method. [a], [b], [c] indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 6-16. Elasticities of output, land, and fertiliser for Germany, 1995–2004 (unrestricted model)

	Price Cereals	Price Maize	Price Protein	Price Oilseed	Price Root Crops	Subsidy Cereals	Subsidy Maize	Subsidy Protein	Subsidy Oilseed	Subsidy Set-aside	Price Fertiliser	AES
Output Cereals	0.547[c]	0.003	0.009[b]	0.005[c]	0.025[b]	0.044[c]	-0.008[c]	-0.012[b]	-0.052[c]	0.547[c]	-0.078[c]	-0.021[c]
	(0.041)	(0.006)	(0.004)	(0.002)	(0.012)	(0.007)	(0.003)	(0.005)	(0.009)	(0.005)	(0.013)	(0.002)
Output Maize	0.123	-0.002	0.021	-0.006	-0.048	-0.033	-0.008	0.032	0.051	-0.025	0.549[c]	-0.035[c]
	(0.218)	(0.070)	(0.035)	(0.009)	(0.087)	(0.062)	(0.026)	(0.043)	(0.077)	(0.043)	(0.101)	(0.013)
Output Protein	0.568[b]	0.034	0.093[a]	0.028[b]	0.104	0.513[c]	0.019	0.045	-0.363[c]	-0.340[c]	-0.826[c]	0.144[c]
	(0.258)	(0.057)	(0.056)	(0.012)	(0.104)	(0.076)	(0.025)	(0.061)	(0.091)	(0.049)	(0.119)	(0.016)
Output Oilseed	0.017[c]	-0.001	0.001[b]	-0.003	0.003	0.001	0.000	0.001	0.001	-0.002[c]	-0.001	0.004
	(0.005)	(0.001)	(0.001)	(0.006)	(0.002)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.009)
Output Roots	0.049[b]	-0.003	0.003	0.002	0.013	-0.001	-0.001	0.002	0.001	0.001	-0.012[a]	-0.011[c]
	(0.025)	(0.005)	(0.003)	(0.002)	(0.015)	(0.005)	(0.002)	(0.004)	(0.006)	(0.004)	(0.007)	(0.002)
Land Cereals	0.100[c]	-0.002	0.020[c]	0.000	-0.001	0.003	-0.005[b]	0.046[c]	-0.026[c]	-0.017[c]	-0.105[c]	-0.006[c]
	(0.017)	(0.004)	(0.003)	(0.001)	(0.006)	(0.009)	(0.002)	(0.007)	(0.009)	(0.004)	(0.014)	(0.001)
Land Maize	-0.770[c]	-0.022	0.033	-0.009	-0.067	-0.211[b]	0.081[a]	-0.026	0.453[c]	-0.211[c]	1.840[c]	0.199[c]
	(0.264)	(0.073)	(0.043)	(0.010)	(0.098)	(0.098)	(0.046)	(0.082)	(0.110)	(0.054)	(0.226)	(0.014)
Land Protein	-0.589[b]	0.044	0.037	0.013	0.044	0.991[c]	-0.012	-0.502[b]	-0.278[b]	-0.426[c]	-0.420	0.145[c]
	(0.265)	(0.058)	(0.051)	(0.011)	(0.095)	(0.141)	(0.040)	(0.207)	(0.127)	(0.054)	(0.310)	(0.014)
Land Oilseed	-0.351[c]	0.009	-0.041[c]	0.002	0.003	-0.077[c]	0.030[c]	-0.038[b]	-0.153[c]	0.214[c]	0.092[b]	-0.010[c]
	(0.064)	(0.014)	(0.010)	(0.002)	(0.022)	(0.026)	(0.007)	(0.017)	(0.035)	(0.014)	(0.045)	(0.003)
Land Set-aside	0.441[c]	-0.023	-0.191[c]	-0.018[c]	0.010	-0.256[c]	-0.069[c]	-0.289[c]	1.052[c]	-0.250[c]	0.917[c]	-0.219[c]
	(0.168)	(0.039)	(0.028)	(0.007)	(0.065)	(0.052)	(0.018)	(0.037)	(0.068)	(0.049)	(0.088)	(0.028)
Fertiliser Use	0.359[c]	-0.069[c]	0.063[c]	0.001	0.029[a]	0.211[c]	-0.082[c]	0.039	-0.062[b]	-0.125[c]	-1.488[c]	-0.011[c]
	(0.060)	(0.013)	(0.009)	(0.002)	(0.017)	(0.029)	(0.010)	(0.029)	(0.030)	(0.012)	(0.100)	(0.002)

Note: Elasticities evaluated at the sample mean. Standard errors in parentheses, obtained with delta method. [a], [b], [c] indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 6-17. Elasticities of output, land, and fertiliser for Germany, 1995–2004 (restricted model)

	Price Cereals	Price Maize	Price Protein	Price Oilseed	Price Root Crops	Subsidy Cereals	Subsidy Maize	Subsidy Protein	Subsidy Oilseed	Subsidy Set-aside	Price Fertiliser	AES
Output Cereals	0.607[c]	0.003	0.007	0.005[c]	0.022[a]	0.049[c]	-0.007[c]	-0.015[c]	-0.061[c]	0.607[c]	-0.092[c]	-0.021[c]
	(0.041)	(0.006)	(0.004)	(0.002)	(0.012)	(0.007)	(0.002)	(0.005)	(0.009)	(0.005)	(0.013)	(0.002)
Output Maize	0.097	0.032[b]	-0.011	-0.004	-0.011	-0.022	0.027[b]	-0.002	-0.033	0.023	0.541[c]	-0.035[c]
	(0.214)	(0.013)	(0.020)	(0.009)	(0.021)	(0.035)	(0.011)	(0.028)	(0.048)	(0.026)	(0.099)	(0.013)
Output Protein	0.394	-0.018	0.207[c]	0.029[b]	0.033	0.292[c]	0.010	0.207[c]	-0.282[c]	-0.291[c]	-0.840[c]	0.143[c]
	(0.256)	(0.033)	(0.043)	(0.012)	(0.063)	(0.052)	(0.016)	(0.045)	(0.068)	(0.038)	(0.118)	(0.016)
Output Oilseed	0.016[c]	0.000	0.002[b]	0.003	0.004[a]	0.000	0.000	0.001	0.000	-0.001	-0.001	0.004
	(0.005)	(0.001)	(0.001)	(0.005)	(0.002)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.009)
Output Roots	0.044[a]	-0.001	0.001	0.003[a]	0.004	0.002	-0.001	-0.001	-0.002	0.001	-0.011	-0.011[c]
	(0.024)	(0.001)	(0.002)	(0.001)	(0.006)	(0.003)	(0.001)	(0.003)	(0.005)	(0.003)	(0.007)	(0.002)
Land Cereals	0.112[c]	-0.001	0.011[c]	0.000	0.002	0.033[c]	-0.004[b]	0.016[c]	-0.036[c]	-0.017[c]	-0.099[c]	-0.006[c]
	(0.017)	(0.002)	(0.002)	(0.001)	(0.004)	(0.006)	(0.002)	(0.003)	(0.007)	(0.003)	(0.014)	(0.001)
Land Maize	-0.752[c]	0.075[b]	0.017	-0.004	-0.043	-0.193[b]	0.127[c]	-0.046	0.116	0.014	1.709[c]	0.196[c]
	(0.256)	(0.030)	(0.028)	(0.010)	(0.046)	(0.075)	(0.032)	(0.068)	(0.082)	(0.037)	(0.221)	(0.014)
Land Protein	-0.728[c]	-0.003	0.172[c]	0.016	-0.029	0.353[c]	-0.022	0.421[c]	-0.430[c]	-0.390[c]	-0.741[b]	0.144[c]
	(0.261)	(0.037)	(0.038)	(0.010)	(0.065)	(0.060)	(0.033)	(0.122)	(0.104)	(0.043)	(0.299)	(0.015)
Land Oilseed	-0.414[c]	-0.006	-0.032[c]	-0.001	-0.006	-0.106[c]	0.008	-0.059[c]	0.137[c]	0.050[c]	0.158[c]	-0.008[b]
	(0.063)	(0.009)	(0.008)	(0.002)	(0.016)	(0.020)	(0.005)	(0.014)	(0.027)	(0.008)	(0.045)	(0.003)
Land Set-aside	0.562[c]	0.021	-0.163[c]	-0.010	0.018	-0.247[c]	0.005	-0.265[c]	0.244[c]	0.306[c]	0.791[c]	-0.029[c]
	(0.167)	(0.024)	(0.021)	(0.007)	(0.044)	(0.038)	(0.012)	(0.029)	(0.041)	(0.037)	(0.087)	(0.010)
Fertiliser Use	0.420[c]	-0.068[c]	0.064[c]	0.001	0.025	0.199[c]	-0.076[c]	0.069[b]	-0.106[c]	-0.108[c]	-1.543[c]	-0.011[c]
	(0.059)	(0.012)	(0.009)	(0.002)	(0.017)	(0.028)	(0.010)	(0.028)	(0.030)	(0.012)	(0.100)	(0.002)

Note: Elasticities evaluated at the sample mean. Standard errors in parentheses, obtained with delta method. [a], [b], [c] indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 6-18. Elasticities of output, land, and fertiliser for the UK, 1995–2004 (unrestricted model)

	Price Cereals	Price Protein	Price Oilseed	Price Root Crops	Subsidy Cereals	Subsidy Protein	Subsidy Oilseed	Subsidy Set-aside	Price Fertiliser	AES
Output Cereals	0.186[c]	-0.016[b]	-0.102[c]	-0.027[c]	0.040[c]	-0.015[c]	-0.096[c]	0.049[c]	-0.077[c]	-0.003[c]
	(0.027)	(0.007)	(0.011)	(0.007)	(0.007)	(0.006)	(0.008)	(0.006)	(0.011)	(0.001)
Output Protein	-0.465[b]	-0.410[c]	-1.145[c]	0.275[c]	0.918[c]	-0.205[b]	-0.892[c]	-0.151[b]	0.594[c]	0.082[c]
	(0.223)	(0.129)	(0.145)	(0.068)	(0.075)	(0.093)	(0.102)	(0.075)	(0.138)	(0.010)
Output Oilseed	-0.751[c]	-0.281[c]	0.593[c]	-0.088[c]	-0.214[c]	-0.226[c]	0.311[c]	0.200[c]	-0.015	0.023[c]
	(0.085)	(0.036)	(0.077)	(0.026)	(0.030)	(0.028)	(0.048)	(0.030)	(0.055)	(0.004)
Output Roots	-0.042[c]	0.014[c]	-0.019[c]	-0.025	-0.017[c]	0.011[c]	-0.008[b]	0.017[c]	0.036[c]	-0.021[c]
	(0.011)	(0.004)	(0.005)	(0.016)	(0.003)	(0.003)	(0.004)	(0.002)	(0.004)	(0.002)
Land Cereals	0.103[c]	0.079[c]	-0.075[c]	-0.027[c]	-0.004	0.106[c]	-0.110[c]	0.002	-0.060[c]	-0.006[c]
	(0.017)	(0.006)	(0.011)	(0.005)	(0.010)	(0.010)	(0.009)	(0.007)	(0.015)	(0.001)
Land Protein	-0.601[c]	-0.271[b]	-1.214[c]	0.276[c]	1.629[c]	-1.313[c]	-0.705[c]	-0.152	0.516[c]	0.091[c]
	(0.231)	(0.123)	(0.153)	(0.066)	(0.160)	(0.263)	(0.135)	(0.095)	(0.195)	(0.009)
Land Oilseed	-0.961[c]	-0.298[c]	0.422[c]	-0.050[b]	-0.425[c]	-0.178[c]	0.670[c]	0.101[c]	0.117[a]	0.010[c]
	(0.082)	(0.034)	(0.065)	(0.023)	(0.036)	(0.034)	(0.061)	(0.035)	(0.069)	(0.003)
Land Set-aside	1.378[c]	-0.142[b]	0.760[c]	0.302[c]	0.021	-0.107	0.283[c]	-0.171[a]	0.166	-0.004
	(0.169)	(0.070)	(0.115)	(0.044)	(0.072)	(0.067)	(0.099)	(0.102)	(0.141)	(0.006)
Fertiliser Use	0.371[c]	-0.096[c]	0.010	-0.111[c]	0.112[c]	-0.063[c]	-0.057[a]	-0.029	-0.588[c]	-0.013[c]
	(0.053)	(0.022)	(0.036)	(0.014)	(0.028)	(0.024)	(0.033)	(0.024)	(0.065)	(0.002)

Note: Elasticities evaluated at the sample mean. Standard errors in parentheses, obtained with delta method. [a], [b], [c] indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 6-19. Elasticities of output, land, and fertiliser for the UK, 1995–2004 (restricted model)

	Price Cereals	Price Protein	Price Oilseed	Price Root Crops	Subsidy Cereals	Subsidy Protein	Subsidy Oilseed	Subsidy Set-aside	Price Fertiliser	AES
Output Cereals	0.264[c]	-0.013[a]	-0.073[c]	-0.012[a]	0.050[c]	-0.019[c]	-0.082[c]	0.028[c]	-0.081[c]	-0.003[c]
	(0.025)	(0.007)	(0.011)	(0.007)	(0.006)	(0.006)	(0.008)	(0.006)	(0.011)	(0.001)
Output Protein	-0.377[a]	0.561[c]	-0.807[c]	0.189[c]	0.320[c]	0.502[c]	-0.781[c]	-0.177[c]	0.405[c]	0.090[c]
	(0.209)	(0.094)	(0.134)	(0.067)	(0.054)	(0.073)	(0.097)	(0.059)	(0.133)	(0.010)
Output Oilseed	-0.541[c]	-0.198[c]	0.806[c]	-0.090[c]	-0.204[c]	-0.196[c]	0.446[c]	0.043[a]	-0.056	0.024[c]
	(0.082)	(0.033)	(0.075)	(0.026)	(0.029)	(0.026)	(0.046)	(0.026)	(0.054)	(0.004)
Output Roots	-0.019[a]	0.010[c]	-0.019[c]	0.037[b]	-0.012[c]	0.009[c]	-0.009[b]	0.013[c]	0.036[c]	-0.022[c]
	(0.010)	(0.003)	(0.005)	(0.015)	(0.003)	(0.003)	(0.004)	(0.002)	(0.004)	(0.002)
Land Cereals	0.130[c]	0.028[c]	-0.072[c]	-0.019[c]	0.067[c]	0.015[c]	-0.099[c]	-0.009	-0.078[c]	-0.006[c]
	(0.017)	(0.005)	(0.010)	(0.005)	(0.008)	(0.005)	(0.009)	(0.006)	(0.015)	(0.001)
Land Protein	-0.757[c]	0.664[c]	-1.053[c]	0.232[c]	0.234[c]	0.657[c]	-0.748[c]	-0.244[c]	0.890[c]	0.099[c]
	(0.218)	(0.096)	(0.141)	(0.065)	(0.076)	(0.085)	(0.113)	(0.070)	(0.189)	(0.009)
Land Oilseed	-0.820[c]	-0.261[c]	0.606[c]	-0.055[b]	-0.384[c]	-0.189[c]	0.798[c]	-0.051	0.073	0.011[c]
	(0.081)	(0.032)	(0.062)	(0.023)	(0.034)	(0.029)	(0.058)	(0.032)	(0.068)	(0.003)
Land Set-aside	0.782[c]	-0.165[c]	0.164[a]	0.234[c]	-0.103	-0.173[c]	-0.142	0.409[c]	0.263[a]	-0.005
	(0.157)	(0.056)	(0.099)	(0.043)	(0.063)	(0.050)	(0.089)	(0.086)	(0.136)	(0.006)
Fertiliser Use	0.392[c]	-0.065[c]	0.037	-0.110[c]	0.145[c]	-0.109[c]	-0.035	-0.045[a]	-0.616[c]	-0.013[c]
	(0.053)	(0.022)	(0.035)	(0.014)	(0.028)	(0.023)	(0.033)	(0.024)	(0.065)	(0.002)

Note: Elasticities evaluated at the sample mean. Standard errors in parentheses, obtained with delta method. [a], [b], [c] indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 6-20. Elasticities of output supply and fertiliser for France, 2005–2016 (unrestricted model)

	Price Cereals	Price Maize	Price Protein	Price Oilseed	Price Root Crops	Price Fertiliser	AES
Output Cereals	0.235 [c]	-0.058 [c]	-0.017 [c]	0.046 [c]	-0.006 [b]	-0.083 [c]	-0.003 [c]
	(0.014)	(0.007)	(0.003)	(0.008)	(0.002)	(0.008)	(0.001)
Output Maize	-0.225 [c]	0.122 [c]	-0.001	0.002	0.017 [c]	0.468 [c]	-0.002 [a]
	(0.027)	(0.025)	(0.007)	(0.019)	(0.006)	(0.016)	(0.001)
Output Protein	-0.391 [c]	-0.007	-0.072 [c]	-0.209 [c]	-0.009	-0.223 [c]	0.013 [c]
	(0.062)	(0.044)	(0.026)	(0.047)	(0.015)	(0.036)	(0.003)
Output Oilseed	0.144 [c]	0.002	-0.028 [c]	0.228 [c]	0.005	-0.501 [c]	-0.003 [c]
	(0.025)	(0.015)	(0.006)	(0.024)	(0.004)	(0.016)	(0.001)
Output Root Crops	-0.005 [b]	0.003 [c]	0.000	0.001	-0.006	0.000	-0.001
	(0.002)	(0.001)	(0.000)	(0.001)	(0.005)	(0.001)	(0.001)
Fertiliser Use	0.220 [c]	-0.321 [c]	0.025 [c]	0.425 [c]	-0.001	-0.501 [c]	-0.004 [c]
	(0.020)	(0.011)	(0.004)	(0.013)	(0.002)	(0.023)	(0.001)

Note: Elasticities evaluated at the sample mean. Standard errors in parentheses, obtained with delta method. [a], [b], [c] indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 6-21. Elasticities of output supply and fertiliser for France, 2005–2016 (restricted model)

	Price Cereals	Price Maize	Price Protein	Price Oilseed	Price Root Crops	Price Fertiliser	AES
Output Cereals	0.260 [c]	-0.054 [c]	-0.016 [c]	0.036 [c]	-0.004 [b]	-0.113 [c]	-0.003 [c]
	(0.013)	(0.007)	(0.003)	(0.008)	(0.002)	(0.007)	(0.001)
Output Maize	-0.208 [c]	0.241 [c]	-0.028 [c]	-0.103 [c]	0.010 [c]	0.375 [c]	-0.002 [a]
	(0.026)	(0.021)	(0.005)	(0.015)	(0.004)	(0.013)	(0.001)
Output Protein	-0.389 [c]	-0.170 [c]	0.080 [c]	-0.052	-0.007	-0.097 [c]	0.014 [c]
	(0.060)	(0.030)	(0.012)	(0.036)	(0.008)	(0.032)	(0.003)
Output Oilseed	0.111 [c]	-0.083 [c]	-0.007	0.309 [c]	0.009 [c]	-0.406 [c]	-0.002 [b]
	(0.024)	(0.012)	(0.005)	(0.021)	(0.003)	(0.013)	(0.001)
Output Root Crops	-0.004 [b]	0.002 [c]	0.000	0.002 [c]	0.000	0.000	-0.001
	(0.002)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Fertiliser Use	0.300 [c]	-0.257 [c]	0.011 [c]	0.344 [c]	0.000	-11.357 [c]	-0.004 [c]
	(0.019)	(0.009)	(0.004)	(0.011)	(0.002)	(2.138)	(0.001)

Note: Elasticities evaluated at the sample mean. Standard errors in parentheses, obtained with delta method. [a], [b], [c] indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 6-22. Elasticities of output supply and fertiliser for Germany, 2005–2016 (unrestricted model)

	Price Cereals	Price Maize	Price Protein	Price Oilseed	Price Root Crops	Price Forage	Price Fertiliser	AES
Output Cereals	0.235[c]	-0.058[c]	-0.017[c]	0.046[c]	-0.006[b]	-0.083[c]	-0.003[c]	0.235[c]
	(0.014)	(0.007)	(0.003)	(0.008)	(0.002)	(0.008)	(0.001)	(0.014)
Output Maize	-0.225[c]	0.122[c]	-0.001	0.002	0.017[c]	0.468[c]	-0.002[a]	-0.225[c]
	(0.027)	(0.025)	(0.007)	(0.019)	(0.006)	(0.016)	(0.001)	(0.027)
Output Protein	-0.391[c]	-0.007	-0.072[c]	-0.209[c]	-0.009	-0.223[c]	0.013[c]	-0.391[c]
	(0.062)	(0.044)	(0.026)	(0.047)	(0.015)	(0.036)	(0.003)	(0.062)
Output Oilseed	0.144[c]	0.002	-0.028[c]	0.228[c]	0.005	-0.501[c]	-0.003[c]	0.144[c]
	(0.025)	(0.015)	(0.006)	(0.024)	(0.004)	(0.016)	(0.001)	(0.025)
Output Root Crops	-0.005[b]	0.003[c]	0.000	0.001	-0.006	0.000	-0.001	-0.005[b]
	(0.002)	(0.001)	(0.000)	(0.001)	(0.005)	(0.001)	(0.001)	(0.002)
Output Forage	0.220[c]	-0.321[c]	0.025[c]	0.425[c]	-0.001	-0.501[c]	-0.004[c]	0.220[c]
	(0.020)	(0.011)	(0.004)	(0.013)	(0.002)	(0.023)	(0.001)	(0.020)
Fertiliser Use	0.235[c]	-0.058[c]	-0.017[c]	0.046[c]	-0.006[b]	-0.083[c]	-0.003[c]	0.235[c]
	(0.014)	(0.007)	(0.003)	(0.008)	(0.002)	(0.008)	(0.001)	(0.014)

Note: Elasticities evaluated at the sample mean. Standard errors in parentheses, obtained with delta method. [a], [b], [c] indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 6-23. Elasticities of output supply and fertiliser for Germany, 2005–2016 (restricted model)

	Price Cereals	Price Maize	Price Protein	Price Oilseed	Price Root Crops	Price Forage	Price Fer- tiliser	AES
Output Cereals	0.260[c]	-0.054[c]	-0.016[c]	0.036[c]	-0.004[b]	-0.113[c]	-0.003[c]	0.260[c]
	(0.013)	(0.007)	(0.003)	(0.008)	(0.002)	(0.007)	(0.001)	(0.013)
Output Maize	-0.208[c]	0.241[c]	-0.028[c]	-0.103[c]	0.010[c]	0.375[c]	-0.002[a]	-0.208[c]
	(0.026)	(0.021)	(0.005)	(0.015)	(0.004)	(0.013)	(0.001)	(0.026)
Output Protein	-0.389[c]	-0.170[c]	0.080[c]	-0.052	-0.007	-0.097[c]	0.014[c]	-0.389[c]
	(0.060)	(0.030)	(0.012)	(0.036)	(0.008)	(0.032)	(0.003)	(0.060)
Output Oilseed	0.111[c]	-0.083[c]	-0.007	0.309[c]	0.009[c]	-0.406[c]	-0.002[b]	0.111[c]
	(0.024)	(0.012)	(0.005)	(0.021)	(0.003)	(0.013)	(0.001)	(0.024)
Output Root Crops	-0.004[b]	0.002[c]	0.000	0.002[c]	0.000	0.000	-0.001	-0.004[b]
	(0.002)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)
Output Forage	0.300[c]	-0.257[c]	0.011[c]	0.344[c]	0.000	-11.357[c]	-0.004[c]	0.300[c]
	(0.019)	(0.009)	(0.004)	(0.011)	(0.002)	(2.138)	(0.001)	(0.019)
Fertiliser Use	0.260[c]	-0.054[c]	-0.016[c]	0.036[c]	-0.004[b]	-0.113[c]	-0.003[c]	0.260[c]
	(0.013)	(0.007)	(0.003)	(0.008)	(0.002)	(0.007)	(0.001)	(0.013)

Note: Elasticities evaluated at the sample mean. Standard errors in parentheses, obtained with delta method. [a], [b], [c] indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 6-24. Elasticities of output supply and fertiliser for the UK, 2005–2016 (unrestricted model)

	Price Cereals	Price Maize	Price Protein	Price Oilseed	Price Root Crops	Price Fertiliser	AES
Output Cereals	0.078[c]	0.019[c]	0.008	-0.013	-0.048[c]	0.012	-0.010[b]
	(0.025)	(0.003)	(0.009)	(0.014)	(0.011)	(0.010)	(0.004)
Output Maize	12.958[c]	1.857[c]	-1.459[b]	3.596[c]	-0.957	-1.440[a]	-0.823[a]
	(1.731)	(0.412)	(0.636)	(1.234)	(1.206)	(0.834)	(0.468)
Output Protein	0.160	-0.042[b]	0.003	0.202[a]	-0.192[c]	-0.587[c]	-0.137[c]
	(0.170)	(0.019)	(0.099)	(0.112)	(0.061)	(0.084)	(0.022)
Output Oilseed	-0.059	0.025[c]	0.047[a]	0.203[c]	-0.016	-0.257[c]	-0.006
	(0.064)	(0.008)	(0.026)	(0.062)	(0.028)	(0.033)	(0.010)
Output Roots	-0.069[c]	-0.002	-0.014[c]	-0.005	-0.033	0.015[b]	-0.002
	(0.015)	(0.003)	(0.004)	(0.009)	(0.029)	(0.006)	(0.011)
Fertiliser Use	-0.043	0.008[a]	0.110[c]	0.205[c]	-0.038[b]	-0.694[c]	-0.021[c]
	(0.039)	(0.005)	(0.016)	(0.026)	(0.015)	(0.027)	(0.005)

Note: Elasticities evaluated at the sample mean. Standard errors in parentheses, obtained with delta method.
[a], [b], [c] indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 6-25. Elasticities of output supply and fertiliser for the UK, 2005–2016 (restricted model)

	Price Cereals	Price Maize	Price Protein	Price Oilseed	Price Root Crops	Price Fertiliser	AES
Output Cereals	0.094[c]	0.016[c]	-0.002	0.013[b]	-0.035[c]	0.007	-0.010[b]
	(0.017)	(0.002)	(0.004)	(0.006)	(0.010)	(0.009)	(0.004)
Output Maize	10.633[c]	2.353[c]	-1.124[a]	2.822[c]	-2.041[a]	-1.119	-0.823[a]
	(1.450)	(0.383)	(0.599)	(1.057)	(1.118)	(0.817)	(0.468)
Output Protein	-0.038	-0.033[a]	0.146[b]	0.119[a]	-0.148[c]	-0.524[c]	-0.137[c]
	(0.086)	(0.017)	(0.058)	(0.061)	(0.054)	(0.076)	(0.022)
Output Oilseed	0.061[b]	0.019[c]	0.028[a]	0.106[c]	-0.023	-0.278[c]	-0.006
	(0.030)	(0.007)	(0.014)	(0.026)	(0.024)	(0.030)	(0.010)
Output Roots	-0.050[c]	-0.004[a]	-0.011[c]	-0.007	0.036[b]	0.014[b]	-0.002
	(0.014)	(0.002)	(0.004)	(0.007)	(0.017)	(0.006)	(0.011)
Fertiliser Use	-0.026	-0.026	0.098[c]	0.222[c]	-0.036[b]	-0.694[c]	-0.021
	(0.035)	(0.004)	(0.014)	(0.024)	(0.015)	(0.058)	(0.005)

Note: Elasticities evaluated at the sample mean. Standard errors in parentheses, obtained with delta method.
[a], [b], [c] indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Part III

Conclusions

7

Summaries and Authors' Contributions

This chapter summarises the four empirical studies embedded in this dissertation, as well as two additional studies that are co-authored by the author of the dissertation and supplementary to the embedded articles. Table 7-1 gives an overview of all studies, including the main research questions and core findings, both from an empirical and a methodological perspective. In addition, the individual summaries in the subchapters 7.1 – 7.6 contain detailed descriptions of authors' contributions to each study.

Table 7-1. Overview of the empirical studies and their findings

Title	Main research question	Core findings (empirical and methodological)
a) Empirical studies embedded in the dissertation		
1. Profitability Development and Resource Reallocation: The Case of Sugar Beet Farming in Germany (Chapter 3)	What is the impact of the 2006 sugar market reform on aggregate productivity in beet production?	Aggregate productivity is mainly determined by within-farm productivity growth, but reallocation between farms contributed to some extent after the 2006 reform. Reallocation varies across sugar companies with different trading schemes for delivery rights.
2. Diversification Economies in Dairy Farming – Empirical Evidence from Germany (Chapter 4)	What is the cost-saving potential of farm diversification in dairy farming?	Small dairy farms can save costs by diversifying between milk and livestock production, while large farms benefit from diversification between milk and crop production. Methodologically, the study shows that Bayesian techniques can be used to improve the theoretical consistency of input distance functions without destroying the flexibility of a translog functional form.
3. Credit Access and Farm Productivity: Evidence from a Field Experiment in Rural China (Chapter 5)	What is the causal effect of credit access on total factor productivity?	Improved credit access causes a 9 %-increase in productivity, mostly via gains in technical efficiency and technical change. As for the method, we show that controlling for endogeneity alters the production function parameters but not the inference on the productivity measure.
4. Green Policies and Farm Production Decisions in Selected EU Member States (Chapter 6)	How do agri-environmental subsidies affect production choices and land allocation between crops?	Current EU agri-environmental programmes reduce fertiliser use and shift crop production from cereals and maize to protein crops. The method of Cholesky factorisation is necessary to obtain theoretically consistent profit function estimates and to facilitate reliable policy recommendations.

(continued on next page)

Table 7-1. *(continued)*

Title	**Main research question**	**Core findings (empirical and methodological)**
b) Additional co-authored articles cited in the dissertation		
5. Is small family farming more environmentally sustainable? Evidence from a spatial regression discontinuity design in Germany (Summary in Chapter 7)	Do small family farms use more environmentally sustainable farming practices than their larger counterparts?	Small family farms are more diversified in terms of crop rotation, but more often rely on monocultures, use fewer cover crops and structural elements (e.g. hedges or trees).
6. Production Intensity and Emission Efficiency – A Latent-Class Meta-Frontier Approach (Summary in Chapter 7)	How do intensive and extensive production technologies compare in GHG emission efficiency?	Without loss of economic output, intensive (extensive) farms could reduce GHG emissions by 21.1 % (48.5%). Intensive dairy farms are more emission efficient than extensive ones on average in our sample. Methodologically, the study shows that latent class stochastic frontier analysis combined with the eco-efficiency concept is able to detect heterogeneous farm technologies.

7.1 Profitability development and resource reallocation: the case of sugar beet farming in Germany

This empirical study examines the profitability and productivity dynamics of sugar beet farming in Germany over a 10-year period from 2004 to 2013. The source of the data is the EU farm accountancy data network (FADN). Our sample consists of 8,749 farm observations with sugar beet production. A major goal of the study is the examination of the role of delivery rights in productivity-enhancing resource reallocation. For this purpose, we decompose the profitability of sugar beet farming into total factor productivity (TFP) and terms of trade effects using a Lowe quantity index. The Lowe index satisfies all economically important axioms from the index number theory, including unity and transitivity (O'Donnell, 2012a). Hence, it is particularly useful to compare profitability and productivity across both time and space. We then compute sector productivity changes as the sum of average productivity change at the farm level ('within-effect') and productivity change through reallocation of production between farms with distinct productivity levels ('between effect') following Olley and Pakes (1996).

The results suggest that sugar beet profitability was mainly driven by changes in terms of trade during the study period. As sugar prices sharply declined after the 2006 reform, the production value of sugar beet was below production cost in the years 2007 to 2010. Moreover, the results show that losses in terms of trade were partially compensated by an increase in TFP. This effect was especially pronounced in the south of Germany, where profitability in 2013 was at its 2004 levels, even though terms of trade were 20 % below their value in 2004. Using a system generalised method-of-moments

(GMM) estimator that incorporates the lagged values of the dependent variable, we investigate whether the contribution of production reallocation on sector productivity growth differed across regions with distinct mechanisms of delivery rights transfer between farms. In line with expectations, we find that productivity-enhancing resource reallocation was most pronounced in the catchment area of sugar factories that promote delivery rights trading between growers and that do not link delivery rights to capital contributions. The magnitude of the effect, however, remains low. A possible explanation is that transaction costs may hamper the trade of delivery rights (Mahler, 1994).

This work has been published in the *Journal of Agricultural* Economics (Wimmer and Sauer, 2020b). Stefan Wimmer developed the research question. Both Stefan Wimmer and Johannes Sauer selected the empirical methods. In particular, the research builds upon previous work by Johannes Sauer on resource reallocation and productivity. Observing that the German sugar sector is dominated by three major sugar companies with distinct ownership structures, Stefan Wimmer developed the hypothesis that resource allocation efficiency may be different across German regions. Having set out the research questions and formulated working hypotheses, both authors applied for access to the EU FADN data. Stefan Wimmer prepared and cleaned the data and conducted the analysis. This involved the econometric estimation of output-specific input usage, derivation of productivity and profitability indices and application of the GMM-estimator to identify the effect of ownership structure on resource reallocation. The latter exploits a natural experiment of different ownership structures of sugar factories operating in distinct regions. Johannes Sauer supervised the econometric estimation and both authors interpreted the results. Stefan Wimmer wrote the manuscript while Johannes Sauer provided reviewing and editing and contributed to the whole process with feedback and further advice.

7.2 Diversification economies in dairy farming – empirical evidence from Germany

Farm diversification becomes increasingly important in the wake of market deregulation. In this empirical study, we investigate diversification economies between various farm outputs for a sample of Bavarian dairy farms. In the context of structural change towards fewer but larger farms, our primary goal is to examine whether cost-saving potentials from diversification depend on farm size. Using accountancy data from 1,647 farms that are observed over the period 2000 to 2014, we estimate an input distance function (IDF) with four outputs: milk, livestock for sale, crops for sale, and other outputs (e.g. provision of farm tourism and energy production). Based on the IDF estimates, we derive cost complementarities for all output pairs following Hajargasht, Coelli and Rao (2008). Since the duality between the IDF and the cost function depends on regularity conditions (e.g. Färe and Primont, 1995), we impose curvature restrictions on the IDF using Bayesian methods as suggested by O'Donnell and Coelli (2005). This procedure maintains the flexibility of the translog functional form while reducing the share of observations inconsistent with economic theory from 40 to 19 %.

Evaluated at the sample mean, we find that the marginal costs of producing livestock for sale can be decreased by extending crop production. Thus, the average farm in our sample could save costs by increasing diversification between livestock and crop production. However, no cost complementarities are prevalent at the sample mean between the output pair milk and livestock production and the output pair milk and crop production. Further, the results also show that farms that are diversified to a large degree are less likely to achieve cost reductions by further diversifying their production portfolio. This finding suggests that there is an optimal level of diversification in terms of associated production costs. Finally, we find that larger farms are more likely to realise cost savings by combining milk and crop production, whereas smaller farms tend to benefit from jointly producing milk and livestock. From a managerial and policy perspective, we conclude that downstream fattening of cattle can increase the competitiveness of small farms, as it allows them to reduce their marginal costs of milk production.

The article has been published in the *European Review of Agricultural Economics* (Wimmer and Sauer, 2020a). Both authors developed the research question. Stefan Wimmer reviewed the literature, selected the methods, prepared the data and conducted the empirical analysis. As the estimation of the IDF resulted in many regularity violations, Johannes Sauer suggested imposing curvature econometrically. Thus, Stefan Wimmer employed a Bayesian estimation framework to impose regularity conditions on the IDF. He also estimated the endogeneity-robust input distance function using the method proposed by Griffiths, W. E. and Hajargasht (2016). Both authors interpreted the results. Stefan Wimmer wrote the original draft of the manuscript, which was improved through comprehensive reviews and edits by Johannes Sauer.

7.3 Credit access and farm productivity: evidence from a field experiment in rural China

In this article, we use data from a field experiment in rural China to measure the effect of improved credit access on farm productivity and its components. The data were collected in three waves in the years 2010, 2012 and 2014. This study involves 1,500 households in 50 villages across 5 provinces in China. After the baseline survey in 2010, the credit programme was initiated in 30 randomly selected villages, and 10 further villages followed after the first follow-up survey in 2012. The loan size of the credit programme varied between 1000 and 5000 *yuan* (130–650 EUR) and participation was voluntary for households in the treated villages. The random assignment of the programme allows us to assess the intent-to-treat (ITT) effect of improved credit access on various household-level outcome variables. Our primary interest is the ITT on farm productivity growth. For this purpose, we estimate total factor productivity (TFP) in two ways. First, we estimate productivity levels as the Solow residual based on a production function. Second, we estimate individual components of productivity change using the Malmquist index based on a production frontier approach.

The production function and frontier parameters suggest that the underlying production technology is characterised by decreasing returns to scale. This finding is consistent with the inverse size-productivity relationship which is often observed in countries characterised by small-scale farming (e.g. Sheng, Ding and Huang, J., 2019; Muyanga and Jayne, 2019). Furthermore, using a difference-in-difference (DID) design, we find that improved credit access increases TFP, derived from both the production function and the production frontier approach. The Solow residual suggests that treatment assignment increases productivity by about 9 %. The effect is driven by an increase in technical efficiency and by technical change, while scale efficiency was not affected.

The article is prepared for submission to the Journal of Development Economics. The three authors Stefan Wimmer, Jing You and Johannes Sauer jointly developed the research question addressed in this article. In particular, they noticed that previous research on the *causal* effect of credit access on productivity is limited to partial productivity measures (e.g. agricultural output per unit of land), which is incomplete as it does consider changes in the use of other inputs. Jing You collaborated with the State Council in China to design and implement the experiment. She also coordinated the data collection. Stefan Wimmer and Jing You cleaned and prepared the data for the specific needs of this research article. Stefan Wimmer conducted the econometric analysis to derive estimates for productivity and its components under the supervision of Johannes Sauer. Stefan Wimmer and Jing You conceptualised the DID estimator (including heterogeneous and dynamic treatment effects) to assess the effect of the credit programme intervention on various outcome variables. Stefan Wimmer wrote the major part of the manuscript while Jing You helped with substantial edits. The background section was provided by Jing You. Johannes Sauer contributed to the conceptual framework, helped interpret the results and reviewed the manuscript.

7.4 Green policies and farm production decisions in selected EU member states

The EU Common Agricultural Policy (CAP) has shifted from purely supporting agricultural production towards a more sustainability orientation in the past decades. A major goal of agri-environmental subsidies is to support agricultural practices that maintain biodiversity, prevent soil degradation and water pollution, and reduce the emission of greenhouse gases. In this article, we use data from the European Farm Accountancy Data Network (FADN) to estimate elasticities of output supply, input demand, and land allocation with respect to agri-environmental subsidies. We distinguish between voluntary agri-environmental schemes (AES) and the mandatory set-aside area scheme. In the context of arable farms, the latter mainly involves the implementation of diversified crop rotations and planting of cover crops (e.g. Mennig and Sauer, 2020). To derive subsidy elasticities, we estimate a profit system consisting of profit-maximising output supply functions, input demand functions, and land allocation equations for three major crop production countries in the EU (France, Germany and the UK). We specify separate profit functions for the period with coupled subsidies (1995–2004) and the period with decoupled subsidies (2005–2014). To ensure that the estimated profit function is consistent to economic theory, we estimate the Cholesky factorisation of the Hessian matrix of the profit system as proposed by Lau (1978) and Diewert and Wales (1987).

The results show that there is considerable heterogeneity across countries with respect to subsidy elasticities. While farms in France tend to substitute cereal and oilseed areas in favour of set-aside areas in France, farms in Germany substitute cereals and protein areas in Germany in response to increasing set-aside subsidy rates. We further find that increased engagement in AES programmes is related to less cereal and maize production, less fertiliser use, and higher supply of protein crops. Finally, the results suggest that production responses to AES subsidies are very similar between the periods with and without coupled subsidies, implying that no fundamental change in the production technology with respect to green policies has occurred.

The research question for this article was developed by Johannes Sauer. Stefan Wimmer reviewed the literature on farm-level responses to agri-environmental subsidies. The authors jointly applied for access to the EU FADN data, together with Denitsa Angelova. Stefan Wimmer cleaned and prepared the data, adapted the conceptual framework and conducted the empirical analysis. This involved the estimation of the Cholesky factorisation for the profit system, including output supply functions, input demand functions and land allocation equations. Both authors interpreted the results. Stefan Wimmer wrote the manuscript, which was continuously improved with feedback and suggestions from Johannes Sauer.

7.5 Is small family farming more environmentally sustainable? Evidence from a spatial regression discontinuity design in Germany

It is often assumed that small family farms are managed in a more environmentally friendly way than large, industrial ones (see, e.g., van der Ploeg, 2013; Rossi and Garner, 2014). Although a meta-analysis by the OECD (2005) shows that there is no clear relationship between farm structure and environmental effects, previous studies were often only able to show empirical correlations due to data limitations. This results may be biased by endogeneity due to omitted variables, for example if regional conditions such as climate and topography influence both the farm structure and agricultural practices. In this study, we exploit a natural experiment to identify the causal effect of small family farming on the adoption of farming practices that are considered less harmful to the environment. Our identification strategy relies on the fact that the relative frequency of small family farms changes abruptly at the historical border between East and West Germany. This set-up allows us to investigate whether family farming results in more environmentally friendly farming practices by making use of a regression discontinuity design.

The results show that small family farming increases crop diversification, but at the same time involves fewer structural elements and soil-covering measures. It also relies more often on monocultures compared to their larger counterparts. We emphasise that the effect on diversification may be more pronounced at the landscape level than it can be documented at the individual farm level: in a given area, five farms, each with a wide crop rotation, contribute significantly more to biodiversity than a single large farm with a less diversified crop portfolio. The lower number of structural elements, the higher proportion of uncovered soils and the increased frequency of monocultures can possibly be explained by higher cost pressure on small businesses.

This article has been published in *Land Use Policy* (Wuepper, Wimmer and Sauer, 2020). All authors jointly developed the research questions addressed in this article. David Wuepper came up with the research design that uses the historical inner German border as exogenous variation in the degree of small family farming and performed the econometric analysis. Stefan Wimmer contributed to the review of the literature, to the data preparation, to the selection of variables for the empirical analysis, and to writing and editing of the manuscript. The results were interpreted and discussed by all three authors. David Wuepper wrote the original draft of the article. Stefan Wimmer substantially contributed to the introduction, the discussion and policy implications. Johannes Sauer supervised the model estimation, provided suggestions to interpreting the results and reviewed the manuscript. The work also benefitted from feedback by project partners from the Free University of Bozen-Bolzano, the Federal Institute of Agricultural Economics in Austria and the Norwegian Institute for Bioeconomy Research.

7.6 Production intensity and emission efficiency – a latent-class meta-frontier approach

Agriculture accounts for a significant portion of global greenhouse gas (GHG) emissions. The trend towards production intensification raises concerns about environmental sustainability. So far, empirical evidence on the relationship between production intensity and environmental impact largely relies on life cycle assessment studies and remains inconclusive (e.g. Basset-Mens, Ledgard and Boyes, 2009; Capper, Cady and Bauman, 2009; Gerber, P. J. et al., 2013). In this article, we use a comprehensive panel data set of Bavarian dairy farms to compare the emission efficiency of extensive and intensive technologies. For this purpose, we combine the latent class stochastic frontier approach with the concept of eco-efficiency. Following Kuosmanen and Kortelainen (2005), we define eco-efficiency as the ability of a farm to "produce goods and services while causing minimal environmental degradation". Since we focus on GHG in our empirical application (see Dakpo, Jeanneaux and Latruffe, 2017), we use the term 'emission efficiency' rather than 'eco-efficiency'.

The latent class approach divides our sample into two groups: 55 % of farm-observations are classified to the extensive group and the remainder is classified to the intensive group. Compared to the own technology class, farms in both groups are about equally emission-efficient: extensive (intensive) farms could reduce emissions by 14 % (13 %) if they were operated at the pressure conversion frontier of the extensive (intensive) technology. We then construct a stochastic meta-frontier that envelops both the extensive and the intensive technologies. Thus, the meta-frontier indicates the superior technology for each data point. We find that the emission efficiency with respect to the meta-frontier is 52 % for extensive farms and 79 % for intensive farms. This result suggests that extensive farms could reduce GHG emissions by 48 % and intensive farms could reduce GHG by 21 % on average without reducing their economic output, if all farms had access to both technologies. The GHG mitigation potential translates to 225 tonnes of CO_2-equivalents for extensive farms and 130 tonnes of CO_2-equivalents for intensive dairy farms per year. Thus, we conclude that intensive farms in our sample are considerably more emission-efficient than their extensive counterparts.

The article is currently under review at the *European Review of Agricultural Economics.* Christian Stetter is the first author of the study. Stefan Wimmer and Christian Stetter have jointly developed the research idea and equally contributed to reviewing and summarising existing literature. Christian Stetter developed the conceptual framework for GHG emission-efficiency, constructed the data, estimated the metafrontier and visualised the results. Christian Stetter and Stefan Wimmer developed the framework for heterogeneity in pressure-generating technologies and Stefan Wimmer performed the latent class analysis. Christian Stetter and Stefan Wimmer jointly interpreted the results and wrote the manuscript under the lead of Christian Stetter. Johannes Sauer contributed to the process through valuable suggestions and feedback as well as by reviewing and editing the manuscript.

8

Discussion and Policy Implications

This chapter presents a discussion across all dissertation topics in relation to the existing literature. The overarching goal of the preceding empirical studies was to provide empirical insights into the microeconomic behaviour of farms as well as their performance with respect to economic and environmental aspects, to provide insights for a scientifically informed approach to agricultural and agri-environmental policymaking. The individual studies are linked by their focus on current developments in agricultural policy, from market deregulation to improved credit access to environmental protection.

The first trend in agricultural policies described in Chapter 1 is the *transition from the most protective measures towards more market orientation*. Against this background, the first and second empirical studies are concerned with the sugar and dairy sectors, respectively. These two sectors have been the last heavily regulated agricultural markets in the EU, before they were largely deregulated in the past decade. In both sectors, production was restricted by quota regulations for a long time. Since the discontinuation of the dairy quota in 2015 and of the sugar quota in 2017, farmers and processors are allowed to expand their production, which in turn increases the competition in the sectors.

Empirical literature has shown that *market deregulation can increase sector productivity* by reallocating production activities away from low-productive towards high-productive firms, both in the manufacturing sector (Eslava et al., 2004) and in the agricultural sector (Kirwan, Uchida and White, 2012 for the U.S. tobacco sector; Gray, Oss-Emer and Sheng, 2014 and Sheng, Chancellor and Jackson, 2020 for the Australian broadacre and dairy sectors; and Frick and Sauer, 2018 for the German dairy sector). For the sugar sector, a number of studies examined the potential effects of market deregulation on total production and trade *ex ante* (e.g. Frandsen, 2003; Elobeid and Beghin, 2006; Gohin and Bureau, 2006). However, its effect on aggregate productivity has not been studied yet. Chapter 3 in this dissertation closes this gap in the literature by evaluating productivity and profitability development in sugar beet farming after the EU sugar market reform in 2006 from an *ex post* perspective. Consistent with the listed literature on other sectors, our results show that deregulating the sugar market increased aggregate productivity by shifting production towards high-productive sugar beet growers. Nonetheless, the magnitude of the effect was rather low on average. We also found that resource allocation is most efficient in regions where farmers can effectively trade delivery rights. Concerning implications for policy, the study highlights that deregulation does not increase the competitiveness of the respective sector immediately and unequivocally. Instead, downstream markets are shown to play a significant role in the effectiveness of deregulation efforts, which should be taken into account if policy aims to improve the competitiveness of the sector. For example, sector productivity could be further improved by reallocating delivery rights to farmers who value them the most, e.g. by auction markets (see, e.g., Bogetoft et al., 2007)

From a managerial perspective, *ongoing market deregulations and the associated increased competition requires farms to optimise their production structure*. The scale of farming and the combination of outputs play a crucial role as they determine farm competitiveness through economies of scale and scope. Against this background, Chapter 4 investigated the economies of diversification for the empirical case of German dairy farming. Previous literature on diversification economies largely relied on cost functions (e.g. Fernandez-Cornejo et al., 1992; Wu and Prato, 2006; Melhim and Shumway, 2011), which is problematic if cost-minimisation cannot be assumed or if farm-level price data is not available. Thus, our study contributes by employing a primal approach to evaluate cost complementarities based on an IDF approach as proposed by Hajargasht, Coelli and Rao (2008). The second contribution is to provide empirical evidence on how diversification economies interact with the size of farms, in light of the structural change towards fewer but larger farms. The analysis unveils that cost complementarities between milk and crop production are decreasing (i.e., joint production becomes more attractive) in farm size, while those between milk and livestock production are increasing (i.e., joint production becomes less attractive) in farm size. This result is not only useful for farm managers who are planning to change the size of their business but also for policymaking, as it shows that promoting investment in on-farm diversification – especially regarding milk and livestock production – could be an effective tool to support smaller dairy farms. Currently, the CAP primarily supports diversification outside of primary agricultural production (e.g. production of renewable energies; providing services and farm tourism; and engaging in food processing and direct marketing). In Bavaria, the empirical case in our study, this is achieved by offering educational measures and investment incentives as well as by support from extension services (BStMELF, 2020). Our findings suggest that these activities may be extended to promote on-farm diversification.

As shown in Chapter 1, deregulation of agricultural markets also takes place in developing and emerging countries. For example, China implemented market and trade reforms prior to its accession to the WTO in 2001 (Baylis, Fan and Nogueira, 2019). In light of the global trend from protective agricultural measures towards more market orientation, credit access is essential for farmers in developing countries to increase productivity and improve their international competitiveness (FAO, 2002). Largely relying on quasi-experimental methods, existing literature shows that credit access has positive effects on total production (Feder et al., 1990; Briggeman, Towe and Morehart, 2009), agricultural investment (Berhane and Gardebroek, 2011), and partial productivity (Guirkinger and Boucher, 2008; Hossain, M. et al., 2019). Empirical evidence on the causal effect on TFP, however, is scarce, even though it is necessary to comprehensively evaluate the success of credit programmes. Using survey data from a randomised controlled trial conducted between 2010 and 2014 in rural China, Chapter 5 of this dissertation revealed that improved credit access causes gains in TFP via technical efficiency improvements and technical change. For policymakers, the results imply that improving credit access for small-scale farms is an effective measure to improve agricultural productivity, not only in the short but also in the long-term, as indicated by the accumulating positive effect on technical change. At the same time, the seemingly decreasing-returns-to-scale technology may prevent farmers to take advantage of scale efficiencies. A possible remedy may be to ensure access to modern technology combined with training and education by extension services. Follow-up research is necessary to examine the relationship between access to credit and technology explicitly.

Besides increasing market orientation, the second trend in global agricultural policies is to *reduce the detrimental effect of productive activities on the environment* (see Chapter 1). This trend is visible in increasing efforts to regulate chemical use, protect agricultural soil and reduce the emission of GHG, amongst others. Against this background, the remaining studies were explicitly concerned with the environmental sustainability of farming. First, Chapter 6 evaluated the effectiveness of green policies in the EU by looking at production responses at the individual farm level. Second, two supplementary studies examined the extent to which environmental sustainability may be related to the type of farming (small family farming vs. large industrial farming) and to heterogeneous production technologies (extensive vs. intensive farming).

The impact of agri-environmental programmes on production and other farm level outcomes are commonly investigated by applying quasi-experimental methods to reduced-form regressions. For example, studies have shown that participation in AES increases per hectare expenditure of chemicals such as fertiliser and pesticides (Pufahl and Weiss, C. R., 2009; Arata and Sckokai, 2016). Contrary to these studies, we use of a structural model that provides the microeconomic parameters describing the production decisions of farms in Chapter 6. The main contribution of this study to the existing literature is the evaluation of agri-environmental subsidy elasticities for individual crop categories. In addition, we compared elasticities across three of the most important crop-producing countries in the EU (France, Germany and the UK). The results suggest that AES participation is related to less cereal and maize production in favour of protein crops as well as to reduced fertiliser use in all countries. The study also revealed significant heterogeneity across countries. For example, the reducing effect of AES participation on fertiliser use is considerably stronger in the UK than in Germany and France, especially in the later sample (2005–2016). As for the set-aside programme, not only the magnitude of farm-level responses but also the directions vary across countries. For example, farmers tend to substitute areas devoted to cereals and oilseed production in favour of set-aside areas in France. This finding is in line with Lacroix and Thomas (2011) who apply the structural model to the same country over the period 1995–2001. For Germany, by contrast, we find that set-aside areas substitute areas devoted to cereal and protein production. This heterogeneos responses to policy incentives should be considered by policymakers to tailor agri-environmental policies for the specific regions. For example, AES programmes in Germany and France may be adjusted to achieve a more elastic response in fertiliser reduction, as it is already the case in the UK. Evaluating farmers' willingness to participate in voluntary agri-environmental programmes in different regions can further help to increase the cost effectiveness of such programmes, as we show in Li, F. et al. (2020) for the case of a green manure planting programme in China.

In light of the structural change towards fewer but larger and more intensive farms, the public and political discourse increasingly evolves around *which type of farming is desirable*. In this context, extensive and small-scale farming seem to be supported, not least because it is assumed that intensive and large-scale farming have more detrimental effects on the environment (see, e.g., van der Ploeg, 2013; Rossi and Garner, 2014). In Wuepper, Wimmer and Sauer (2020), however, we found that small family farming does not unequivocally lead to farm practices that are considered more environmentally friendly. In particular, small family farms are shown to be more diversified but they also use fewer cover crops and structural elements such as hedges, walls and trees. Overall, these results suggest that there is a lot of variation in the use of sustainable farming practices, but this variation does not seem to be determined by the size and ownership of farms. Hence, our empirical study confirms the findings of previous work, as summarized by OECD (2005), but improves the internal validity of previous results through a new identification strategy. Furthermore, we found in Stetter, Wimmer and Sauer (2020) that intensive dairy farming are more emission-efficient than extensive dairy farming: Holding economic output constant, intensive farms could reduce GHG emissions by 21.1 %, while extensive farms could reduce GHG emissions by 48.5 % if they had access to the same technology. Again, similar results have been found in previous studies based on life cycle assessments (e.g. Capper, Cady and Bauman, 2009; Gerber, P. J. et al., 2013). However, these studies are conducted based on a limited number of farms because of expensive data collection. Hence, the main contribution of our study to the literature is the use of a more comprehensive data set, adding to the external validity of previous studies. From a policy perspective, this study implies that there is large potential for climate change mitigation without risking the economic viability of farms, for example by promoting a sustainable intensification of dairy farms.

In summary, the empirical studies in this dissertation provide empirical evidence that a) downstream markets play an important role in the effect of market deregulation on resource reallocation; b) economic benefits from farm diversification vary with farm size; c) improving credit access for rural small-scale farmers improves agricultural productivity via gains in technical efficiency and technical change but does not affect scale efficiency; d) the effect of green policy incentives on farm production decisions is heterogeneous across countries; and e) intensified and large farms are not necessarily bad for the environment. These empirical findings emphasise that sectoral characteristics, farm heterogeneity and the environment in which farms operate must be taken into account when predicting and evaluating the effect of policy changes. Since it is challenging, if not impossible, to consider all possibly influencing factors *ex ante*, *ex post* evaluation studies – as provided in this dissertation – will remain essential to guide policymakers, in particular in light of increasingly complex policy measures that often involve multiple goals such as rural support, environmental sustainability and social equitability (see Esposti and Sotte, 2013).

Methodologically, this dissertation contributes with the empirical application of production theory using state-of-the-art econometric techniques that consider economic consistency and endogeneity concerns. The four embedded empirical studies rely on both primal (production and distance functions) and dual (profit function) approaches to represent the underlying farming technologies. As discussed and illustrated by Sauer (2006) and Sauer, Frohberg and Hockmann (2006), *theoretical consistency of econometric models* is essential to derive reliable policy recommendations. To meet this demand, Chapter 4 employed a Bayesian estimation technique to impose monotonicity and concavity on the distance function following O'Donnell and Coelli (2005) and Chapter 6 estimated the Cholesky factorisation of the Hessian matrix to impose convexity on the profit function proposed by Lau (1978) and Diewert and Wales (1987). The production function in Chapter 5, employing data from smallholder farmers in China, satisfied curvature requirements at most data points, hence econometric imposition was not necessary.

Another common concern in the production economics literature is *endogeneity in production and distance functions*. To ensure that the distance function parameters in Chapter 4 are not affected by endogeneity, we applied an extension of the Mundlak (1978) random effects model with correlated effects in a Bayesian framework as proposed by Griffiths, W. E. and Hajargasht (2016). Chapter 5 employed the Levinsohn and Petrin (2003) estimator to account for the correlation between input use and unobserved productivity shocks in the production function and frontier estimation. Finally, Chapter 3 used on a non-parametric approach to measure and decompose profitability, which is not subject to endogeneity problems and curvature inconsistencies. Nonetheless, the index is selected based on theoretical considerations. Specifically, we make us of the Lowe quantity index, because it satisfies all economically relevant axioms from index number theory, including additivity and transitivity

(O'Donnell, 2012a). These two properties are particularly important in our empirical application, as they allow consistent comparisons across both time and space.

Despite the efforts to produce unbiased and theoretically-consistent estimates, significant limitations to the studies exist, which at the same time offer *scope for further research*. For example, the relationship between delivery rights mechanism and reallocation efficiency in Chapter 3 was investigated by defining catchment areas of sugar companies based on the location of farms. Farms in border regions between different companies had to be excluded from the analysis. As the aggregate productivity is likely to be affected by unobserved regional conditions, the *internal validity* of this analysis could be improved by comparing reallocation activities between farms in close regional proximity to each other that deliver to sugar factories owned by companies with different ownership structures. Unfortunately, FADN data does not include information on market relationships, so that primary data collection is needed to identify the exact causal effect of the trading mechanism and sectoral productivity change. The causal identification could also be improved in Chapter 5 on smallholder credit access and productivity. The expirimental design of the Village Fund implementation allowed us to identify the ITT effect of improved credit access, which is essential for the evaluation of the programme. Nevertheless, identifying the average treatment effect (ATE) of credit access would provide additional insights to understanding the consequences of binding credit constraints. Since participation in the programme was voluntary, we were not able to estimate the ATE. Further limitations of randomised controlled trials in the social sciences are summarised in Deaton and Cartwright (2018). The assessment of production decisions in the context of agri-environmental subsidies (Chapter 6) could be extended to evaluate climate change adaptation, considering farmers' risk attitudes.

Finally, the external validity of the results reported in this dissertation can be improved by repeating the studies in additional locations and for different sectors. For example, diversification economies (Chapter 4) are also relevant in mixed livestock-crop farming and at the individual crop level (i.e., crop rotation effects). Equivalently, scientifically informed policies would benefit from empirical evidence on subsidy-related elasticities (Chapter 6) for the livestock sector as well as in additional EU member countries. The field experiment conducted in rural China (Chapter 5) may also be repeated in other regions both within and outside of China where the production technology of farms can be expected to be significantly different. Finally, the study on productivity and profitability of sugar beet farming (Chapter 3) should be extended with more recent data. With the abolishment of the quota in 2017, the EU sugar sector is going through a long process of change. Thus, is important to re-investigate the impact of the market deregulation on profitability and (aggregate) productivity of sugar beet farming with data from 2017 on.

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Technical Appendix

TA. 1 Concave and convex functions

A function f is concave if and only if

$$\theta f(u) + (1-\theta) f(v) \leq f(\theta u + (1-\theta) v) \qquad \text{(TA-1)}$$

for any combination of distinct points u and v in the domain of f and for $0 \leq \theta \leq 1$, while it is convex if and only if

$$\theta f(u) + (1-\theta) f(v) \geq f(\theta u + (1-\theta) v) \qquad \text{(TA-2)}$$

for any combination of distinct points u and v in the domain of f and for $0 < \theta < 1$ (Chiang and Wainwright, 2005, p. 322). Definitions for strict concavity and strict convexity are obtained by replacing the two weak inequalities $\leq$ and $\geq$ by strict inequalities $<$ and $>$, respectively (Chiang and Wainwright, 2005, p. 322).

If the function is twice continuously differentiable, (strict) concavity and (strict) convexity can be tested using the second-order partial derivatives. The Hessian matrix of a twice continuously differentiable function $z = f(x_1, \dots x_n)$ is defined as

$$\boldsymbol{H} = \begin{bmatrix} f_{11} & f_{12} & \dots & f_{1n} \\ f_{21} & f_{22} & & f_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ f_{n1} & f_{n2} & \cdots & f_{nn} \end{bmatrix}; \; f_{ij} = \frac{\partial f(x)}{\partial x_i x_j} \qquad \text{(TA-3)}$$

A twice continuously differentiable function $z = f(x_1, \dots x_n)$ is concave (convex) if and only if its Hessian matrix $\boldsymbol{H}$ is everywhere negative (positive) semidefinite, and it is strictly concave (convex) if (but not only if) its Hessian is everywhere negative (positive) definite (Chiang and Wainwright, 2005, p. 326).

The definiteness of a matrix can be checked using principle minors or eigenvalues. A quadratic matrix $\boldsymbol{H}$ is negative semidefinite if and only if all its kth-order principle minors are non-positive for k being odd and non-negative for k being even, and it is positive semidefinite if all its principle minors are non-negative (Simon and Blume, 1994, p. 514). A quadratic matrix $\boldsymbol{H}$ is negative definite if and only if its first leading principal minor is negative and the following principal minors alternate in sign, and it is positive definiteness if and only if its leading principal minors are all positive (Chiang and Wainwright, 2005, p. 307). Finally, the matrix $\boldsymbol{H}$ is negative (positive) definite if and only if all eigenvalues of $\boldsymbol{H}$ are negative (positive), and it is negative (positive) semidefinite if and only if all eigenvalues of $\boldsymbol{H}$ are non-positive (non-negative) (Chiang and Wainwright, 2005, p. 311).

TA. 2 Quasi-concave and quasi-convex functions

A function f is quasi-concave if and only if

$$f(v) \geq f(u) \Rightarrow f(\theta u + (1-\theta)v) \geq f(u) \tag{TA-4}$$

for any combination of distinct points u and v in the domain of f and for $0 \leq \theta \leq 1$, while it is quasi-convex if and only if

$$f(v) \geq f(u) \Rightarrow f(\theta u + (1-\theta)v) \leq f(u) \tag{TA-5}$$

for any combination of distinct points u and v in the domain of f and for $0 \leq \theta \leq 1$ (Chiang and Wainwright, 2005, p. 365). Definitions for strict quasi-concavity and strict quasi-convexity are obtained by replacing the two weak inequalities $\geq f(u)$ and $\leq f(u)$ by strict inequalities $> f(u)$ and $< f(u)$, respectively (Chiang and Wainwright, 2005, p. 366).

If the function is twice continuously differentiable, (strict) quasi-concavity and (strict) quasi-convexity can be tested using the second-order partial derivatives. The bordered Hessian matrix of a twice continuously differentiable function $z = f(x_1, \dots x_n)$ is defined as

$$\boldsymbol{B} = \begin{bmatrix} 0 & f_1 & & f_n \\ f_1 & f_{11} & \cdots & f_{1n} \\ f_2 & f_{21} & & f_{2n} \\ \vdots & & \ddots & \vdots \\ f_n & f_{n1} & \cdots & f_{nn} \end{bmatrix};\ f_i = \frac{\partial f(x)}{\partial x_i};\ f_{ij} = \frac{\partial f^2(x)}{\partial x_i x_j} \tag{TA-6}$$

A necessary condition for $z = f(x_1, \dots x_n)$ to be quasi-concave on the non-negative orthant is that the leading principal minors $|B_1| \leq 0$, $|B_2| \geq 0$, ..., $|B_n| \leq 0$ for n being odd and $|B_n| \geq 0$ for n being even wherever the partial derivatives are evaluated in the non-negative orthant, where

$$|B_1| = \begin{vmatrix} 0 & f_1 \\ f_1 & f_{11} \end{vmatrix};\ |B_2| = \begin{vmatrix} 0 & f_1 & f_2 \\ f_1 & f_{11} & f_{12} \\ f_2 & f_{21} & f_{22} \end{vmatrix};\ \dots;\ |B_n| = \begin{vmatrix} 0 & f_1 & & f_n \\ f_1 & f_{11} & \cdots & f_{1n} \\ f_2 & f_{21} & & f_{2n} \\ \vdots & & \ddots & \vdots \\ f_n & f_{n1} & \cdots & f_{nn} \end{vmatrix}, \tag{TA-7}$$

and the sufficient condition is obtained by replacing weak inequalities with strict inequalities (Chiang and Wainwright, 2005, p. 369). A necessary condition for quasi-convexity is that all leading principal minors $|B_k| \leq 0$, and a sufficient condition for quasi-convexity is that all determinants $|B_k| < 0$ (Henningsen, 2019, p. 39).

TA. 3 Bayesian regression analysis

While frequentist statistics assumes the data to be random variables while parameters are unknown fixed quantities, Bayesian statistics treats both data and parameters as random variables with probability distributions. By Bayes' Theorem, the posterior probability density function is proportional to the likelihood function multiplied with the probability density function of the prior (Coelli et al., 2005, p. 232):

$$p(\theta|y) \propto p(y|\theta) \times p(\theta) \tag{TA-8}$$

In this equation, θ contains the unknown parameters and y represents the data. The posterior combines sample information (contained in the likelihood function $p(y|\theta)$) and pre-sample information (contained in the prior $p(\theta)$).

For a simple linear regression model, let us consider

$$y_i = x_i'\beta + \epsilon_i \quad , \tag{TA-9}$$

where y_i is the output and x_i is the input vector of unit i for $i = 1, \ldots, N$. Further, β is a vector of regression coefficients and ϵ is the error term assumed to be independently and identically distributed with zero mean and variance σ^2 ($\epsilon_i \sim iidN(0, \sigma^2)$). For technical reasons, it proves useful to replace the variance by error precision defined as $h = 1/\sigma^2$. The likelihood function is the joint probability density function for the data conditional on the unknown parameters, i.e. $P(y|\beta, h)$. For the linear regression model, this is (Koop, 2003, p. 17)

$$p(y|\beta, h) = \frac{h^{\frac{N}{2}}}{(2\pi)^{\frac{N}{2}}} exp\left(-\frac{h}{2}\sum_{i=1}^{N}(y_i - x_i'\beta)^2\right) \tag{TA-10}$$

Next, prior distributions for the unknown parameters have to be specified. If one does not have any prior information on the structures of the parameter, non-informative priors should be used, such as the Normal-Gamma prior

$$p(\beta, h) \propto \frac{1}{h} \quad , \tag{TA-11}$$

implying that all values are equally likely. The joint posterior probability density function is then obtained by multiplying the likelihood function and the prior. In the case of a linear regression model with a Normal-Gamma prior, the joint posterior probability density function can be written out analytically and the marginal posterior probability density functions for individual parameters can be obtained by integrating out the remaining parameters. With more complex models, such as stochastic frontier models or models with parameter restrictions, simulation techniques are used to describe the posterior distribution numerically.