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Essays on Output Market Power and Its Determinants in EU Food Supply Chains

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Abstract

This thesis examines output market power and its determinants for the farming, food processing and food retailing sector in the EU in three first-authored articles and two supplementary co-authored articles. The studies apply advanced methods for the estimation of markups of output price over marginal cost as a measure of firm-level output market power. Markups are related to firm as well as industry characteristics. As the explanation of output market power with firm characteristics has only very limitedly been the focus of earlier research, this thesis makes an important contribution to the literature.

The dissertation starts with the motivation for the thesis as well as the theoretical background of research on market power. This is followed by a description of the structure of the agricultural, food processing as well as food retailing sectors in the EU and its implications for market power. After a review of previous literature on market power in the EU food sector, Chapter 2 explains the methods used in the five articles.

Article one (Chapter 3) investigates the drivers of dairy farmers' market power in the EU and the United Kingdom with an emphasis on the role of organic production for the period 2008-2017. With data from the EU's Farm Accountancy Data Network, a sample of almost 40,000 farms comprising more than 200,000 observations is used to estimate a translog cost function to obtain farms' marginal cost and, subsequently, markups. The analysis reveals that organic farmers have significantly larger markups compared to conventional farmers. Besides, markups are positively related to farm size and the market share of large dairy processors whereas it is negatively related to the market share of large retailers.

The second article (Chapter 4) analyzes market power and its firm-specific determinants in the EU dairy processing industry using France, Italy and Spain as a case study for 421, 1,095, and 686 firms, respectively, from 2008 to 2017 where a stochastic frontier approach is applied. Relating markups to firm characteristics delivers a strong negative and robust link between firm size and markups which is also significantly different from zero across all regression models. In addition, the models detect a positive link between firms' profitability and markups pointing towards welfare decreasing market power. The results are inconclusive regarding firm age, the equity ratio and revenue growth.

Article three (Chapter 5) presents a comparison of the stochastic frontier approach and the production function approach to recover markups of price over marginal cost in five important and diverse food retailing sectors in the EU. The results show that the correlation between the

markups delivered by the two methods is low, i.e., the conclusions drawn from the two methods likely differ from each other. The markups of the production function approach, on average, exceed those of the stochastic frontier approach despite the stochastic frontier approach assumes markups to be positive only. Even though the estimates of the technology explain some part of the deviations in markups, the distributional assumptions that the two methods impose on markups are more important.

Supplementary article one (Chapter S1) assesses the link between market power and firms' exporting behavior in the French food processing industry. The study yields a higher likelihood of exporting for firms with higher markups as well as a positive association between markups and export intensity. Further, firms entering export markets realize an immediate increment in markups once they start exporting, and gain additional markup increases with rising export experience. Finally, exporters' self-selection into export markets allows them to charge even higher markups compared to non-exporters.

Last, supplementary article two (Chapter S2) focuses on the effect of belonging to one of the dominant national food retail chains on market power in the French food retailing industry. The estimation of markups in the French food retail sector yields that retailing is a rather competitive sector. However, the investigation of markup differences between top retail chains and fringe retailers delivers that dominant retailers charge markups that are significantly larger than those of fringe firms.

Zusammenfassung

Diese Dissertation untersucht Verkaufsmarktmacht und ihre Determinanten in der Landwirtschaft, Lebensmittelindustrie und dem Einzelhandelssektor in der EU in drei vom Doktoranden als Erstautor verfassten Artikeln und zwei ergänzenden Artikeln mit Koautorenschaft. Die Studien verwenden fortschrittliche Methoden zur Schätzung des Markups, welcher als Quotient des Verkaufspreis‘ geteilt durch die Grenzkosten definiert ist und als Kennzahl für Verkaufsmarktmacht auf Firmenebene dient. Zudem wird die Beziehung von Markups zu Firmen- und Industriecharakteristika analysiert. Da sich frühere Studien nur in sehr begrenztem Maß mit dem Zusammenhang von Verkaufsmarktmacht und Firmencharakteristika beschäftigt haben, leistet diese Arbeit einen wichtigen Beitrag zur Literatur.

Die Dissertation beginnt mit der Motivation für die Arbeit und dem theoretischen Hintergrund zur Erforschung von Marktmacht. Darauf folgt eine Beschreibung der sektoralen Strukturen der Landwirtschaft, der Lebensmittelindustrie und des Einzelhandels und ihren Konsequenzen für Marktmacht. Im Anschluss an einen Literaturüberblick erläutert Kapitel 2 die verwendete Methodik für die fünf Artikel.

Der erste Artikel (Kapitel 3) untersucht Faktoren, welche die Marktmacht von milcherzeugenden Betrieben in der EU und dem vereinigten Königreich zwischen 2008 und 2017 bedingen. Eine zentrale Rolle spielt hierbei der Unterschied zwischen biologischen und konventionellen Betrieben. Auf Basis von Daten des Farm Accountancy Data Networks der EU wird eine translogarithmische Kostenfunktion für mehr als 40.000 landwirtschaftliche Betriebe geschätzt, um damit Grenzkosten und anschließend Markups zu ermitteln. Die Analyse zeigt, dass biologische Betriebe gegenüber konventionellen Betrieben signifikant höhere Markups erzielen. Des Weiteren ist der Zusammenhang zwischen Betriebsgröße und Markups ebenso wie der Zusammenhang zwischen dem Marktanteil von großen milchverarbeitenden Unternehmen und Markups positiv, wohingegen der Marktanteil von großen Unternehmen im Lebensmitteleinzelhandel einen negativen Einfluss auf Markups der landwirtschaftlichen Betriebe hat.

Der zweite Artikel (Kapitel 4) analysiert Verkaufsmarktmacht und ihre firmenspezifischen Determinanten in der Milchverarbeitungsindustrie in der EU mithilfe einer Fallstudie zu Frankreich, Italien und Spanien. In einem Stochastic-Frontier-Ansatz werden Daten zu 421 (Frankreich), 1.095 (Italien) und 686 (Spanien) Firmen zwischen 2008 und 2017 verwendet,

um Markups auf Firmenebene zu schätzen. Anschließend geschätzte Regressionsmodelle zeigen einen stark negativen und robusten Zusammenhang zwischen Firmengröße und Markups, welcher signifikant unterschiedlich von null ist. Außerdem besteht eine positive Beziehung zwischen Markups und Profitabilität, was auf die Präsenz von wohlfahrtsverringernder Marktmacht hindeutet. Die Ergebnisse lassen hingegen keine klare Schlussfolgerung bezüglich der Verbindung von Markups und Firmenalter oder der Eigenkapitalquote zu.

Artikel drei (Kapitel 5) stellt einen Vergleich des Stochastic-Frontier-Ansatz‘ und des Produktionsfunktionsansatz‘ zur Ermittlung Markups dar. Dabei werden fünf wichtige und unterschiedliche Lebensmitteleinzelhandelssektoren in der EU analysiert. Die Ergebnisse zeigen eine niedrige Korrelation zwischen den Markups, welche mithilfe der beiden Methoden geschätzt werden, d.h. die Schlussfolgerungen basierend auf den beiden Ansätzen unterscheiden sich. Die Markups des Produktionsfunktionsansatz‘ übersteigen im Mittel die des Stochastic-Frontier-Ansatz‘, obwohl der Stochastic-Frontier-Ansatz im Gegensatz zum Produktionsfunktionsansatz ausschließlich Markups größer als null zulässt. Auch wenn die geschätzten technologischen Parameter der beiden Ansätze einen Teil der Unterschiede in den Markups erklären, ist die zuvor genannte Verteilungsannahme von größerer Bedeutung.

Der erste ergänzende Artikel (Kapitel S1) untersucht die Beziehung zwischen Verkaufsmarktmacht und dem Exportverhalten von Firmen in der französischen Ernährungsindustrie. Die Studie zeigt, dass mit steigenden Markups sowohl die Wahrscheinlichkeit zu exportieren als auch die Exportintensität zunehmen. Zudem realisieren Firmen, die in einen Exportmarkt eintreten, sofortige Markupgewinne. Steigende Exporterfahrung führt ebenfalls zu höheren Markups. Die Eigenselektion exportierender Unternehmen in den Exportmarkt erlaubt es ihnen verglichen mit nicht exportierenden Unternehmen höhere Markups zu verlangen.

Im Fokus des zweiten ergänzenden Artikels (Kapitel S2) steht die Differenz zwischen Markups von dominanten, nationalen Ketten und Markups von kleinen Firmen im französischen Lebensmitteleinzelhandel. Auf Basis der Schätzungen ist der französische Lebensmitteleinzelhandel nicht weit von perfektem Wettbewerb auf der Verkaufsseite entfernt. Allerdings sind die Markups und damit die Verkaufsmarktmacht der dominanten Ketten signifikant größer als die von kleinen Firmen des Lebensmitteleinzelhandels.

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1 Introduction

1.1 Motivation

The percentage of total household expenses citizens of the European Union (EU) spend on food has declined over the past few decades. However, it still amounts to 13 percent (Eurostat 2022e). This means, expenditures for food represent an important component of overall consumer spending. An abuse of market power by actors in the food supply chain raising prices above the competitive level could therefore have considerable adverse consequences for consumers. In 2019, the food and beverage sector's share in overall value added in the EU has been almost five percent, and it has provided employment for 4.4 percent of the entire EU population (Eurostat 2022g; Eurostat 2022h). These numbers reflect the economic importance of the sector. In addition, exports of food and beverage products have equaled eight percent of total extra-EU exports in 2021 (Eurostat 2022c). Thus, the competitiveness of actors in food value chains is of interest to consumers as well as from an economic viewpoint, and therefore presents a top priority on the EU policy agenda.

During the past decades, several developments have changed the nature and intensity of competition along the food value chains: First, due to technological progress crop yields have increased significantly since the 1960s (Brisson et al. 2010; Ewert et al. 2005; Finger 2010),[1] while the number of farms has declined steadily (Neuenfeldt et al. 2019). Second, globalization, the creation of the Single Market within the EU and increasingly liberalized world trade have given rise to intense international competition in agricultural and food markets (Curzi et al. 2015; Olper et al. 2014; Timmer 2009). Third, the intensified world trade has resulted in the availability of a wider variety of food products. This increasing availability has entailed increments in vertical coordination of food supply chains to ensure the supply of high quality goods demanded by consumers (Saitone and Sexton 2017; Sexton 2013; Swinnen and Maertens 2007). Fourth, several sectors have undergone immense consolidation processes with few multi-/national players dominating their respective markets: the sector of primary inputs to agriculture (Bonanno et al. 2017), the food processing industry (OECD 2014; Saitone and Sexton 2017), and the food retailing sector (Bukeviciute et al. 2009; Hirsch et al. 2021; Swinnen et al. 2021).

[1] For instance, the average yield of wheat in the EU has risen from 1.81 tons per hectare in 1961 to 5.54 tons per hectare in 2021 (FAO 2022).

These trends can affect competition in the food sector negatively. When large companies possess substantial market shares they may exercise market power to the detriment of other supply chain actors and consumers (De Loecker et al. 2020; McCorriston 2014). Small- and medium-sized enterprises get pushed out of the market when they are not able to compete with the multi-/national firms. Both factors further concentrate profits in the sector on fewer large firms. In addition, market power entails a decline in the demand for labor, capital investments and innovation (De Loecker et al. 2020). Due to the above discussed dynamics and the importance of the food sector in the EU economy, research on market power in the EU's agricultural and food markets has a longstanding history (McCorriston 2002; Perekhozhuk et al. 2017). However, with the exception of two studies (Curzi et al. 2021; Lee and van Cayseele 2022), previous research focused on the mere analysis of the presence of anti-competitive behavior, and has failed to identify firm-level characteristics allowing companies to maintain or gain market power.

This thesis therefore presents an overall examination of firm-level output market power and its determinants in the EU food sector. Three first-authored articles and two supplementary co-authored articles analyze market power in the farming, food processing and food retailing sectors with new advanced methods. Article one (Chapter 3) investigates the drivers of dairy farmers' market power in the EU and the United Kingdom with an emphasis on the role of organic production for the period of 2008 to 2017. The second article (Chapter 4) analyzes market power and its firm-specific determinants in the EU dairy processing industry using France, Italy and Spain as a case study. The third article (Chapter 5) compares two contemporary methods to estimate markups of price over marginal cost. In addition, article three analyzes the correlation of markups and industry concentration in five important and diverse food retail sectors (Finland, France, Italy, Portugal and Sweden). Supplementary article one (Chapter S1) assesses the relationship between market power and companies' export behavior in the French food processing industry. Supplementary article two (Chapter S2) focuses on the effect of belonging to one of the dominant national food retail chains on market power in the French food retail industry.

The results of this thesis are applicable in manifold ways. Of interest to policy makers are three aspects: First, the identification of market power indicates whether anti-trust investigations are necessary or not in order to avoid losses of economic welfare. Second, the analysis of determinants of market power on the firm-level enables policymakers to introduce more targeted policy measures such as penalties for specific firms or restrictions regarding further mergers and acquisitions. Third, although the term market power often carries negative connotations, it may also be desirable. Take, for example, the case of small- and medium-sized enterprises; they usually operate in niche markets where the ability to raise prices above the competitive level allows them to survive and increase their competitiveness vis-à-vis large multinational corporations. The findings also provide valuable insights for farmers and firms in the EU food sector on how to increase and/or sustain their competitiveness and profitability. In addition, the comparison and evaluation of two contemporary methods to estimate market power (Chapter 5) benefits future studies in the selection of the appropriate method.

The next section (Chapter 1.2) describes the theoretical background for the thesis and provides a working definition of market power. Chapter 1.3 consists of an overview of the EU food sector. Chapter 1.4 reviews the literature on market power in the EU food sector. Chapter 2 explains the methods applied in the studies conducted within the framework of this thesis. Thereafter, the three first-authored articles (Chapter 3, 4 and 5) build the core of this work. The results of the three articles are discussed in Chapter 6 (including the findings from the two supplementary articles (Chapter S1 and S2) which can be found in the Supplement).

1.2 Theoretical Background and a Definition of Market Power

Starting with the work of Bain (1954) and Mason (1939) almost 100 years ago, the analysis of market power has been of significant interest to the economics proficiency. In the early stages of research on market power, there was consensus that firms operating in concentrated industries attain higher profits due to a lack of competition (Bain 1954; Viaene and Gellynck 1995). Accordingly, it was assumed that a significantly positive relationship between concentration and profitability presents an indicator of market power. The theoretical framework obtained its name from this relationship: the Structure-Conduct-Performance Paradigm (Bain 1954). However, there are several issues regarding the measurement of concentration and the use of well-defined economic markets (Berry et al. 2019). But more importantly, average profits in more concentrated industries do not necessarily originate from the firms' exercise of market power but may also be a result of other industry and firm characteristics (Berry et al. 2019). In addition, firms with higher profits may gain larger market shares which will in turn increase concentration. In such cases, the causality between concentration and profits is reversed.

In 1982, Appelbaum (1982), Bresnahan (1982) and Lau (1982) pioneered the New Empirical Industrial Organization (NEIO) framework. In the NEIO framework, market power is estimated based on demand, cost and pricing conduct (Berry et al. 2019). In contrast to the Structure-Conduct-Performance Paradigm, the NEIO approach focuses on the measurement of firm conduct as a direct measure of market power. In NEIO studies, the conjectural elasticity is the central measure. The conjectural elasticity proxies an expected change in total industry output conditional on a change in a firm's output (Azzam and Pagoulatos 1990; Geneseove and Mullin 1998; Wann and Sexton 1992). The NEIO approaches overcome the shortcoming of the Structure-Conduct-Performance paradigm by using a direct instead of an indirect measure of market power. This advantage has led to a significant increase in the number of empirical studies on market power, particularly discernable in the literature on agricultural and food economics (Bonanno et al. 2018; Perekhozhuk et al. 2017; Sheldon 2017).

Despite these advantages of the NEIO framework it comes with several drawbacks. In NEIO studies, market power estimates become inaccurate as soon as the large set of necessary underlying assumptions is not fulfilled. First of all, the models are sensitive to the ex-ante choices of functional forms for supply, demand and production technology (Mei and Sun 2008; Perekhozhuk et al. 2017; Sexton 2000). Second, the results depend on the identification method, the estimation techniques (Hyde and Perloff 1995; Perekhozhuk et al. 2017), and the set of explanatory variables included in estimating the supply, demand, production and/or cost functions (Sexton and Xia 2018). Third, the implicit assumption of perfect competition in up- and downstream markets usually does not hold in real markets (Sexton 2000). Fourth, a game played between the market actors needs to be specified, e.g., Stackelberg, Cournot or Bertrand competition (Corts 1999; Sheldon 2017). Fifth, NEIO methods conceptually aim to estimate the average relationship between price-cost margins and quantity, whereas most studies identify the marginal relationship. But, the marginal relationship is valid only exceptional circumstances (Corts 1999; Sexton and Xia 2018). Sixth, the accurate estimation in NEIO frameworks has high data requirements. However, respective data is usually not available on a disaggregated level (Sexton and Xia 2018).

Over time, these drawbacks and the development of other methods to estimate market power have limited the influence of NEIO approaches (Sexton and Lavoie 2001; Sexton and Xia 2018). With an increasing availability of firm-level data as well as retail scanner data, new methods to analyze market power have emerged. To their advantage, they avoid the estimation of either production/cost parameters or conduct parameters (Sexton and Xia 2018). In contemporary research using these new methods, the prevalent measure of market power on the output side consists in the markup of output price over marginal cost, with larger values of markup, ceteris paribus, implying greater market power[2] (Basu 2019; Bonanno et al. 2018; Syverson 2019).

The corresponding indicator of market power on the input side is markdown. The markdown measures how much the price of an input is below the marginal value product of that input (Jung et al. 2022; Morrison Paul 2001; Panagiotou and Stavrakoudis 2017). In particular, the degree of input market power of processors and retailers are of interest in the food sector. However, agricultural products are mostly perishable and bulky, and thus, costly to transport over long distances (Rogers and Sexton 1994). Spatial competition is therefore vital in the analysis of input market power in food supply chains (Graubner et al. 2011a; Graubner et al. 2011b; Perekhozhuk et al. 2015). The available datasets deployed in this thesis provide information on the companies' headquarters but not on the single plant-level which would be necessary to reliably estimate input market power, i.e., markdowns. Therefore, I abstain from estimating markdowns and focus on output market power measured by markups.

The methods to derive markups can be divided in i) demand-side approaches relying on sales data and ii) supply-side approaches using production data. Introduced by Berry et al. (1995), the demand-side approach nests in the estimation of consumers' utility functions to generate market-level demand functions for single products. The shape of the demand function faced by the selling firm, i.e., the price elasticity of demand, then determines the firm's markup (Nevo 2001). To obtain markups based on supply-side data, the first derivative of an estimated cost function with respect to output, i.e., marginal cost, allows to directly compute markups using output price data. However, estimating markups based on a cost function requires input price and output price data which are rarely available. Kumbhakar et al. (2012) show that the duality between the cost and the input distance function can be exploited to identify markups without observing input prices in a stochastic frontier analysis. Alternatively, an approach initiated by Hall (1988) and extended by De Loecker and Warzynski (2012) consists in computing markups using the output elasticity with respect to a variable input of an estimated production function along with a firm's revenue and input expenditures.

Hence, the aforementioned methods demonstrate superiority over NEIO methods as they i) have less demanding data requirements, ii) do not implicitly assume perfect competition in up- and/or down-stream markets, iii) do not require a specification of a game that is played between

[2] Note that increments in markups may also arise because increasing fixed costs, e.g., for research and development, must be covered. Therefore, further investigations into the connection between markups and profits is necessary to make inference on welfare decreasing market power (De Loecker et al. 2020).

competitors (supply-side methods) and iv) deliver average instead of marginal markup values (supply-side methods).

It should be noted that markups and markdowns will not reflect other mechanisms of exercising market power and trends in agricultural and food value chains (Bonanno et al. 2018). First, the presence of credence attributes and asymmetric information is inherent to food products, particularly in times of increasing importance of ecological footprint, social aspects and animal welfare concerns (Rondoni and Grasso 2021; Vanhonacker et al. 2013). Second, vertical coordination in food supply chains by large actors, e.g., processors and retailers, enforcing their standards vis-à-vis small actors, e.g., farmers, might not necessarily become obvious in analyzing markups or markdowns but represents a different form of market power (Bonanno et al. 2018). Similarly, prices will not necessarily reflect unfair trading practices such as delayed payments by retailers to farmers and processors which can be seen as a form of market power impairing the liquidity of the seller (Di Marcantonio et al. 2020; Swinnen et al. 2021).

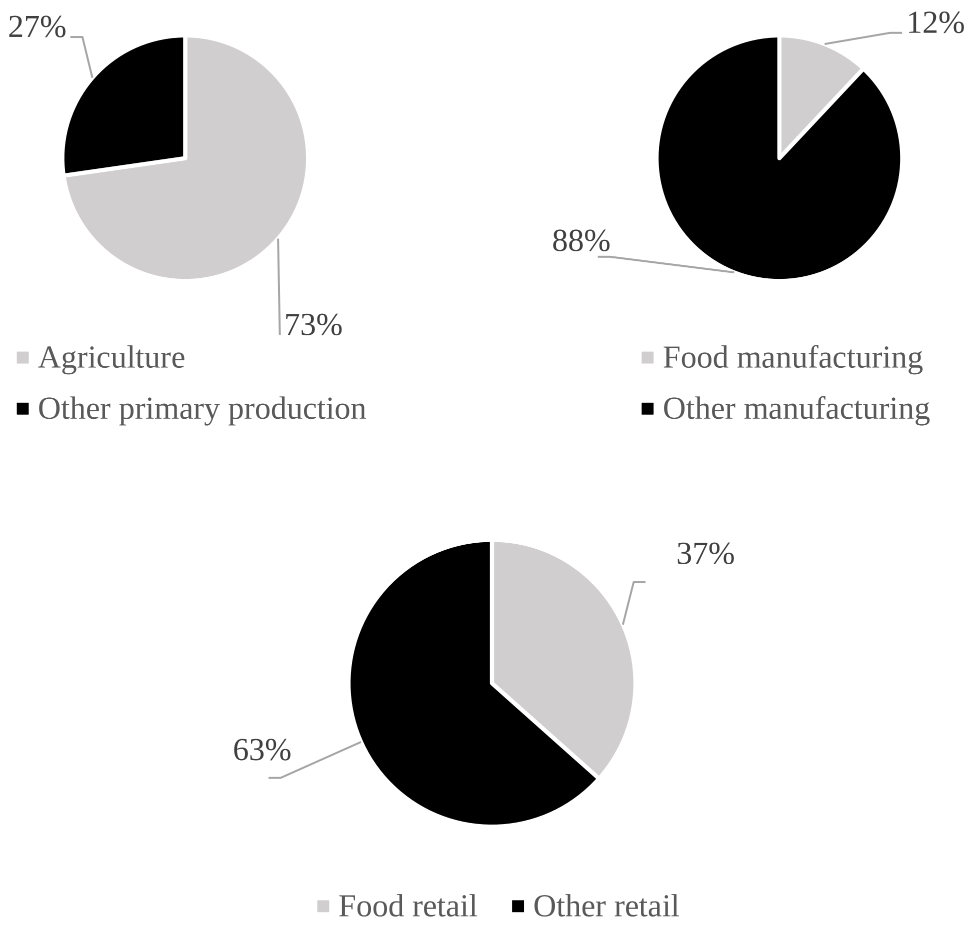
Even though the aforementioned issues are of importance, the ultimate goal of a company is survivorship which will only be possible, if sufficient profits are generated in the long-term. For this purpose, firms need to create a competitive advantage over their competitors which results in a certain level of markup. Therefore, this thesis uses markups as a measure of output market power throughout.

1.3 Overview of the EU Food Sector

In the EU, the food sector is an important part of the overall economy in regards to value added, as well as the employment (Eurostat 2021b; Federal Foreign Office 2022). In 2019, the value added of the food sector[3] has amounted to approximately €623 billion to which agriculture has contributed €193 billion, food manufacturing €251 billion and food retailing €179 billion (Eurostat 2022b; Eurostat 2022g). All in all, the food sector's share in value added of the EU economy adds up to almost five percent (Eurostat 2022g). During the same time period, the EU food sector has employed 19.7 million people, of which almost 8.8 million have worked in agriculture, 4.6 million in food manufacturing and 6.3 million in food retailing. (Eurostat

[3] The EU food sector includes agriculture, food manufacturing and retail trade of food. The sectors are defined based on their codes in the Statistical Classification of Economic Activities in the European Community which are abbreviated as NACE (nomenclature statistique des activités économiques dans la Communauté européenne) codes. The codes corresponding to agriculture, food manufacturing and food retailing are 01 ("Crop and animal production, hunting and related service activities"), 10-12 ("Manufacture of food products; beverages and tobacco products"), 4711 ("Retail sale in non-specialised stores with food, beverages or tobacco predominating") and 472 ("Retail sale of food, beverages and tobacco in specialised stores").

2022b; Eurostat 2022h). In total, these 19.7 million people equal approximately 4.4 percent of the entire EU population (Eurostat 2022b; Eurostat 2022h).



Notes: Primary production is defined as NACE codes 01-09 (“Agriculture, forestry, fishing, mining and quarrying”). Manufacturing is defined as NACE codes 10-33 (“Manufacturing”). Retail is defined as NACE code 47 (“Retail trade except of motor vehicles and motorcycles”).

Source: Own illustration based on Eurostat (2022b) and Eurostat (2022g)

Figure 1.1 Share of Agriculture, Food Manufacturing and Food Retail in Respective Industry Value Added

Figure 1.1 illustrates the importance of agriculture, food manufacturing and food retailing in terms of value added in their respective industries. Agriculture’s share in total value added in primary production is as high as 73 percent. Even though food manufacturing is the largest manufacturing sector in the EU, its share only amounts to 12 percent of value added in the entire EU manufacturing sector while food retailing contributes more than a third (37 percent) to total value added in the retail sector (cf. Figure 1.1). Still, most important regarding value added in their respective industries are all three sectors (Eurostat 2022b; Eurostat 2022g).

1.3.1 Agriculture

As of 2016, there have been 10.5 million active farms cultivating more than 147 million hectares of land (Eurostat 2022d). 54.07 percent (5.6 million) of the farms have engaged in livestock farming with 111 million livestock units[4] on the farms (Eurostat 2022d). The total turnover, i.e., the output valued at respective product prices, has been equal to €322 billion in 2016 (Eurostat 2022d).

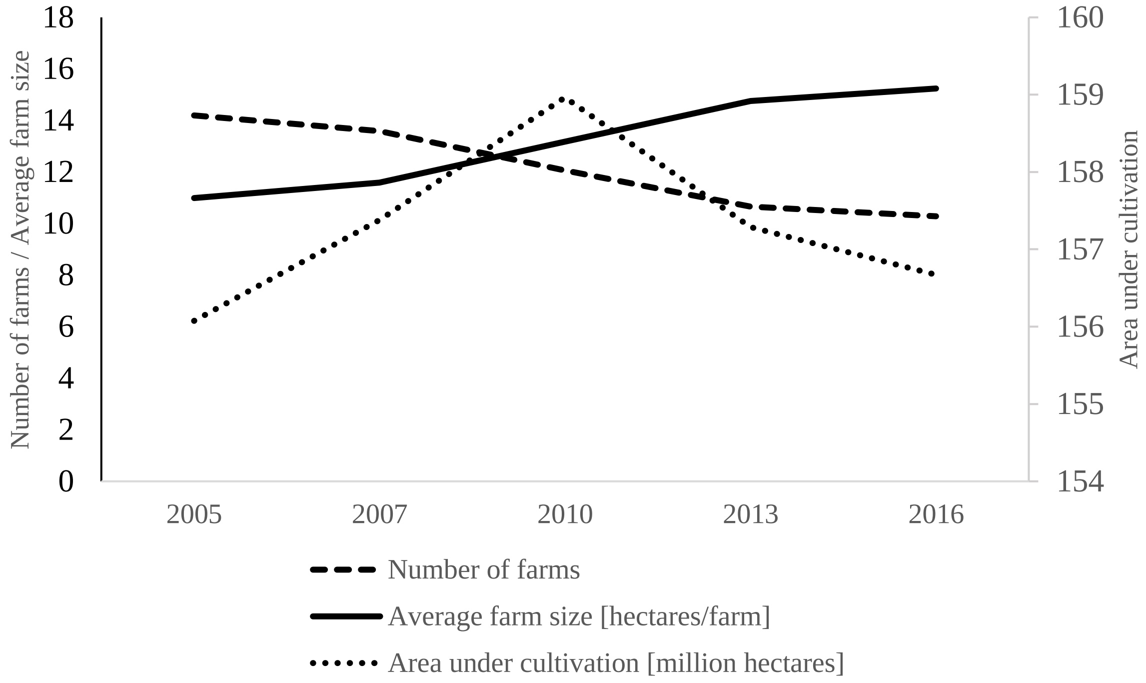
Table 1.1 provides an overview of the agricultural sector by member state in 2016. Considering the countries' population and area, the ranking of the total area under cultivation is largely as one would expect. Accordingly, the five largest countries France, Germany, Italy, Poland and Spain have the largest agricultural sectors regarding area under cultivation, livestock units and output (Table 1.1), whereas Luxembourg, Cyprus and Malta have the smallest farming sectors. Remarkably, Dutch and Danish figures for livestock rank sixth and ninth although they are not among the top 15 in regards to the area under cultivation (cf. Table 1.1). However, both countries are known for their intensive livestock production relying on feed imports. Another notable figure is the large number of farms in Romania (more than 3.4 million). Nonetheless, 86 percent of the farms in Romania consume more than 50 percent of their produce within their own household which is by far the highest value in the EU[5] (Eurostat 2022d).

As depicted in Table 1.1, the average farm size in hectares of land per farm is highest in Czechia (130.25 hectares/farm) followed by Denmark (74.60 hectares/farm), Slovakia (73.65 hectares/farm), Luxembourg (66.32 hectares/farm) and France (60.93 hectares/farm). The smallest farms can, on average, be found in Malta (1.21 hectares/farm), Cyprus (3.20 hectares/farm) and Romania (3.65 hectares/farm) (cf. Table 1.1). As mentioned earlier, the overall trend in the EU goes in the direction of fewer and larger farms. Over the course of 11 years, the average farm size in the EU has increased by 38.67 percent from 10.99 hectares per farm in 2005 to 15.24 hectares per farm (cf. Figure 1.2). Within the same timeframe, the number of farms has decreased by 27.61 percent from 14.20 million (2005) to 10.28 million (2016). The farm structural change is driven by different factors, such as producer prices, subsidies, macroeconomic variables, natural conditions and population variables (Neuenfeldt et al. 2019;

[4] A livestock unit is a reference unit to make different animal species comparable in terms of farm size. The reference point is an adult dairy cow, i.e., a dairy cow equals one livestock unit. Using the definition of Eurostat (2022f), a breeding sow amounts to 0.5 livestock units and a laying hen 0.014 livestock units.

[5] Slovakia is the country with the second highest self-consumption with 62 percent of farms consuming more than 50 percent of their production in their own household (Eurostat 2022d).

Zimmermann and Heckelei 2012). Since the promotion of rural areas presents one of the main goals of the Common Agricultural Policy in the EU, and farming is an important income source in rural areas, decelerating farm structural change is considered an important task within the framework of the Common Agricultural Policy (European Commission 2022b).



Source: Own illustration based on Eurostat (2022d)

Figure 1.2 Farm Structural Change in the EU (2005-2016)

Table 1.1 Overview of the EU Farm Structure (2016)

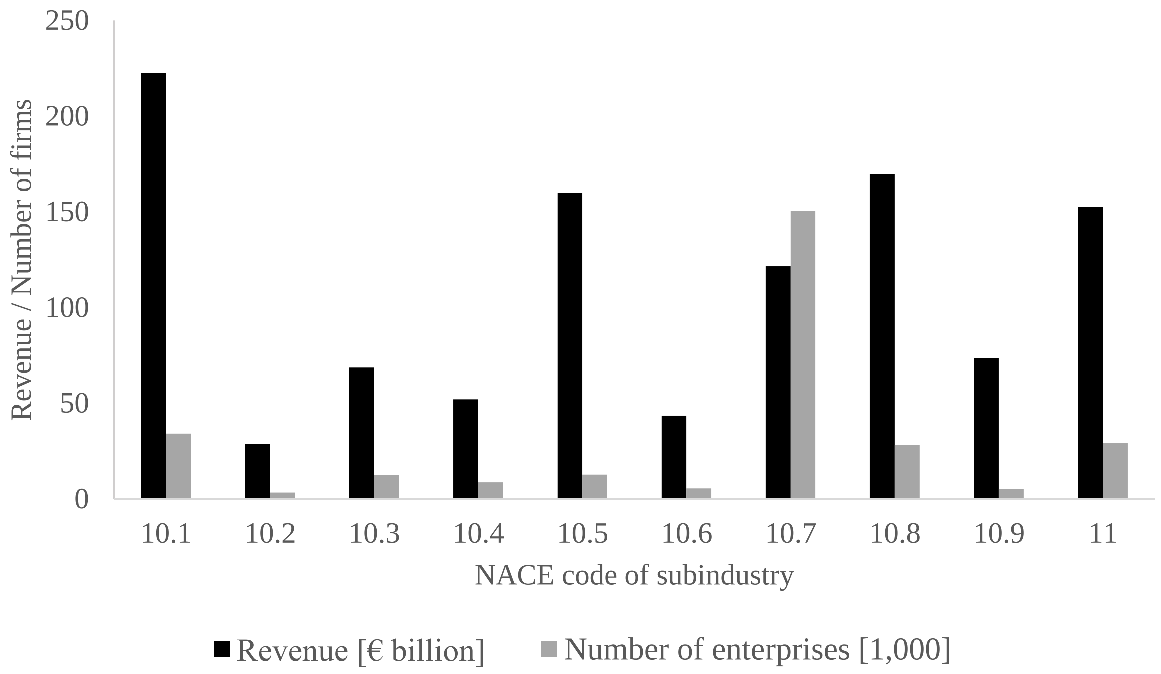
Country	Area [million hectares]	Rank	Livestock [million livestock units]	Rank	Number of farms	Rank	Output [€ billion]	Rank	Average farm size [hectares/farm]	Rank
France	27.81	1	22.08	1	456,520	6	61.34	1	60.93	5
Spain	23.23	2	14.44	3	945,020	4	38.37	4	24.58	14
Germany	16.72	3	18.18	2	276,120	8	49.25	3	60.54	6
Poland	14.41	4	9.44	5	1,410,700	2	25.01	5	10.21	22
Italy	12.60	5	9.47	4	1,145,710	3	51.69	2	11.00	20
Romania	12.50	6	4.83	8	3,422,030	1	12.11	7	3.65	25
Ireland	4.88	7	6.20	7	137,560	12	6.32	12	35.50	11
Hungary	4.67	8	2.44	11	430,000	7	6.53	11	10.86	21
Greece	4.55	9	2.10	14	684,950	5	7.57	10	6.65	24
Bulgaria	4.47	10	1.09	18	202,720	10	3.84	16	22.04	15
Portugal	3.64	11	2.22	13	258,980	9	5.14	15	14.06	18
Czechia	3.46	12	1.76	15	26,530	23	not available		130.25	1
Sweden	3.01	13	1.70	16	62,940	17	5.16	14	47.87	8
Lithuania	2.92	14	0.85	19	150,320	11	2.23	18	19.46	17
Austria	2.67	15	2.43	12	132,500	14	6.14	13	20.15	16
Denmark	2.61	16	4.13	9	35,050	21	10.06	8	74.60	2
Finland	2.23	17	1.10	17	49,710	19	3.51	17	44.92	9
Latvia	1.93	18	0.50	23	69,930	15	1.22	21	27.61	13
Slovakia	1.89	19	0.62	21	25,660	24	1.93	20	73.65	3
Netherlands	1.80	20	6.82	6	55,680	18	23.09	6	32.26	12
Croatia	1.56	21	0.75	20	134,460	13	2.03	19	11.62	19
Belgium	1.35	22	3.77	10	36,890	20	8.04	9	36.71	10

Estonia	1.00	23	0.28	24	16,700	25	0.80	23	59.59	7
Slovenia	0.49	24	0.51	22	69,900	16	1.16	22	6.99	23
Luxembourg	0.13	25	0.17	25	1,970	27	0.37	25	66.32	4
Cyprus	0.11	26	0.17	26	34,940	22	0.62	24	3.20	26
Malta	0.01	27	0.03	27	9,210	26	0.10	26	1.21	27
EU-27	156.67		118.12		10,282,700		333.63		15.24	

Source: Eurostat (2022d)

1.3.2 The Food Manufacturing Industry

Food manufacturing (including beverages) is the largest industry in EU manufacturing (Eurostat 2021a) with a revenue of €1,093 billion in 2018 which amounts to 14 percent of the overall EU manufacturing revenue (Eurostat 2022a). Out of the two million firms in EU manufacturing, in 2018 289,257 have operated in the food industry resulting in a share of 14 percent as well (Eurostat 2022a). Food manufacturers within their ten subindustries (cf. Figure 1.3) produce a large variety of goods that are also popular abroad as indicated by the food manufacturing industry's share in extra-EU exports of eight percent (Eurostat 2022c).



Note: 10.1 = Processing and preserving of meat and production of meat products; 10.2 = Processing and preserving of fish, crustaceans and molluscs; 10.3 = Processing and preserving of fruit and vegetables; 10.4 = Manufacture of vegetable and animal oils and fats; 10.5 = Manufacture of dairy products; 10.6 = Manufacture of grain mill products, starches and starch products; 10.7 = Manufacture of bakery an farinaceous products; 10.8 = Manufacture of other food products; 10.9 = Manufacture of prepared animal feeds; 11 = Manufacture of beverages

Source: Own illustration based on Eurostat (2022a)

Figure 1.3 Revenue and Number of Firms in EU Food Manufacturing by Subindustry (2018)

Figure 1.3 illustrates the importance of the subindustries for overall food manufacturing by displaying the revenue and the number of enterprises for each subindustry in 2018. The three subindustries with the largest revenue are meat processing (NACE code 10.1), dairy processing (NACE code 10.5) and manufacturing of other food products (NACE code 10.8). Together, these three subindustries generate half of the revenue in EU food manufacturing (cf. Figure 1.3;

Eurostat 2022a). The smallest subindustries are fish processing (NACE code 10.2), the manufacturing of grain mill products (NACE code 10.6) and the manufacturing of vegetable and animal oils and fats (NACE code 10.4). Industries 10.2 and 10.6 have also been the subindustries with the smallest number of enterprises together with the manufacturing of prepared animal feeds (NACE code 10.9) (cf. Figure 1.3). In contrast, more than half (150,392) of all enterprises operate in the manufacturing of bakery and farinaceous products (NACE code 10.7), followed by meat processing (34,066 enterprises) (NACE code 10.1) and the manufacturing of beverages (29,000 enterprises) (NACE code 11).

Regarding the structure of the EU food industry, the vast majority of firms are small- and medium-sized enterprises while only 0.86 percent are large firms with at least 250 employees (Eurostat 2022a). However, the 2,500 large companies have generated almost 60 percent of the total industry revenue in 2018 (Eurostat 2022a). Table 1.2 depicts the number of micro, small, medium and large companies and their shares for all ten subindustries as well as the revenue and its share for each size class. The share of large companies has been below two percent in all subindustries while the revenue share of these companies varies from slightly below 43 percent in manufacturing of prepared animal feeds to almost 76 percent in manufacturing of dairy products (cf. Table 1.2). At the other end of the size distribution, micro-sized companies with less than ten employees have made a share of between 60 percent (processing and preserving of fish, crustaceans and molluscs) and 90 percent (manufacture of vegetable and animal oils and fats) of the number of companies within the subindustry (Table 1.2). But, even in manufacturing of bakery products where the revenue share of micro companies has been the largest compared to all other subindustries, their contribution only amounts to 16 percent (Table 1.2). In the entire food industry, almost 80 percent of the companies are micro-sized generating only 5.48 percent of the overall industry revenue. Hence, the subindustries are all considerably concentrated with a few large companies generating most of the revenue in the industry. This consolidation process started decades ago but has slowed down recently (Bukeviciute et al. 2009; OECD 2014; Wijnands et al. 2007). However, as the following section will show, the importance of small- and medium-sized firms in the food manufacturing industry still exceeds the importance of small- and medium-sized companies in the food retail sector (in terms of revenue).

Table 1.2 Structure of Subindustries in EU Food Manufacturing (2018)

NACE code (industry)	Size class[a]	Number of firms	Share	Revenue [€ billion]	Share
10.1 ("Processing and preserving of meat and production of meat products")	Micro	21,959	64.46%	9.27	4.17%
	Small	9,488	27.85%	29.37	13.20%
	Medium	2,085	6.12%	51.64	23.20%
	Large	534	1.57%	132.27	59.43%
	Total	*34,066*	*100.00%*	*222.56*	*100.00%*
10.2 ("Processing and preserving of fish, crustaceans and molluscs")	Micro	1,981	60.32%	0.90	3.14%
	Small	876	26.67%	4.72	16.39%
	Medium	362	11.02%	10.69	37.12%
	Large	65	1.98%	12.48	43.35%
	Total	*3,284*	*100.00%*	*28.79*	*100.00%*
10.3 ("Processing and preserving of fruit and vegetables")	Micro	9,548	76.70%	2.67	3.89%
	Small	1,969	15.82%	9.39	13.66%
	Medium	728	5.85%	17.93	26.09%
	Large	203	1.63%	38.73	56.36%
	Total	*12,448*	*100.00%*	*68.72*	*100.00%*
10.4 ("Manufacture of vegetable and animal oils and fats")	Micro	7,754	90.43%	3.59	6.90%
	Small	645	7.52%	6.94	13.37%
	Medium	146[b]	1.70%	16.01	30.83%
	Large	43[b]	0.50%	25.41	48.91%
	Total	*8,588*	*100.15%*[c]	*51.95*	*100.00%*
10.5 ("Manufacture of dairy products")	Micro	9,658	76.44%	4.26	2.67%
	Small	2,067	16.36%	9.80	6.13%
	Medium	660	5.22%	24.48	15.31%
	Large	249	1.97%	121.31	75.89%
	Total	*12,634*	*100.00%*	*159.84*	*100.00%*
10.6 ("Manufacture of grain mill products, starches and starch products")	Micro	4,199	76.23%	2.05	4.72%
	Small	971	17.63%	7.38	16.96%
	Medium	275	4.99%	13.05	30.01%
	Large	63	1.14%	21.01	48.31%
	Total	*5,508*	*100.00%*	*43.49*	*100.00%*
10.7 ("Manufacture of bakery and farinaceous products")	Micro	124,572	82.83%	19.90	16.37%
	Small	22,042	14.66%	21.67	17.82%
	Medium	3,198	2.13%	25.08	20.63%
	Large	580	0.39%	54.94	45.18%
	Total	*150,392*	*100.00%*	*121.59*	*100.00%*
10.8 ("Manufacture of other food products")	Micro	22,482	79.85%	4.90	2.89%
	Small	4,017	14.27%	14.39	8.48%
	Medium	1,278	4.54%	33.90	19.98%
	Large	377	1.34%	116.50	68.65%
	Total	*28,154*	*100.00%*	*169.69*	*100.00%*

10.9 (“Manufacture of prepared animal feeds”)	Micro	3,600	69.28%	3.46	4.71%
	Small	1,134	21.82%	14.11	19.20%
	Medium	394	7.58%	24.51	33.34%
	Large	69	1.33%	31.43	42.75%
	Total	*5,197*	*100.02%[d]*	*73.51*	*100.00%*
11.0 (“Manufacture of beverages”)	Micro	24,652	85.01%	8.80	5.77%
	Small	3,424	11.81%	18.59	12.19%
	Medium	918	3.17%	29.50	19.35%
	Large	250[b]	0.86%	95.56	62.68%
	Total	*29,244*	*100.84%[c]*	*152.46*	*100.00%*
10-11 (Overall)	**Micro**	**230,402**	**79.65%**	**59.82**	**5.48%**
	Small	**46,634**	**16.12%**	**136.35**	**12.48%**
	Medium	**10,118[b]**	**3.50%**	**246.78**	**22.59%**
	Large	**2,500[b]**	**0.86%**	**649.63**	**59.46%**
	Total	***289,654***	***100.14%[c]***	***1092.59***	***100.00%***

Notes: [a]Size classes are defined based on the guidelines for the number of employees provided by the European Commission (2022a): micro: <10 employees, small: 10-49 employees, medium: 50-249 employees, large: >249 employees. [b]Since data are not available for 2018, the figures for 2019 have been used for this case. [c]The shares do not add up to 100 percent, as the number of firms in 2019 instead of 2018 had to be used for some size classes in a few industries. [d]There is one firm more in single size classes than given for the entire subindustry.

Source: Eurostat (2022a)

1.3.3 The Food Retail Sector

The food retail sector is a key element of the EU food sector. Representing the last stage of the supply chain before food products are consumed, food retailing provides food processors with access to final consumers (Richards and Pofahl 2010; Sheldon 2017). In 2018, the turnover of the EU food retail industry was €1,036.82 billion (Eurostat 2022b), making it the largest retail sector.[6] According to Eurostat (2022b), in 2018, 791,514 enterprises have engaged in retailing of food products. Hence, although the revenue of the food retail sector has been slightly below that of the food manufacturing industry, almost three times as many companies operate in food retailing compared to food manufacturing.

One of the most significant characteristics of the EU food retail industry is the presence of large multi-/national retail chains. These chains dominate the markets in the vast majority of all member states (EY et al. 2014; Hirsch et al. 2021; Sexton and Xia 2018; Swinnen et al. 2021). Particularly in central and northern Europe, on the national level, the accumulated market shares

[6] The food retail sector is defined by NACE codes 47.11 (“Retail sale in non-specialised stores with food, beverages or tobacco predominating”) and 47.2 (“Retail sale of food, beverages and tobacco in specialised stores”).

of the five largest retail chains amount to well above 60 percent (EY et al. 2014). Even though market shares of large retailers are currently smaller in eastern Europe, multi-/national players have entered these markets where they are realizing the highest growth rates (EY et al. 2014). In the near future, it is to be expected that eastern Europe will see a level of concentration similar to the rest of the EU.

Table 1.3 Ten Largest European Food Retailers (2020)

Company	Revenue [€ million]	Stores	Headquarter
Schwarz group	125.3	12,600	Germany
Aldi (Nord and Süd)	106.3	8,826	Germany
Rewe group	63.7	8,369	Germany
Edeka	61.0	3,600	Germany
Tesco	56.67	4,613	United Kingdom
Carrefour	55.37	11,145	France
E.Leclerc	40.9	1,500	France
Les Mousquetaires	40.0	2,659	France
Sainsbury's	36.4	2,297	United Kingdom
Auchan	31.6	4,084	France

Source: Retail-Index (2022)

Another indication for the dominance of large retailers is their persistence in the market. In regard to revenue, nine of the top ten chains have remained at the top for twenty years (2001-2020) (EY et al. 2014; Retail-Index 2022; Statista 2022). Such persistence points to significant entry barriers into the market and/or strong competitiveness among the largest firms in the sector. Table 1.3 provides a list of the ten largest food retailers in Europe in the year 2020. The largest four retailers are German companies, the other six are headquartered in France and the United Kingdom.

1.3.4 Implications for Competition in the Food Supply Chains

Considerable public attention has been paid to the high concentration in the European food manufacturing and food retail subindustries. High levels of concentration may distort competition along the food supply chains. For instance, farmers have repeatedly accused dairy processors to abuse their market power in procurement (Grau and Hockmann 2018). Such accusations have led German cartel authorities to investigate the German milk market (Bundeskartellamt 2009). Within the food sector, it is food processing/manufacturing and retail companies that have been examined most frequently by the European anti-trust agencies (European Competition Network 2012). Of a total of 182 cases opened between 2004 and 2012[7], almost 70 percent were related to these two sectors; whereas only 13 percent have targeted primary producers, i.e., farmers (European Competition Network 2012).

While half of the infringements referred to agreements between horizontal competitors from the same industry, 19 percent referred to price-related anti-competitive agreements in output markets involving successive stages of the respective supply chain (European Competition Network 2012). The European Commission's investigation of a potential collusion between French retailers Les Mosquetaires and Casino represents a recent and prominent example. The two retailers have been accused of coordinating their consumer pricing policies (European Commission 2019). In another case, the European Commission is investigating the potentially anti-competitive behavior of Mondelēz. The company is accused of limiting intra-EU trade of its products leading to excessive consumer prices (European Commission 2021).

As mentioned earlier, high levels of concentration may result in output and/or input market power. However, concentration and the presence of multinational manufacturers, processors and retailers leads to economies of scale implying lower per unit costs, and ultimately, lower consumers prices (Bonnet et al. 2018; Demsetz 1973; Swinnen et al. 2021). In addition, the presence of dominant retail chains may offset the market power multinational manufacturers could potentially exercise (Chen 2003; Dobson and Waterson 1997; Swinnen et al. 2021). This dynamic is referred to as the countervailing-power hypothesis (Galbraith 1954). It has been favored by scholars in the late 1990s and early 2000s. At that time, the concentration in the manufacturing sector was high whereas the consolidation had not proceeded as much in the retailing sector (Swinnen et al. 2021). Increasing concentration in the food retail sector was expected to decrease the market power of the highly concentrated food manufacturing sector.

In addition, concentration does not necessarily cause the exploitation of market power towards suppliers (buyer power) or customers/consumers (seller power) (Sheldon 2017). Still, from the perspective of economic welfare, the abuse of market power entails more severe consequences given that some large firm abuses its market power. If a multinational firm exercises market power, significantly more suppliers and/or customers/consumers will be adversely affected than if a small- or medium-sized firm exercises market power. Therefore, it is important to know which firms exercise market power in order to gain above-normal profits. Moreover, the high

[7] Newer data are not available.

concentration in the food sector makes it challenging for the many small- and medium-sized firms to remain competitive against the large multinational players. Thus, it is of great importance to understand how small fringe food processors and retailers can manage to gain and sustain a competitive advantage vis-à-vis large companies. Likewise, an essential question is how farmers can countervail the power of large manufacturers and retailers to enhance their bargaining position and subsequently their income. Accordingly, this question is a top priority on the policy agenda of the Common Agricultural Policy of the EU (European Commission 2022b).

1.4 Review of the Literature on Market Power in EU Food Supply Chains

Previous research on competition in the EU food sector has, however, focused on the mere identification of market power rather than identifying relevant factors influencing market power. The majority of prior studies has adopted NEIO methodologies in an effort to estimate output price markups above marginal costs or input price markdowns below the marginal value product. The stream of NEIO studies in the food sector starts with Deodhar and Sheldon (1995) and Deodhar and Sheldon (1996) who analyze the German market for banana imports. They find slight departures from perfect competition. In the subsequent years, there have been numerous studies investigating imperfect competition in EU food manufacturing/processing and retailing.

For the food processing industry, Millàn (1999) estimates the degree of imperfect competition in the Spanish food, drink and tobacco industries from 1978 to 1991. Assuming constant returns to scale, the largest markup he identifies amounts to 11 percent, i.e., prices exceed marginal cost by 11 percent. Mérel (2009) researches the French Comté cheese market from 1985 to 2005. The author cannot reject the Nullhypothesis of perfect competition even though the producer organization representing Comté cheese manufacturers had previously been fined by French anti-trust authorities for its supply control scheme. Results for the fluid milk value chain in Italy (1996-2003) suggest that the market does not deviate from perfect competition either (Cavicchioli 2018). By contrast, Perekhozhuk et al. (2013) and Perekhozhuk et al. (2015) find that dairy processors exercise significant buyer power in raw milk procurement in Hungary and Ukraine, respectively. They estimate markdowns of up to 49 percent, i.e., processors undercut raw milk prices by up to 49 percent compared to the purchase prices prevailing in a perfectly competitive setting.

In the food retail sector, Anders (2008) finds negligible output market power in German food retailing in the period 1995-2000. His markups amount to 3.4 and 0.5 percent in selling beef and pork, respectively. On the input side, retailers undercut the competitive prices in beef and pork procurement by 9.33 and 2.53 percent, respectively (Anders 2008). Consequently, retailers' buyer power is larger than their seller power. Between 1993 and 1997, French retailers are found to infringe against perfect competition on the buying side more severely than German retailers (Gohin and Guyomard 2000). Gohin and Guyomard (2000) analyze the purchase prices paid by French retailers to processors of dairy products, meat products and other food products. The study yields that purchase prices of dairy products, meat products and other food products are 16.68, 14.84 and 1.02 percent below those under perfect competition, respectively. For Austrian food retailing, Salhofer et al. (2012) reach comparable results between 1997 and 2008. According to their estimates, retailers undercut the competitive price for dairy products by 19.55 percent in the procurement from dairy processors.

As noted earlier, the NEIO methods rely on a considerable set of assumptions that may not hold in real markets. But, studies on the EU food sector applying the more advanced methods to recover markups introduced by Berry et al. (1995), De Loecker and Warzynski (2012) or Kumbhakar et al. (2012) are scarce. For the supply-side methods, only Čechura et al. (2014) make use of the stochastic frontier approach introduced by Kumbhakar et al. (2012). They analyze buyer and seller power in European food manufacturing industries from 2003 to 2012. Mean markdowns in procuring agricultural products from farmers range from 6.6 percent in dairy processing to 15.8 percent in meat processing. On the output side, the lowest markups are observed in meat processing (8.9 percent) and the largest in dairy processing (12.1 percent) (Čechura et al. 2014), i.e., the results are similar to those obtained using NEIO methods.

For the production function approach (De Loecker and Warzynski 2012), Vancauteren (2013) examines the Dutch food processing sector (1992-2005). He finds that the harmonization of EU food regulations increases the intensity of competition. His markups range from -0.020 in the manufacturing of bakery products to 0.700 in the manufacturing of other food products. These results exceed estimates of the other studies. Curzi et al. (2021) analyze the impact of import competition on markups in the French food processing industry and obtain median markups between 0.140 (manufacture of prepared animal feeds) and 0.410 (manufacture of bakery). In addition, their study yields that import competition decreases markups in French food processing. Last, Lee and van Cayseele (2022) identify the role of cooperatives for markups and markup volatility of farmers and processors. They analyze the Italian fruit and vegetables and dairy sectors between 2007 and 2014. Their results suggest that average markups (mean and median) of dairy farmers and processors are below zero. That means output prices are below marginal costs. Markups in the fruit and vegetable sector are above zero for farmers (median = 0.096) and processors (median=0.121). Besides, membership in a cooperative decreases markups. The results for markup volatility do not indicate any difference between members and non-members of cooperatives (Lee and van Cayseele 2022).

In regards to the application of the demand-side approach (Berry et al. 1995) to compute markups, the literature in EU food value chains is limited as well. Hirsch et al. (2018) estimate the degree of market power of retailers for fluid milk in two Italian cities. They find average markups of 16 percent in Turin and 19 percent in Naples. Numerous other studies of the food sector use the demand-side approach to estimate consumer demand for various food products (e.g., Bonnet et al. 2013; Bonnet and Réquillart 2013; Bonnet and Bouamra-Mechemache 2016; Draganska et al. 2010). However, except for Hirsch et al. (2018), none of these studies identifies markups in Europe.

As the above discussion illustrates, for EU food processing and retailing previous studies suggest only minor deviations from perfect competition in output markets. At the same time, processors exert some degree of market power when procuring from farmers, and retailers exert some degree of market power when procuring from processors. This raises the question how farmers can raise their bargaining power (markups), in negotiations with processors to sustain a livable income. The first article (Chapter 3) addresses this question. I use European dairy farming to examine whether organic production generates a markup premium over conventional farming as an example of a niche market.

A second question derived from the literature is: How can small- and medium-sized companies compete with multi-/national players? The second article (Chapter 4) analyzes the French, Italian and Spanish dairy processing industries to identify the drivers of markups in food processing. The first supplementary article (Chapter S1) elicits the role of firms' export behavior for markups in the French food processing industry. Both articles (Chapter 4 and S1) can serve as guidance for strategic behavior of food processors in dealing with the bargaining power of retailers. The findings are also important for policy makers in the design of targeted competition policies.

Perekhozhuk et al. (2017) point out that results of NEIO approaches are sensitive with regards to the underlying models of supply and demand, the functional form in estimation and even the estimation algorithm. This sensitivity may cause unrealistically small markup estimates. Despite their earlier listed advantages, a study reviewing the assumptions of the advanced supply-side methods, i.e., the production function approach (De Loecker and Warzynski 2012) and the stochastic frontier approach (Kumbhakar et al. 2012) has not been conducted so far. Although both methods require fewer assumptions, whether both approaches lead to the same conclusions remains an open question. This is the objective of the third article (Chapter 5). It compares the assumptions of both approaches. In a case study, the methods are applied empirically to food retailing in five EU countries (France, Finland, Italy, Portugal and Sweden). Thereby, this analysis also provides evidence on the retailers' output market power. Retailers' output market power has, so far, only been covered for narrow geographical markets and specific product categories in the studies by Anders (2008) and Hirsch et al. (2018). Supplementary co-authored article two (Chapter S2) also estimates markups in food retailing. In addition, the article (Chapter S2) investigates the difference in markups between the top retailers, i.e., multi-/national retail chains, and fringe firms in France.

Therefore, the main contributions of this thesis are threefold. First, firm-level markups are connected to firm characteristics to derive recommendations for firm-strategic behavior in sectors that face strong bargaining power by buyers in their output markets. Second, markups are estimated from production data using advanced methods which overcome weaknesses of earlier studies using NEIO frameworks to analyze market power in EU food supply chains. Third, the advanced supply-side methods are compared and evaluated to guide future studies in the methodological choice to estimate markups.

2 Methods

2.1 Microeconomic Principles and Econometrics of Markup Estimation

As previously mentioned, supply-side as well as demand-side methods exist to estimate the percentage markup of output price over marginal cost. While demand-side approaches are well-suited to identify markups at the single product-level, they come with some drawbacks which I briefly discuss in the beginning of this chapter. In addition, the focus of this thesis lies on the identification of firm-level seller market power and its determinants, i.e., a further breakdown of markups by product is beyond the scope of the thesis. Hence, supply-side methods have been applied in all subsequently presented articles that comprise the main part of this dissertation.

First, demand-side methods are very data intensive as the researcher needs information on prices, quantities and other product characteristics determining demand for each product in the market under consideration in each period to estimate a demand function. These data are seldomly available and/or very expensive for an entire country. More importantly, the method requires to define a geographical market in which different products compete and to which the estimated demand functions are unique, such that usually only small regional markets are examined (see e.g., Hirsch et al. 2018; Lopez and Fantuzzi 2012; Lopez and Lopez 2009; Tiboldo et al. 2021). However, the identification of market power is often desirable on a national level to provide meaningful policy recommendations such that analyses of single regional markets only suffice as long as they are representative for an entire country or at least for a large part of it. It is intuitive that this assumption is violated as soon as the regional heterogeneity in a country increases which is particularly the case for large nations like China, India or the United States (US) and also applies to the EU. Even though it would be possible to aggregate markups across an entire country and all products, the computational effort was tremendous. Suppose there is one product, e.g., bananas, for which one would like to calculate the average markup charged by retailers in the U.S. in only one time period assuming that each U.S. county constitutes a market. This would already require the estimation of 3,143 demand functions (one for each county). The number of demand functions for multiple products will then be a multiple of 3,143 so that the demand-side approach becomes infeasible.

That being said, the definition of a relevant geographical market in which buyers purchase and sellers compete is a challenge itself. If markets are defined too small, the choice set of buyers and the competitive environment of sellers will probably be smaller than in reality. If markets are defined too large, buyers will have a larger set of suppliers and/or products than they actually do, and sellers' competition, ceteris paribus, will be assumed to be more intense than it truly is. Both situations will entail biased estimates of the demand function yielding biased estimates of markups.

In contrast, supply-side approaches yield one function for an entire industry or sector. In addition, the availability of data needed for supply-side approaches has increased during the past years. There are different possibilities to uncover markups from cost and production data which I explain below.

Suppose that a firm (i) maximizes its profit and engages in perfect competition in the output market. It will then charge an output price (P_i) that equals its marginal cost (MC_i), i.e., $P_i = MC_i$ (Kumbhakar et al. 2012; Nicholson and Snyder 2008; Varian 2010).[8] As soon as firm i possesses some market power, it will raise prices above the competitive level so that P_i will exceed MC_i ($P_i > MC_i$). The most frequently used measure to assess the degree of market power exercised by a firm is the percentage markup (μ_i) of P_i over MC_i which can be expressed as

$$\mu_i = \frac{P_i - MC_i}{MC_i} \quad \text{or} \quad \rho_i = \frac{P_i}{MC_i} \quad \text{where } \mu_i = \rho_i - 1 \quad . \tag{1}$$

Both measures are frequently used in the literature and do not lead to any different conclusions. μ_i and ρ_i range from minus one and zero, respectively, to infinity. A value below zero (one) for markup μ_i (ρ_i) means that output price P_i undercuts marginal cost MC_i. Under perfect competition, μ_i (ρ_i) is equal to zero (one), i.e., firm i does not exert any market power. When a firm's market power increases, the markup will rise as the firm drives a larger wedge between price and marginal cost. The only two measures needed for the estimation of markups are output price and a firm's marginal cost. While output prices may be readily available in a dataset, it is not possible to observe marginal cost which is the first derivative of the cost function with respect to output quantity. There are different possibilities to elicit marginal costs or approaches that do not require to estimate marginal cost which are illustrated below.

2.1.1 The Cost Function Approach

The possibly most intuitive approach -which is applied in article one (Chapter 3)- is to estimate a cost function and taking its first derivative with respect to output to arrive at marginal cost.

[8] In fact, the optimality condition in a profit maximization framework yields that firms equal marginal revenue an marginal cost. However, under perfect competition, i.e., if firms are price takers, marginal revenue is equal to the product price.

For this purpose, I consider a firm's short-run cost minimization problem. Note that one could also use the full profit function which in turn requires to take a stand on the type of competition that firms engage in. Instead, looking at cost minimization as part of the profit maximization problem suffices to estimate markups with minimal assumptions (Basu 2019; De Loecker and Warzynski 2012). The firm's variable cost function (C) is given by

$$C_i = \boldsymbol{W}_{\boldsymbol{i}}'\boldsymbol{X}_{\boldsymbol{i}} + \boldsymbol{R}_{\boldsymbol{i}}'\boldsymbol{K}_{\boldsymbol{i}} \;\; s.t. \;\; f(\boldsymbol{X}_{\boldsymbol{i}}, \boldsymbol{K}_{\boldsymbol{i}}) = Y_i \quad . \tag{2}$$

$\boldsymbol{W}$ is a vector of prices of variable inputs $\boldsymbol{X}$, and $\boldsymbol{R}$ is a vector of prices of quasi-fixed or often referred to as dynamic inputs $\boldsymbol{K}$. Variable inputs can be freely adjusted in the short-run. For changing the use of quasi-fixed/dynamic inputs, the firm incurs adjustment cost. Let Y denote the quantity of output produced subject to the production technology which is represented by the production function $f(.)$. C is non-decreasing in Y and $\boldsymbol{W}$ (costs cannot decrease for increments in output quantity or input prices) and is linearly homogeneous in $\boldsymbol{W}$ (an a-fold increase in all variable inputs' prices entails an a-fold increase in costs) (Coelli et al. 2005). In addition, C is concave in each element of $\boldsymbol{W}$ implying that the percentage increase in costs is smaller than the percentage increase in one of the variable input's prices given that this input price rises. The firm will substitute a certain share of that input by other inputs. The Lagrangian (L) for cost minimization can be written as:

$$L_i = \boldsymbol{W}_{\boldsymbol{i}}'\boldsymbol{X}_{\boldsymbol{i}} + \boldsymbol{R}_{\boldsymbol{i}}'\boldsymbol{K}_{\boldsymbol{i}} - \lambda_i(f(\boldsymbol{X}_{\boldsymbol{i}}, \boldsymbol{K}_{\boldsymbol{i}}) - Y_i) \tag{3}$$

where λ is the Lagrange multiplier. Setting the derivatives of L with respect to $\boldsymbol{X}$ and λ equal to zero provides the first-order conditions of the optimization problem. The contingent input demand functions can be obtained by solving the system of equations for the variable input quantities. Substituting these contingent input demand functions into equation (2) yields the firm's minimum cost function $C(Y, \boldsymbol{W}, \boldsymbol{K})$. The first derivative of $C(Y, \boldsymbol{W}, \boldsymbol{K})$ with respect to Y will be the marginal cost function that allows to compute markups.

To be able to estimate $C(Y, \boldsymbol{W}, \boldsymbol{K})$, it is necessary to approximate the true but unknown cost function by imposing a functional form on $C(Y, \boldsymbol{W}, \boldsymbol{K})$. In that regard, the trans-log function provides the highest flexibility (Christensen et al. 1973; Perekhozhuk et al. 2017) and is widely applied (e.g., Alem et al. 2019; Curzi et al. 2021; De Loecker et al. 2020; Hirsch et al. 2020;

Wimmer and Sauer 2020) such that it is used in all articles comprising this thesis. The translog cost function can be written as[9]

$$lnC = \alpha_Y lnY + 0.5\, \alpha_{YY} lnYlnY + \sum_{j=1}^{J} \beta_j lnW_j + 0.5\, \sum_{j=1}^{J} \sum_{k=1}^{K} \beta_{jk} lnW_j lnW_k + \sum_{j=1}^{J} \gamma_{Yj} lnY lnW_j + \sum_{r=1}^{R} \upsilon_r lnK_r + 0.5 \sum_{r=1}^{R} \sum_{s=1}^{S} \upsilon_{rs} lnK_r lnK_s + \sum_{r=1}^{R} \eta_{Yr} lnY lnK_r + \sum_{j=1}^{J} \sum_{r=1}^{R} \omega_{jr} lnW_j lnK_r \quad , \tag{4}$$

where α, β, γ, υ, η and ω are parameters to estimate. j and k, and r and s represent subscripts for variable and quasi-fixed/dynamic inputs, respectively. The number of parameters in equation (4) can become quite large with an increasing number of inputs posing a challenge for precise identification. However, it is possible to use Shepard's Lemma to derive the contingent input demand function from equation (4). The first derivative of $C(.)$ with respect to a variable's input price equals the contingent input demand (Nicholson and Snyder 2008):

$$\left(\frac{\partial C}{\partial W_j}\right)_i = X_{ij} \quad . \tag{5}$$

One can then substitute $\partial C = \partial lnC \cdot C$ and $\partial W_j = \partial lnW_j \cdot W_j$ into (5) such that the input demand functions are transformed into equations of each variable input's share in total variable costs:

$$\left(\frac{\partial lnC}{\partial lnW_j}\right)_i = \frac{W_{ij}X_{ij}}{C_i} \quad . \tag{6}$$

As the j cost shares (equation (6)) are available when estimating the cost function (equation (4)) anyway, it is possible to estimate the share equations along with the cost function as a system of equations in, e.g., a seemingly unrelated regression framework (Zellner 1962). Thereby, information is added to the model without increasing the number of parameters.

2.1.2 The Stochastic Frontier Approach

As an alternative to the cost function approach, Kumbhakar et al. (2012) have introduced the stochastic frontier approach. Again, starting from the inequality of price and marginal cost, i.e., $P_i > MC_i$, one can multiply both sides of this inequality by the ratio of firm output Y_i over total variable cost C_i such that:

$$P_i \frac{Y_i}{C_i} > MC_i \frac{Y_i}{C_i} = \left(\frac{\partial C}{\partial Y}\right)_i \frac{Y_i}{C_i} = \left(\frac{\partial lnC}{\partial lnY}\right)_i \quad . \tag{7}$$

[9] The firm subscript i is omitted to ensure readability of the equation.

To turn the inequality into an equality, Kumbhakar et al. (2012) add a non-negative term u_i to the right hand side of equation (7):

$$\frac{P_iY_i}{C_i} = \left(\frac{\partial lnC}{\partial lnY}\right)_i + u_i \quad , \quad u_i \geq 0 \quad . \tag{8}$$

The one-sided term u_i captures the markup component by which the ratio of revenue (P_iY_i) over variable costs (C_i) exceeds firm i's cost elasticity $\left(\frac{\partial lnC}{\partial lnY}\right)_i$. Transforming equation (8) allows to derive the markup of price over marginal cost. First, divide both sides of equation (8) by the cost elasticity $\left(\frac{\partial lnC}{\partial lnY}\right)_i$ such that

$$\frac{P_iY_i}{C_i}\left(\frac{\partial Y}{\partial C}\right)_i \frac{C_i}{Y_i} = 1 + \frac{u_i}{\left(\frac{\partial lnC}{\partial lnY}\right)_i} \quad . \tag{9}$$

Subsequently, the left-hand side of equation (9) can be simplified to the ratio of price P_i over marginal cost, i.e., $\left(\frac{\partial C}{\partial Y}\right)_i$ which is the same as ρ_i. To arrive at μ_i, subtract the ratio of $\left(\frac{\partial C}{\partial Y}\right)_i$ over $\left(\frac{\partial C}{\partial Y}\right)_i$ on both sides of equation (9) yielding:

$$\frac{P_i - \left(\frac{\partial C}{\partial Y}\right)_i}{\left(\frac{\partial C}{\partial Y}\right)_i} = \frac{P_i - MC_i}{MC_i} = \frac{u_i}{\left(\frac{\partial lnC}{\partial lnY}\right)_i} = \mu_i \quad . \tag{10}$$

As can be seen in equation (10), the percentage markup of price over marginal cost is obtained when dividing the markup term u_i by the cost elasticity $\left(\frac{\partial lnC}{\partial lnY}\right)_i$. The advantage of the stochastic frontier approach compared to the cost function approach is that only the cost elasticity has to be estimated and not the entire cost function from equation (4). The first derivative of equation (4) with respect to lnY_i provides the estimable cost elasticity:

$$\left(\frac{\partial lnC}{\partial lnY}\right)_i = \alpha_Y + \alpha_{YY} lnY_i + \sum_{j=1}^{J} \gamma_{Yj} lnW_{ij} + \sum_{r=1}^{R} \eta_{Yr} lnK_{ir} \quad . \tag{11}$$

Given that information on input prices, output, revenue and total variable cost is available, the function to estimate is:

$$\frac{P_iY_i}{C_i} = \alpha_Y + \alpha_{YY} lnY_i + \sum_{j=1}^{J} \gamma_{Yj} lnW_{ij} + \sum_{r=1}^{R} \eta_{Yr} lnK_{ir} + u_i \quad . \tag{12}$$

Adding a two-sided error term v_i to the right-hand side of equation (12) operationalizes the model such that it can be estimated using stochastic frontier techniques. The two-sided error term v_i is usually assumed to follow a normal distribution with mean zero and variance σ_v^2, i.e.,

$v \sim N(0, \sigma_v^2)$ (Hirsch et al. 2020; Kumbhakar 2011; Kumbhakar et al. 2012). For the one-sided term u_i, the most frequently used distribution is the half-normal so that $u \sim N^+(0, \sigma_u^2)$ (e.g., Amsler et al. 2016; Badunenko and Kumbhakar 2016; Kumbhakar et al. 2012) which is also adopted in the second and third article (Chapter 4 and 5). The model can then be estimated by means of maximum likelihood estimation.

An issue often arising in the context of firm-level data are missing input prices. In such cases, Kumbhakar et al. (2012) show that one can use the duality of the cost and the transformation function to infer markups using input quantities instead of input prices. This approach is also followed in articles number two and three. Based on the Envelope theorem, the first-order condition for cost minimization is given by (Kumbhakar et al. 2012):

$$\left(\frac{\partial lnC}{\partial lnY}\right)_i = -\left(\frac{\partial lnh(.)}{\partial lnY}\right)_i / \sum_j \left(\frac{\partial lnh(.)}{\partial lnX_j}\right)_i \quad , \tag{13}$$

where h denotes the transformation function. Imposing homogeneity of degree one on the transformation function, i.e., $\sum_j \left(\frac{\partial lnh(.)}{\partial lnX_j}\right)_i = -1$ (Kumbhakar 2011), simplifies equation (13) to:

$$\left(\frac{\partial lnC}{\partial lnY}\right)_i = \left(\frac{\partial lnh(.)}{\partial lnY}\right)_i \quad . \tag{14}$$

Choosing a trans-log form for the transformation function and applying the correct normalizations allows to express $h(.)$ as an input distance function (Kumbhakar et al. 2012; Kumbhakar 2011):

$$\begin{aligned} lnX_1 = {} & \alpha_Y lnY + 0.5\, \alpha_{YY} lnY lnY + \sum_{j=2}^{J} \beta_j \ln(X_j/X_1) + 0.5 \sum_{j=2}^{J} \sum_{k=2}^{K} \beta_{jk} \ln(X_j/X_1) ln(X_k/X_1) + \\ & \sum_{j=2}^{J} \gamma_{Yj} lnY\, ln(X_j/X_1) + \sum_{r=1}^{R} \upsilon_r lnK_r + 0.5 \sum_{r=1}^{R} \sum_{s=1}^{S} \upsilon_{rs} lnK_r lnK_s + \sum_{r=1}^{R} \eta_{Yr} lnY\, lnK_r + \\ & \sum_{j=2}^{J} \sum_{r=1}^{R} \omega_{jr} ln(X_j/X_1) lnK_r \quad . \end{aligned} \tag{15}$$

Taking the first derivative of equation (15) with respect to log output delivers a different formulation for the cost elasticity resembling equation (11) but uses input quantities instead of input prices (Kumbhakar et al. 2012):

$$\left(\frac{\partial lnX_1}{\partial lnY}\right)_i = \alpha_Y + \alpha_{YY} lnY_i + \sum_{j=2}^{J} \gamma_{Yj} ln(X_{ij}/X_{i1}) + \sum_{r=1}^{R} \eta_{Yr} lnK_{ir} = \left(\frac{\partial lnC}{\partial lnY}\right)_i \quad . \tag{16}$$

The input distance function is non-decreasing and concave in variable input quantities and non-increasing in output and quasi-fixed/dynamic inputs (Coelli et al. 2005). Markups can be calculated after estimation according to equation (10) using the predicted value of equation (16). Hence, information on input quantities, output quantity, total revenue and total variable cost suffice to compute markups based on the stochastic frontier approach without the need to know input prices.

2.1.3 The Production Function Approach

The third approach to estimate market power is based on the estimation of a production function. It is therefore also referred to as the production function approach and is utilized in article three (Chapter 5) as well as the two supplementary articles (Chapter S1 and S2). Again starting from the Lagrangian for cost minimization (equation (3)), the first derivatives of L with respect to the variable input quantities are:

$$\left(\frac{\partial L}{\partial X_j}\right)_i = P_i - \lambda_i \left(\frac{\partial f(.)}{\partial X_j}\right)_i = 0 \quad . \tag{17}$$

Since $\left(\frac{\partial L}{\partial Y}\right)_i = \lambda_i$, marginal cost of production at a given level of output is equal to λ (De Loecker and Warzynski 2012). Solving equation (17) for $\left(\frac{\partial f(.)}{\partial X_j}\right)_i$ and multiplying both sides by the ratio of input j's quantity X_j over output Y leads to the an expression for the output elasticity with respect to variable input j (De Loecker and Warzynski 2012):

$$\left(\frac{\partial f(.)}{\partial X_j}\right)_i \frac{X_{ij}}{Y_i} = \frac{1}{\lambda_i}\frac{W_{ij}X_{ij}}{Y_i} \quad . \tag{18}$$

The last step to obtain an expression for markup is to multiply both sides of equation (18) by the ratio of P over P which is equal to:

$$\left(\frac{\partial f(.)}{\partial X_j}\right)_i \frac{X_{ij}}{Y_i} = \frac{P_i}{\lambda_i}\frac{W_{ij}X_{ij}}{P_i Y_i} \quad . \tag{19}$$

As λ equals marginal cost, P divided by λ provides the definition of markup ρ. Plugging ρ into equation (19) and solving for ρ gives:

$$\rho_i = \left(\frac{\partial lnY}{\partial lnX_j}\right)_i \frac{P_i Y_i}{W_{ij}X_{ij}} \quad . \tag{20}$$

As noted earlier the subtraction of one from ρ yields μ, i.e., the percentage markup of price over marginal cost. All one is left with consists in the estimation of a production function to derive the output elasticity. Consistent with the beforehand approaches and applied in many of empirical studies (e.g., Autor et al. 2020; De Loecker et al. 2020; Gandhi et al. 2020), a translog representation of the production function ($f(.)$) is adopted by which inputs X and K are transformed into output Y:

$$lnY_i = \sum_{j=1}^{J} \beta_j lnX_{ij} + \sum_{r=1}^{R} \beta_r lnK_{ir} + \sum_{j=1}^{J} \sum_{k=1}^{K} \beta_{jk} lnX_{ij} lnX_{ik} + \sum_{r=1}^{R} \sum_{s=1}^{S} \beta_{rs} lnK_{ir} lnK_{is} + \sum_{j=1}^{J} \sum_{r=1}^{R} \beta_{jr} lnX_{ij} lnK_{ir} + \omega_i \quad . \tag{21}$$

In this case, ω_i denotes a firm's productivity which may be known to the firm but is unknown to the researcher (Ackerberg et al. 2015; Levinsohn and Petrin 2003; Olley and Pakes 1996). Since firms may have information on how productive they are, e.g., due to management skills, average breakdown times of machinery or soil quality in the case of farmers, they will also likely make decisions on the quantity of inputs used in the production process based on their productivity (Ackerberg et al. 2015; Bond et al. 2021; Gandhi et al. 2020). The most prominent way to recover the unobserved productivity from observables in contemporary research is the control function approach by Ackerberg et al. (2015) using a firm's intermediate input demand to proxy for productivity. The procedure is presented in detail in article three (Chapter 5) and the two supplementary articles (Chapter S1 and S2).

2.2 Markups and Firm Characteristics

The identification of variables impacting markups requires further analytical steps. The general framework in all articles (except for article three) is:

$$\mu_{it} = \boldsymbol{\delta}' \boldsymbol{Z_{it}} + \boldsymbol{\varepsilon_{it}} \quad . \tag{22}$$

where $\boldsymbol{\delta}$ is a vector of coefficients to estimate and $\boldsymbol{Z}$ denotes a vector of covariates that are correlated and some of them also causally related with markups. ε is an idiosyncratic error term which is assumed to be independently and identically distributed. t is a subscript for the year since all five articles use panel data such that there are several observations available per firm. The basic estimator to obtain estimates of $\boldsymbol{\delta}$ is ordinary least squares (OLS). An issue arising related to OLS for the analysis of panel data is the presence of unobserved heterogeneity jointly affecting μ and $\boldsymbol{Z}$. The unobserved heterogeneity leads to biased estimates of $\boldsymbol{\delta}$ because $\boldsymbol{Z}$ will be correlated with ε (Wooldridge 2010). Managerial ability of a firm's manager is a classic example causing such endogeneity. For instance, suppose that firm size is one of the variables contained in $\boldsymbol{Z}$. A better manager may be a better negotiator entailing larger μ. At the same time, causes the firm to expand such that the firm's size grows. OLS will then ascribe the positive effect of managerial ability on markups at least partly to firm size which is wrong. The parameter estimate for firm size will be biased upwards (Wooldridge 2010). The fixed effects estimator is well suited in such cases to deal with unobserved time invariant heterogeneity between firms. By adding firm-specific constants (θ) to equation (22), all unobserved time invariant heterogeneity due to, e.g., managerial ability, location or soil quality will be removed (Wooldridge 2010):

$$\mu_{it} = \theta_i + \boldsymbol{\delta}'\boldsymbol{Z_{it}} + \boldsymbol{\varepsilon_{it}} \quad . \tag{23}$$

If there was only time invariant unobserved heterogeneity affecting markups and firm characteristics, the fixed effects model will provide unbiased estimates of $\boldsymbol{\delta}$. In the presence of time variant unobserved heterogeneity causing changes in markups and other firm characteristics included in $\boldsymbol{Z}$, the estimates will still be biased. In these cases, an instrumental variable estimator can be applied to resolve the problems of endogeneity. The idea is to use exogenous variables that are correlated with $\boldsymbol{Z}$ but uncorrelated with μ. These exogenous variables serve as instruments for the endogenous $\boldsymbol{Z}$ in (22) or (23). That is, they replace the original endogenous variable in the estimation. The instruments must fulfill the exclusion restriction so that they only influence μ through $\boldsymbol{Z}$ and have no direct impact on μ (Wooldridge 2010). Usually, a first stage regression is estimated to obtain predicted values of an endogenous variable Z:

$$Z_{it} = \boldsymbol{\tau}'\boldsymbol{Z_{it}^{*}} + \boldsymbol{\varepsilon_{it}} \quad , \tag{24}$$

where $\boldsymbol{\tau}$ are parameters to be estimated and $\boldsymbol{Z}^{*}$ are the instruments for Z including the exogeneous variables from (22)/(23). The predicted values ($\hat{Z}$) of Z replace the endogenous explanatory variables in (22)/(23) yielding unbiased estimates of $\boldsymbol{\delta}$.

Besides, least squares estimates will be unreliable in the presence of a considerable number of extreme markup values or non-normally distributed markups. It is possible to use quantile regression to alleviate this problem (Koenker and Bassett, JR. 1978). Quantile regression does not provide estimates of the conditional mean but estimates of the conditional quantile such as the median. It can also be extended by fixed effects and is able to account for endogeneity (Powell 2022).

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3 Markups, Organic Agriculture and Downstream Concentration at the Example of European Dairy Farmers

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Authors' Contribution: Maximilian Koppenberg developed the research objectives, the methodology, analyzed the data and wrote the manuscript.

Abstract

A competitive environment, highly concentrated processing and retailing sectors as well as increasing decoupling of direct payments from production volumes and the area under cultivation incentivizes farmers to find alternative ways to improve their bargaining position towards downstream companies. This article explores the possibilities of organic agriculture to enhance the bargaining power of farmers along with the role of concentration in downstream industries. Using a dataset with more than 200,000 observations from approximately 40,000 dairy farms, I estimate markups of price over marginal cost of cows' milk production as a measure of market power in 18 European countries. The results show that organic farmers achieve a significant markup premium over conventional farmers. With increasing market shares of organic milk in total milk production markups of conventional farmers diminish whereas those of organic farmers are unaffected. While farm-level markups decrease with increasing market shares of medium-sized dairy processors, they rise with the market shares of large processors. The presence of large multinational retail chains shows an adverse impact on farmers' markups.

3.1 Introduction

Farmers are often seen as being exposed to market power exercised by downstream companies in food supply chains (Sexton 2013; Sexton and Xia 2018). This may cause farm-gate prices to be below the competitive level, thereby reducing farmers' income. While the financial support of farmers still accounts for 36 percent (=€59 billion) of the overall EU budget, the subsidies get stepwise decoupled from production volumes and the area under cultivation, and are increasingly bound to the provision of ecosystem services (European Commission 2020a). This development reinforces the incentive for farmers to seek ways achieving higher prices and circumvent downstream market power. One of these ways is organic agriculture generating price premia over conventional products (Crowder and Reganold 2015). However, organic agriculture also entails higher average costs of production compared with conventional agriculture (European Commission 2013; Uematsu and Mishra 2012). Hence, whether organic farmers have an improved bargaining position towards downstream companies or higher prices only result from increased production costs, remains an open question.

I investigate farm-level seller market power of dairy farmers and its determinants in Europe to shed light on the relationship between market power and organic production. Milk production represents a good case study since dairy processors have been accused repeatedly to abuse market power in raw milk procurement (Di Marcantonio et al. 2020; Grau and Hockmann 2018). I calculate farmers' markups of price over marginal cost as an indicator of market power estimating a translog cost function. Further, I identify determinants of markups with a particular emphasis on markup differences between conventional and organic farms. My data cover the years 2004-2017 and 18 European countries with more than 200,000 observations comprised by approximately 40,000 farms. My results are of particular interest for farmers who seek improving their bargaining position in price negotiations with downstream companies, or achieving higher prices in direct marketing to consumers. Moreover, the insights generated by this study may guide policy makers in adapting the Common Agricultural Policy towards more targeted measures in supporting farmers.

The theory of niche markets suggests that firms operating in small markets realize higher margins as they offer differentiated products (Ilbery and Kneafsey 1999; Smallbone Shaw et al. 1999). Despite the fact that sales of organic food products along with the area under production have experienced a steep incline during the past two decades (Reganold and Wachter 2016), the area under organic production has contributed less than 10 percent to the total farm area in approximately 70 percent of the European countries in 2017 (Eurostat 2020d). The shares of organic in total milk production are even smaller (Eurostat 2020b; Eurostat 2020e) such that the market for organically produced milk must still be considered as a niche market. In that regard, Bonnet and Bouamra-Mechemache (2016) find that an organic label improves the bargaining position of dairy processors towards retailers compared to unlabeled products in the French fluid milk market, resulting in margins of organic milk exceeding those of conventional milk by 25 percentage points.

Nevertheless, this does not necessarily imply that organic farmers also have a better bargaining position towards processors since processors have been found to exercise input market power in raw milk procurement from farmers. Čechura et al. (2014) estimate an average markdown of the input price below the marginal value product of raw milk of 6.6 percent (2003-2012). Grau and Hockmann (2018) estimate conjectural elasticities[10] of dairy processors in purchasing raw milk from farmers between 0.04 and 0.07 in Germany for 2010-2011 indicating a mild departure from perfect competition. Therefore, it may be that processors absorb a certain share of the organic price premium, and organic farmers' bargaining position may be the same as for conventional farmers.

Compared with conventional agriculture, organic farming entails a larger share of land, labor and capital costs in total costs due to restrictions on the use of synthetic fertilizer and the ban of synthetic pesticides leading to a larger importance of mechanical weed control and higher requirements regarding land to produce feed (European Commission 2013; Heinrichs et al. 2021; Uematsu and Mishra 2012). The extensive production system of organic dairy farming also entails milk yields that are 4 to 30 percent smaller than for conventional dairying depending on the country (European Commission 2019).

Another important difference between organic and conventional dairy farming is the role of international competition. In 2019 for instance, less than 0.1 percent of total dairy imports were certified as organic (European Commission 2021b; European Commission 2022). In contrast, considerable quantities of conventional dairy products are traded internationally entailing spatial price transmission between countries on a global level (Fousekis and Trachanas 2016; Newton 2016). When it comes to organic food products, however, consumers prefer short transport distances (Pedersen et al. 2018). Besides, there is a lack of demand for products with longer shelf life made from organic milk such as milk powder also hindering trade of organic

[10] The conjectural elasticity ranges from zero to one. A value of zero indicates perfect competition and a value of one a monopsony.

dairy products (European Commission 2019). Therefore, trade plays a negligible role so that the vast majority of organic dairy consumption is produced domestically (European Commission 2021b), and prices for organic milk are unlikely to be affected by price changes of organic products in foreign markets. Along these lines, Curzi et al. (2021) analyze the French food processing industry and find that decreasing levels of import competition in output markets lead to higher markups. Therefore, one may expect that this is also the case for organic agriculture. Despite the absence of direct international competition concerning organic dairy products, there has been evidence that price changes for conventional milk also affect the demand for organic milk (Alviola IV and Capps Jr. 2010; Jonas and Roosen 2008), i.e., prices on international markets may also affect the price for organic milk via the cross-price elasticity. However, there is no study empirically investigating the market power of dairy farmers and the role of organic agriculture in improving farmers' bargaining power, yet.

First, I contribute to the literature on market power in food supply chains by estimating farm-level markups of output price over marginal cost of milk production in 18 European countries. Second, estimating markups on the farm-level enables me to identify farm-specific drivers of markups. In that respect, organic production is of key interest. Third, I examine whether markups vary for changing market shares of organic milk in total milk. Thereby, I provide evidence of whether the increased margins in niche markets are robust when the size of the niche varies. Further, I analyze how markups relate to farm size, which helps to understand farm structural change in Europe. Last, I explore the impact of concentration in downstream industries on farm-level markups since concentration in food processing and retailing is widely perceived as being responsible for declining prices of agricultural outputs (e.g., Crespi et al. 2012; Sexton and Xia 2018).

The rest of the paper is structured as follows. In the next section, I illustrate the theoretical basis for the markup estimation. This is followed by the empirical strategy to uncover markups. Subsequently, I derive my hypotheses with respect to the relationship of markups and farm characteristics. Thereafter, I present the data used in the analysis and discuss the results. Finally, I conclude by deriving the implications of my findings.

3.2 Theoretical Considerations

Under perfect competition in output markets, an output's price (P) equals its marginal cost (MC). The prevalent measure to capture deviations from competitive pricing is the ratio of P over MC, also known as markup (μ) (e.g., Bonanno et al. 2018; De Loecker et al. 2020;

Kumbhakar et al. 2012). Assuming that prices will not become negative, μ ranges from zero to infinity while $\mu = 1$ indicates perfect competition. For $\mu > 1$, the farmer possesses oligopolistic or monopolistic market power. The further μ increases, the closer is the pricing to that of a monopoly. Values for $\mu < 1$ are also admissible. Farmers might be forced to sell below MC due to the perishability of milk or if the delivered milk did not suffice the qualitative requirements of the dairy processor.

To calculate markups, I need to obtain an estimate of MC, which I derive from an estimated cost function.[11] However, accuracy of the estimated cost function depends on the behavioral assumption made. The economic behavior of dairy farmers can be represented by either cost minimization or profit maximization. Cost minimization implies that farmers choose their deployment of variable inputs for given levels of output and quasi-fixed inputs such that the total cost are minimum. In contrast, profit maximization entails free adjustment of both variable inputs along with output at given levels of quasi-fixed factors. In the case of dairy farming in the EU, the milk quota system has been in place for a long period (1984-2015). The quota system meant to stabilize farm-gate milk prices by allocating a certain amount of milk production to each dairy farmer. If a farmer produced more than the allocated quota, he/she had to pay a levy such that production beyond the quota volume was infeasible. Despite the possibility to trade quota certificates, the certificates have been very costly for the buyer (Wieck and Heckelei 2007). Therefore, I assume that farmers could not freely adjust their milk output under the quota regime. Since my data cover the years 2004-2017, i.e., the quota system was in place for most of the years, I follow previous studies on dairy farming in Europe and assume that dairy farmers are cost minimizing as they take milk output quantities as given (e.g., Alem

[11] There are several other methods to estimate markups. The production function approach introduced by De Loecker and Warzynski (2012) is one of them where one uses input expenditures, revenue, and an estimate of the output elasticity to recover markups. However, for joint production processes with multiple outputs such as agriculture, it is not possible to display the technology using single production functions as they are not able to depict the dependencies of the different outputs (Hall 1973; Lence and Miller 1998). Alternatively, it would be possible to use the stochastic frontier approach introduced by Kumbhakar et al. (2012) which comes at the cost of assuming markups being strictly larger than or equal to one. But, since farmers receive a considerable amount of subsidies, they may continue their operations even though they incur markups being smaller than one (Caselli et al. 2018; Koppenberg and Hirsch 2022). Last, demand side approaches to estimate markups (Berry et al. 1995; Nevo 2001) are not possible to apply in my case since the necessary data are not available. Therefore, I abstained from using one of the other approaches.

et al. 2019; De Frahan et al. 2011; Pierani and Rizzi 2003;Wieck and Heckelei 2007).[12] The corresponding farmers' short-run variable cost function (C) is given by:

$$C = \boldsymbol{W}'\boldsymbol{X} + \boldsymbol{R}'\boldsymbol{K} \quad s.t. \quad f(\boldsymbol{X}, \boldsymbol{K}) = \boldsymbol{Q} \tag{1}$$

where $\boldsymbol{W}$ is a vector of prices for the variable inputs and $\boldsymbol{X}$ denotes the vector of the quantities of variable inputs. $\boldsymbol{R}$ and $\boldsymbol{K}$ are price and quantity vectors of quasi-fixed factors, respectively. Quasi-fixed factors cannot be adjusted in the short-run, i.e., farmers minimize cost conditional on the quantities chosen for $\boldsymbol{K}$. $\boldsymbol{Q}$ is a vector of output quantities, and the technology by which inputs are transformed into outputs is represented by $f(.)$. The cost function is non-decreasing in outputs ($\boldsymbol{Q}$) and variable input prices ($\boldsymbol{W}$), and is linearly homogeneous in input prices (Coelli et al. 2005). Linear homogeneity entails a b-fold increase in costs for an increase in all variable input prices by factor b. Moreover, C is concave in each W implying that, for a given relative increment in some variable input's price (W), costs will increase to a lesser extent due to input substitutability. The Lagrangian (L) for the short-run cost minimization problem is:

$$L = \boldsymbol{W}'\boldsymbol{X} + \boldsymbol{R}'\boldsymbol{K} - \lambda(f(\boldsymbol{X}, \boldsymbol{K}) - \boldsymbol{Q}) \tag{2}$$

where λ denotes the Lagrange multiplier. Taking the first derivatives with respect to the variable input quantities along with λ and setting them equal to zero yields the first-order conditions (FOC) of the optimization problem. Solving the system of equations for the variable input quantities, I obtain the contingent input demand functions. These can be substituted into (1) to obtain the farmers' short-run minimum cost function $C(\boldsymbol{Q}, \boldsymbol{W}, \boldsymbol{K})$, which is the target function to estimate.

3.3 Empirical Implementation

I approximate the true short-run minimum cost function using a multi-input, multi-output translog cost function, which is the most flexible functional form (e.g., Christensen et al. 1973) and widely applied (Alem et al. 2019; Renner et al. 2014; Wimmer and Sauer 2020). Even though some studies also have used simpler specifications, e.g., by assuming linear marginal cost curves (Kinoshita et al. 2006; Sexton et al. 2007), the majority of earlier research on dairy farming has found that simple technology specifications such as Cobb-Douglas are to be rejected against more complex functions forms (Alem et al. 2019; Atsbeha et al. 2012; Moreira

[12] Note that this assumption is to be relaxed when studying other geographical areas since farmers could adjust their output strategically as a response to outputs of other farmers or as a reaction to price changes in international markets.

and Bravo-Ureta 2010; Tauer 2016). The multi-input multi-output translog cost function is given by

$$lnC = \kappa_0 + \sum_{l=1}^{L} \alpha_l lnQ_l + 0.5 \sum_{l=1}^{L} \sum_{m=1}^{M} \alpha_{lm} lnQ_l lnQ_m + \sum_{j=1}^{J} \beta_j lnW_j + 0.5 \sum_{j=1}^{J} \sum_{k=1}^{K} \beta_{jk} lnW_j lnW_k + \sum_{l=1}^{L} \sum_{j=1}^{J} \gamma_{lj} lnQ_l lnW_j + \sum_{r=1}^{R} \upsilon_r lnK_r + 0.5 \sum_{r=1}^{R} \sum_{s=1}^{S} \upsilon_{rs} lnK_r lnK_s + \sum_{l=1}^{L} \sum_{r=1}^{R} \eta_{lr} lnQ_l lnK_r + \sum_{j=1}^{J} \sum_{r=1}^{R} \omega_{lr} lnW_j lnK_r + \sum_{t=1}^{T} \delta_t Tech_t + \varepsilon \,. \tag{3}$$

$\alpha, \beta, \gamma, \delta, \upsilon, \eta, \omega$ and κ_0 are parameters to estimate, and l and m (j and k, r and s) are subscripts for outputs (variable inputs, quasi-fixed inputs). The $L = 3$ outputs are (1) milk, (2) meat and (3) crop output other than feedstuff[13]. The $J = 3$ variable inputs are (1) purchased feed, (2) energy and (3) seeds, fertilizer and plant protection products. Last, the $R = 6$ quasi-fixed inputs comprise (1) unpaid labor[14], (2) paid labor, (3) land, (4) capital and (5) dairy cows and (6) other livestock. Note that I use a panel data set but omit subscripts for farm (i) and year (t) to keep the equations concise. $Tech$ is a set of year dummies accommodating for Hicks-neutral technical change and ε is an error term capturing optimization and measurement error.

The translog cost function is symmetric meaning that $\alpha_{lm} = \alpha_{ml}$, $\beta_{jk} = \beta_{kj}$ and $\upsilon_{rs} = \upsilon_{sr}$ for all $l, m, j, k, r\ and\ s$ (Coelli et al. 2005). With respect to the regularity conditions, linear homogeneity of the cost function requires the following parametric restrictions: $\sum_{j=1}^{J} \beta_j = 1$, $\sum_{k=1}^{K} \beta_{jk} = \sum_{l=1}^{L} \gamma_{lj} = \sum_{r=1}^{R} \omega_{jr} = 0$ (Alem et al. 2019; Liu et al. 2014; Ray 1982). I impose the restrictions a priori by normalizing (3) by one variable input price, i.e., I divide C and the variable input prices by one variable input price such that (3) turns into:

$$ln(\frac{C}{W_J}) = \kappa_0 + \sum_{l=1}^{L} \alpha_l lnQ_l + 0.5 \sum_{l=1}^{L} \sum_{m=1}^{M} \alpha_{lm} lnQ_l lnQ_m + \sum_{j=1}^{J-1} \beta_j ln\widetilde{W}_j + 0.5 \sum_{j=1}^{J-1} \sum_{k=1}^{K-1} \beta_{jk} ln\widetilde{W}_j ln\widetilde{W}_k + \sum_{l=1}^{L} \sum_{j=1}^{J-1} \gamma_{lj} lnQ_l ln\widetilde{W}_j + \sum_{r=1}^{R} \upsilon_r lnK_r + 0.5 \sum_{r=1}^{R} \sum_{s=1}^{S} \upsilon_{rs} lnK_r lnK_s + \sum_{l=1}^{L} \sum_{r=1}^{R} \eta_{lr} lnQ_l lnK_r + \sum_{j=1}^{J-1} \sum_{r=1}^{R} \omega_{jr} ln\widetilde{W}_j lnK_r + \sum_{t=1}^{T} \delta_t Tech_t + \varepsilon \tag{4}$$

[13] An aggregation into one single output is not feasible for the scope of my study as I am particularly interested in the markups for milk production. Creating a compound output measure would lead to an overall markup across all outputs, i.e., milk, meat and crops. I would then not be able to separate the different markups for each output. A further aggregation of outputs is hence inappropriate (Mosheim and Knox Lovell 2009).

[14] If unpaid labor were a variable input, I would have to assign a shadow price to unpaid labor since it would also have to suffice the equality in (6).

where $\widetilde{W}_j = W_j / W_J$. Monotonicity in $\boldsymbol{Q}$ and $\boldsymbol{W}$ as well as concavity in $\boldsymbol{W}$ cannot be imposed a priori but are tested a posteriori. For monotonicity, it suffices that all partial first derivatives of C with respect to the elements of $\boldsymbol{Q}$ and $\boldsymbol{W}$ are non-negative. C will be concave in $\boldsymbol{W}$, if the Hessian of second derivatives with respect to the elements of $\boldsymbol{W}$ is negative semi definite (Diewert and Wales 1987). This will be fulfilled, if all Eigenvalues of the Hessian are non-positive (Morey 1986). I follow the previous literature pointing towards the importance of consistency between the properties of the estimated and the theoretical function, and exclude all observations from further analysis that do not adhere to the regularity conditions (Salvanes and Tjøtta 1998).

From (3), I can derive the cost share equations for each variable input in total cost. Shepard's lemma yields that the partial first derivative of C with respect to a variable input's price yields the contingent demand for that input (Nicholson and Snyder 2008):

$$\frac{\partial C}{\partial W_j} = X_j \tag{5}$$

By substituting $\partial C = \partial lnC \cdot C$ and $\partial W_j = \partial lnW_j \cdot W_j$ in (5) I obtain the cost share equation of each variable input as

$$\frac{\partial lnC}{\partial lnW_j} = \frac{W_j X_j}{C} = \beta_j + 0.5 \sum_{k=1}^{K} \beta_{jk} lnW_k + \sum_{l=1}^{L} \gamma_{lj} lnQ_l + \sum_{r=1}^{R} \omega_{lr} lnK_r \tag{6}$$

where $W_j X_j / C$ is the expenditure share of variable input j in total variable cost. Since I can observe the inputs' expenditure shares in my data, estimating (4) along with the share equations adds further information to the model without inflating the number of parameters to estimate, thereby providing more efficient estimates. Note that I end up with $j - 1$ cost share equations as I normalise (6) in the same way as (3). To estimate (4) and the share equations jointly, I use the seemingly unrelated regression (SUR) model proposed by Zellner (1962). I within-difference the data to account for farm-specific effects, that do not change over time and are correlated with costs and output quantities, input prices and/or quantities of quasi-fixed factors, such as managerial ability of the farmer and quality of inputs and outputs (e.g., Alem et al. 2019; Wieck and Heckelei 2007). After estimation of the system of equations, I can derive MC of milk production by taking the first derivative of (4) with respect to the natural log of milk quantity, and multiply this with the ratio of total variable cost over the milk quantity. Finally, I obtain an estimate of markup ($\hat{\mu}$) by calculating $P/\widehat{MC}$.

An issue arising in the context of the translog function is the occurrence of zero values for any of the variables contained in the function because the natural log is not defined at zero. There are two popular approaches to deal with this. The first possibility consists in substituting the zero values by a positive number that is arbitrarily close to zero (e.g., Alem et al. 2019; Morrison Paul et al. 2000). However, this procedure will probably generate biased parameter estimates, if the number of zero observations is large and depends on the units of measurement of the variables (Battese 1997). Alternatively, to obtain consistent parameter estimates, Battese (1997) proposes to include a dummy variable for each variable in the estimable equation. This dummy variable will be equal to one if the respective variable's value is equal to zero, and equal to zero, if the respective variable's value is larger than zero. The value of the variable itself will then be replaced by a value of one, if the original value was zero. The variable's natural log will hence be equal to zero after the transformation. I follow the second approach which is also frequently used in current applications (e.g., Rasmussen 2010; Renner et al. 2014; Villano et al. 2015; Wimmer and Sauer 2020).

In addition, I test for differences in technology between different farm types. Technological differences are observed as soon as some of the $\alpha, \beta, \gamma, \delta, \upsilon, \eta, \omega$ deviate for certain groups of farms, i.e., the transformation process of inputs into outputs is different. Assuming that all farm types operate under the same technology even though they do not can lead to biased estimates and wrong conclusions (e.g., Bottasso et al. 2011; Triebs et al. 2016; Wenninger 2003). First, I test whether the parameters of the cost functions are different between conventional and organic milk farmers. The intuition is that organic farms are confronted with many legal restrictions in their production process which do not apply to conventional farms, e.g., the prohibition of using chemically synthesized inputs, a maximum amount of livestock per hectare or permanent access for livestock to outside areas (European Commission 2007). Hence, I expect differences in technologies between organic and conventional dairy farming which has also been found by Mayen et al. (2010) for a sample of dairy farms in the United States. Second, Alem et al. (2019) have found that a common technology across specialized dairying, mixed farms and specialized crop farms is to be rejected in the case of Norwegian agriculture (1991-2014). Therefore, I test whether the technologies differ between farms that only produce milk and meat (specialized dairying), and farms that produce milk as well as crops other than feed (mixed farms).

To implement a test for a common technology across organic and conventional farms, and specialized dairying and mixed farms, I employ the flexible technology approach suggested by Triebs et al. (2016). Recent applications of this approach in agricultural economics are Alem et al. (2019) testing for technological differences across farm types in Norwegian agriculture, and Gezahegn et al. (2019) examining whether farms belonging to different cooperatives produce under different technologies in Ethiopia. The idea is to estimate a joint model for all farm types (in my case organic and conventional or specialized dairying and mixed farms) while allowing the technological parameters to differ across farm types (Triebs et al. 2016). This can be implemented using two dummy variables in (4):

$$
\begin{aligned}
\ln\left(\frac{C}{W_J}\right) = {} & d_{CON}\ (\kappa_0 + \textstyle\sum_{l=1}^{L}\alpha_l lnQ_l + 0.5\ \sum_{l=1}^{L}\ \sum_{m=1}^{M}\alpha_{lm} lnQ_l lnQ_m + \sum_{j=1}^{J-1}\beta_j ln\widetilde{W}_j + \\
& 0.5\ \textstyle\sum_{j=1}^{J-1}\ \sum_{k=1}^{K-1}\beta_{jk} ln\widetilde{W}_j ln\widetilde{W}_k + \sum_{l=1}^{L}\ \sum_{j=1}^{J-1}\gamma_{lj} lnQ_l ln\widetilde{W}_j + \sum_{r=1}^{R}\upsilon_r lnK_r + \\
& 0.5 \textstyle\sum_{r=1}^{R}\ \sum_{s=1}^{S}\upsilon_{rs} lnK_r lnK_s + \sum_{l=1}^{L}\ \sum_{r=1}^{R}\eta_{lr} lnQ_l lnK_r + \\
& \textstyle\sum_{j=1}^{J-1}\ \sum_{r=1}^{R}\omega_{jr} ln\widetilde{W}_j lnK_r + \sum_{t=1}^{T}\delta_t Tech_t) \\
& + d_{ORG}\ \ (\kappa_0 + \textstyle\sum_{l=1}^{L}\alpha_l lnQ_l + 0.5\ \sum_{l=1}^{L}\ \sum_{m=1}^{M}\alpha_{lm} lnQ_l lnQ_m + \sum_{j=1}^{J-1}\beta_j ln\widetilde{W}_j + \\
& 0.5\ \textstyle\sum_{j=1}^{J-1}\ \sum_{k=1}^{K-1}\beta_{jk} ln\widetilde{W}_j ln\widetilde{W}_k + \sum_{l=1}^{L}\ \sum_{j=1}^{J-1}\gamma_{lj} lnQ_l ln\widetilde{W}_j + \sum_{r=1}^{R}\upsilon_r lnK_r + \\
& 0.5 \textstyle\sum_{r=1}^{R}\ \sum_{s=1}^{S}\upsilon_{rs} lnK_r lnK_s + \sum_{l=1}^{L}\ \sum_{r=1}^{R}\eta_{lr} lnQ_l lnK_r + \\
& \textstyle\sum_{j=1}^{J-1}\ \sum_{r=1}^{R}\omega_{jr} ln\widetilde{W}_j lnK_r + \sum_{t=1}^{T}\delta_t Tech_t) +\ \varepsilon
\end{aligned} \tag{7}
$$

where d_{CON} is a dummy variable being equal to one for conventional farms and zero for organic farms, and d_{ORG} is a dummy variable being equal to one for organic farms and zero for conventional farms. The share equations will be adjusted correspondingly in the system of equations. To test for a significant difference between the two technologies, I perform a Likelihood-ratio test between (4) and (7). The Null hypothesis is that the technologies are not different across the two farm types. In case, a common technology is to be rejected, I estimate the model separately for each farm type. Thereafter, I apply the same procedure to check for technological differences between specialized dairying and mixed farms.

A potential problem frequently observed in analyses of organic agriculture is self-selection into the conversion to organic agriculture (e.g., Ibanez and Blackman 2016; Mayen et al. 2010; Sipiläinen and Oude Lansink 2005). That is, there are differences between farmers converting to organic agriculture and those that do not convert which also drive costs and subsequently markups. Ignoring these differences would lead to endogeneity and therefore to biased estimates. Previous studies use different approaches to solve this issue such as propensity score matching (Mayen et al. 2010) and Heckman type corrections (Sipiläinen and Oude Lansink 2005; Wollni and Brümmer 2012). Since many of the characteristics driving the conversion to organic dairying are time invariant (Läpple and van Rensburg 2011; Mayen et al. 2010; Sipiläinen and Oude Lansink 2005), the within-differencing of my data before estimation remove this part of the bias (Bravo-Ureta et al. 2011; Bravo-Ureta et al. 2012; Rodriguez et al. 2007).

With respect to time variant determinants of the conversion decision, farm size is the most mentioned characteristic in the literature (e.g., Läpple and van Rensburg 2011; Mayen et al. 2010) which my models control for by including size related variables. Besides, my data set does not contain further observables that would allow to apply propensity score matching or Heckman type models. However, based on the aforementioned discussion the remaining bias should be small.

3.4 Determinants of Markups

After estimating farm-level markups, I investigate the link between markups and farm characteristics, in particular the role of organic production. It is well known that organic products provide a price premium over conventionally produced food on the retail level (e.g., Ankamah-Yeboah et al. 2016; Connolly and Klaiber 2014; Nieberg and Offermann 2003). For fresh milk in the United States, Kiesel and Villas-Boas (2007) find an organic price premium of approximately 40 percent whereas Smith et al. (2009) estimate the premium to be between 60 percent and 109 percent depending on the fat content. In the case of European dairy processing, Bonnet and Bouamra-Mechemache (2016) show that organic milk prices are higher than those of conventional milk, and dairy processors exhibit higher bargaining power towards retailers for organic vis-à-vis conventional milk in France. As yet however, there is no evidence of the effects of organic production on the market power of farmers in terms of markup as a direct measure of market power towards downstream sectors or consumers in direct marketing.

Removing the organic price premium, a meta-analysis on 55 crops on five continents has found that organic farming performs ten percent worse than conventional farming in terms of gross premium (Crowder and Reganold 2015) since organic farming leads to higher average cost than conventional farming (Uematsu and Mishra 2012). Nevertheless, as previous literature has found evidence for a significant price premium of organic food, I expect that organic dairy farms achieve higher markups compared to conventional dairy farms (Hypothesis 1). This would also be in line with the theory of niche markets which suggests that firms operating in small specialized markets realize higher margins (Ilbery and Kneafsey 1999; Smallbone Shaw et al. 1999). Given a mean volume share per country of organic in total milk production of approximately four percent in Europe in 2018 (Eurostat 2020b, 2020e), organic milk can still be considered as a niche product. I capture the characteristic of organic production by a dummy which is equal to zero for conventional farms and equal to one for organic farms.

While the average market share of organic in total milk production is small, these market shares still show considerable heterogeneity across European countries. In 2018, the share of organic in total milk production varied from below one percent (e.g., Bulgaria, Poland, Spain) to more than ten percent (e.g., Latvia, Denmark, Sweden) with a maximum of approximately 20 percent in Austria (Eurostat 2020b, 2020e). This dispersion allows me to further shed light on the theory of niche markets in the given context. With an increasing market share of organic milk, the distinguishing attribute of specialty decays. In addition, organic dairy farmers face difficulties in finding processing sites and/or retailers to sell their milk to in countries where organic production plays a minor role (European Commission 2019). I expect that an increasing market share of organic milk leads to improvements regarding the infrastructure of the entire organic dairy supply chain such that the asset specificity and uncertainty related to producing organic milk decreases, thereby decreasing transaction costs (Williamson 1979), prices, and ultimately, markups. Of course, increasing/decreasing demand may also lead to increasing/decreasing markups outweighing the aforementioned mechanisms. However, the supply of organic milk is restricted in the short-term since farmers are bound to a conversion time of 18 to 24 months before they can market their products as organic. Hence, prices for organic milk may vary in the short-term due to increased/decreased demand while the market share of organic milk is predetermined largely by the supply quantity given that the market is cleared.

Assuming that supply and demand shifters are exogenous, i.e., not determined simultaneously[15], increasing market shares of organic milk will ceteris paribus lead to a downward shift of the supply curve due to increasing supply quantities and due to decreasing transaction costs for farmers and hence imply smaller prices and markups. Therefore, I hypothesize that markups of organic farmers decrease with an increasing market share of organic milk since the distinguishing attribute decays (Hypothesis 2a).

Moreover, I expect that markups of conventional farms decrease with an increasing market share of organic milk. The total demand for dairy products in the EU has been almost constant with growth rates slightly below one percent per year during the study period (2004-2017)

[15] Reviews by Aertens et al. (2009) and Kushwah et al. (2019) show that most of the determinants for organic food purchases are not related to factors determining the conversion to organic agriculture on the supply side.

(OECD 2022). Projections of the demand for dairy products predict that total dairy product consumption in the EU will be as high as in 2021 (European Commission 2021a). Hence, conventional and organic dairy products are competing products in a market with a more or less fixed size such that I hypothesize that the demand for conventional milk decreases with an increasing market share of organic milk, and therefore, markups of conventional dairy farmers diminish with increasing market shares of organic milk in total milk production (Hypothesis 2b).

An issue regarding the measurement of the market share of organic milk is that statistics of organic milk production are only partially available in terms of country coverage, and only since 2012 (Eurostat 2020e). To alleviate this problem, I use the share of agricultural area under organic production in the total agricultural area as a proxy because it is readily available for all countries and the complete sampling period. An ordinary least squares regression of organic milk output in total milk output on the agricultural area under organic production in the total agricultural area and a set of country dummies yields an R-squared of 0.985 for the periods available. Thus, I perceive the share of area under organic production in total farming area as a good proxy for the share of organic milk in total milk production.

Third, I examine the link between farm size and markups. Previous literature in economics has found that large firms exhibit higher markups than small firms (Autor et al. 2020; Barla 2000). In previous work conducted on agri-food supply chains, most researchers investigate the role of farmer cooperatives on the bargaining power of farmers. Cooperatives negotiate the prices with downstream companies for all their members jointly, and thereby, achieve higher prices due to scale advantages over single farmers who deliver their milk to investor-owned firms (Hendrikse 2009). In that respect, numerous studies have found that cooperatives significantly improve the bargaining power of cooperative members compared with non-members (e.g., Cakir and Balagtas 2012; Fałkowski et al. 2017; Liang and Wang 2020; Prasertsri and Kilmer 2008). Besides, a meta-analysis on asymmetric price transmission between the farm- and the retail-level concludes that smaller farms are more likely to suffer from asymmetric price transmission (Bakucs et al. 2014). Accordingly, I expect that larger farms yield higher markups because their bargaining power towards dairy processors or food retailers is higher (Hypothesis 3). I proxy farm size by the natural logarithm of milk output since milk output will be the only size variable of interest concerning price negotiations with downstream companies.

Last, I investigate whether concentration in downstream sectors negatively affects farmers' markups as the traditional view on market power and concentration suggests (Sexton and Xia 2018; Wijnands et al. 2007). Along these lines, earlier research has detected that price and price volatility transmission from farmers to processors and retailers are hampered in agri-food sectors which are highly concentrated at downstream stages (Assefa et al. 2017; Cutts and Kirsten 2006). As downstream sectors, I consider separately i) the dairy processing industry, and ii) the food-retailing sector. For each of those two sectors, I introduce two variables in the empirical model to measure concentration. I use the cumulative market share (in total sales) of firms with 50-249 employees (medium-sized firms), and the cumulative market share of firms with more than 249 employees (large firms) to proxy concentration (Eurostat 2020f). The inclusion of the market share of small firms (<50 employees) would lead to issues with respect to collinearity. I conjecture that farmers' markups decrease with increasing market shares of medium-sized and large-sized food processors (Hypothesis 4a) as well as food retailers (Hypothesis 4b).

In my estimations, I control for the share of fixed in total cost as well as the deployment of unpaid labor. De Loecker et al. (2020) argue that larger markups might not necessarily be a result of welfare decreasing market power but could origin from an increased share of quasi-/fixed in total cost that are covered by higher markups. In my case, these would be inter alia costs of capital, paid labor or land. If a positive link between the share of quasi-/fixed in total cost and markups was absent, this would be evidence for the presence of welfare decreasing market power (De Loecker et al. 2020; Hirsch and Koppenberg 2020). Similarly, I test whether farms with higher deployment of unpaid labor charge higher markups. The intuition is that family members provide most of the unpaid labor on farms. Due to foregone earnings from an alternative employment, i.e., opportunity cost, I anticipate that farms with higher deployment of unpaid labor have higher markups.

To test the hypotheses derived, I apply the following linear model:

$$\mu_{ict} = \beta_0 + \beta_1\, ORG_{it} + \beta_2\, OSHORG_{ict} + \beta_3\, OSHCON_{ict} + \beta_4\, ln(MILK_{it}) + \beta_5\, PRSHM_{ict} + \beta_6\, PRSHL_{ict} + \beta_7\, RETSHM_{ict} + \beta_8\, RETSHL_{ict} + \beta_9\, SHFC_{it} + \beta_{10}\, UNPLAB_{it} + \sum_{t=1}^{T} \beta_{11+t} D_t \tag{8}$$

where μ is markup and $\boldsymbol{\beta}$ are the parameters to estimate. I use i, c and t as subscripts for farm, country and year, respectively. ORG is a dummy variable being equal to one for organic farms, and zero otherwise (Hypothesis 1). $OSHORG$ ($OSHCON$) denote the share of organic milk in total milk production for organic (conventional) farms and is equal to zero for conventional (organic) farms in the respective country. I use $OSHORG$ to identify the effect of an increasing market share of organic milk on markups of organic farms (Hypothesis 2a) and $OSHCON$ for the effect of an increasing market share of organic milk on markups of conventional farms (Hypothesis 2b). $ln(MILK)$ denotes the natural log of the quantity of raw milk [million tons] produced by the farmer (Hypothesis 3). $PRSHM$ and $PRSHL$ depict the market share of medium and large dairy processors in the dairy processing industry of each country, respectively (Hypothesis 4a). $RETSHM$ and $RETSHL$ represent the corresponding variables for the food retail sector (Hypothesis 4b). The control variables are represented by the share of quasi-/fixed in total cost ($SHFC$), the number of hours of unpaid labor deployed on the farm [hundred hours] ($UNPLAB$) and a set of year dummies ($\boldsymbol{D}$) which control for changes in world market prices and other macroeconomic factors.

I estimate (8) by pooled ordinary least squares regression (OLS) and a fixed effects regression (FE). The pooled OLS is meant to identify the gross difference in markups between organic and conventional farms. Note that the pooled OLS also includes country fixed effects to control for regional differences on both the supply- and demand-side. To account for unobserved factors, which may influence markups as well as the independent variables of the model raising concerns of endogeneity, I estimate FE where I add farm-specific constants α_i to (8). For instance, the farmers' negotiation skills are unobserved which would have an impact on markup and probably on the hours of unpaid labor on the farm since higher negotiation skills would lead to higher markups incentivizing the deployment of unpaid (family) labor.

3.5 Data

The data used in the analysis are provided by the European Farm Accountancy Data Network (FADN). My dataset covers the years 2004-2017 and 24 of 27 EU countries plus the United Kingdom (Cyprus, Luxembourg and Malta are missing). The FADN data include information on farm-level inputs, outputs and other financial data of the holding per year. Besides, I retrieve several country- and year-specific price indices from Eurostat (2020a). For six countries, the price indices were insufficiently available such that I omit them from the analysis: Bulgaria, Croatia, Estonia, Ireland, Lithuania and Romania.

Table 3.A1 gives an overview of the variable specifications used for the estimation of the translog cost function. The outputs are i) the milk quantity sold [kg], ii) the quantity of livestock sold [€] defined as the revenue from selling farm animals deflated by the price index of animals

sold obtained from Eurostat, and iii) the quantity of crops sold [€] defined as the revenue from crop sales deflated by the price index of crop output from Eurostat. The variable input prices are price indices for i) feedstuff purchases, ii) energy and iii) crop inputs, i.e., plant protection products, seeds and fertilizer. The quasi-fixed inputs are i) unpaid labor [hours], ii) paid labor [hours], iii) land [hectares], iv) capital defined as the value of fixed assets except for land and livestock [€], v) the number of dairy cows on the farm [livestock units] and vi) other livestock on the farm [livestock units].

While the use of price indices is common in recovering a technology's parameters (e.g., Alem et al. 2019; De Frahan et al. 2011; Gullstrand et al. 2013; Wieck and Heckelei 2007), it potentially introduces a bias in the estimation of the cost function parameters as soon as there is unobserved cross-farm variation in input and/or output prices (De Loecker et al. 2016; Morlacco 2020). Factors that cause such variation are e.g., location as well as quality differences of inputs and outputs. Examples in the farming context are quality of land, climatic conditions or access to infrastructure. However, as long as this cross-farm variation is farm-specific and changes little over time, introducing fixed effects or conducting within-differencing will resolve this issue (De Loecker et al. 2016). Since I within-difference the data before the estimation, I assume that the bias due to the use of price indices is negligible.

Moreover, I only observe ex-post outputs while the farmer minimizes cost based on expected output which can lead to biased estimates of the cost function (e.g., Chambers and Serra 2019; Chavas 2008; Moschini 2001). In agriculture, deviations of realized from expected output typically result from weather conditions that differ from the farmers' expectations (e.g., Finger et al. 2018; Key and Sneeringer 2014; Schlenker and Roberts 2009). Supposing that the weather conditions for a given year are less favorable than expected by farmers, realized output falls short of expected output such that the estimated parameters for output in the cost function will be overestimated. Hence, MC estimates will be biased as well.

However, since my geographical scope is large, there will be some locations where weather conditions will be better than expected, some locations where weather conditions will be worse than expected and some locations where the weather conditions will be as expected. Hence, some farmers will overestimate expected output, some farmers will underestimate expected output and some farmers realize their expected output. Therefore, I expect that, on average, expected output is close or equal to realized output such that only standard errors of the estimates are inflated. In addition, systematic pessimism/optimism of a farmer will be eliminated by the within-differencing that I apply to the data. Besides, in the absence of good instruments for output, two-stage least squares or three-stage least squares are performing much worse than SUR (Johnston 1963; Wieck and Heckelei 2007). Anyway, my main interest does not lie in the absolute size of markups but the results of the second stage regressions, which will be unaffected by potential biases in the estimation of the technology as long as the bias is the same for all farms (De Loecker and Warzynski 2012).

I identify the sample farms by the FADN TF14 farming types 45 ("specialist milk"), 49 ("specialist cattle") and 80 ("mixed crops and livestock") (see European Commission 2020b for the complete list of farming types). The sample contains 203,979 observations comprised by 39,786 farms producing cows' milk between 2004 and 2017. The sample contains 11,378 (5.58 percent) observations comprised by 2,878 farmers for organic production and 192,601 (94.42 percent) observations comprised by 37,761 farmers for conventional production (2004-2017). For 115,333 (28,106) observations (farms), farmers produced milk and meat as well as crops and for 88,646 (22,079) observations (farms), farmers did not produce crops. The descriptive statistics are given in Table 3.A2 in the appendix.

A detailed comparison of the constitution of the sample and the population for farming type 45 in 2016 is given in Table 3.A3 in the appendix. I evaluate the representativeness of the sample using livestock units and the number of farms only for farming type 45 ("specialist milk") since the other two farming types ("specialist cattle" and "mixed crops and livestock") do not allow to break down the on-farm livestock into dairy cows and cattle kept for fattening/other animals. For all countries together, the number of farms in the sample for 2016 and farming type specialist milk is 10,798 while there have been 341,140 farms in the population resulting in a share of sample farms in the population of 3.17 percent (see Table 3.A3 in the appendix). For comparison, the number of dairy cows in the sample amounts 859,694 livestock units while the respective value for the population is 25,633,200 (3.35 percent). Hence, larger farms in terms of dairy cows [livestock units] are slightly overrepresented considering all countries. Contrasting the same figures differentiating between countries, there is a tendency that the average farm size in the sample slightly falls short of the population average in western and northern countries (e.g., Belgium, Denmark and Sweden), i.e., the very large farms are slightly underrepresented. Oppositely, the average farm size in the sample exceeds the population average in eastern countries (e.g., Hungary, Latvia and Slovakia). This stems from the presence of many small farms in the population whose households consume more than 50 percent of the final farm production, i.e., subsistence farmers, in Eastern Europe (Eurostat 2020c). Since my interest lies in identifying the seller market power of farmers towards downstream companies, the underrepresentation of these small-scale operations consuming most of their produce in their own households does not pose any harm.

For the regression of markups on farm and country characteristics, ORG is a dummy variable equal to one for organic farms and zero otherwise, and is obtained from the FADN data. $OSHORG$ equals the market share of organic milk in total milk [percent] in each country for organic farms and zero otherwise, and $OSHCON$ is the market share of organic milk in total milk [percent] in each country for conventional farms and zero otherwise. Both are retrieved from Eurostat (2020d, 2020e). $MILK$ is the log quantity of raw milk [thousand tons] produced by each farmer and is given in the FADN data. The market share of medium-sized and large downstream companies [percent] are given by Eurostat (2020f). Note, that the market shares of downstream companies are not available for all countries and years such that the number of observations reduces to 81,490 for the second stage regressions.[16] I calculate quasi-/fixed costs by subtracting variable costs from total costs and divide this difference by total costs to arrive at $SHFC$ [percent] for each farm for which the FADN data contain the necessary information. The amount of unpaid labor ($UNPLAB$) also stems from the FADN data and is measured in hundred hours. The variable description is summarized in Table 3.A1 and the descriptives are given in Table 3.A2.

3.6 Results and Discussion

The parameter estimates of the joint model and the model with flexible technology for organic and conventional farms are presented in Table 3.A4 in the appendix. The test statistic of the likelihood ratio test amounts to 891.13 with 96 degrees of freedom resulting in a p-value of <0.01 such that I reject the Nullhypothesis of a common technology of organic and conventional farms. Thereafter, I have tested whether farms producing crops and milk jointly (mixed farms) and farms producing milk and meat only (specialized dairying) operate under the same technology. I have carried out this test separately for conventional and organic farms (cf. Table 3.A5 and Table 3.A6). For conventional farms, the likelihood ratio test rejects a common technology for mixed and specialized dairy farms (χ^2 = 2,606.88; p<0.01). The same holds for organic farms (χ^2 = 198.07; p<0.01). Hence, the technology, and therefore, the cost functions for the four farm groups (conventional specialized dairying, conventional mixed, organic

[16] Concentration data are completely missing for the Czech Republic, Denmark, Finland, Slovakia, Slovenia and Sweden. However, the coefficients of the other variables do not change signs when I omit the concentration measures and run the analysis on the full sample with the limited set of independent variables.

specialized dairying and organic mixed) differ such that a joint estimation would result in biased parameters.[17]

With respect to the properties of the cost function, I observe 1,379 observations that do not fulfil monotonicity in output (0.68 percent of all observations) whereas all observations fulfil monotonicity and concavity in input prices. I follow previous literature and omit these observations from further analysis to avoid misleading conclusions (e.g., Henningsen and Henning 2009; Hirsch et al. 2020; Wimmer and Sauer 2020).

Table 3.1 shows the descriptive statistics of MC of milk production and output for conventional and organic farmers. Mean and median MC are slightly larger for conventional (0.13 €/kg and 0.08 €/kg) compared with organic (0.11 €/kg and 0.07 €/kg) milk farmers (Table 3.1). For both farming types the MC density curves exhibit a positive skew which is more pronounced for conventional than for organic farmers as indicated by the 99th percentile (1.12 €/kg vs. 0.81 €/kg) (Table 3.1). When comparing MC between conventional and organic farmers at the same level of output, the MC of conventional farmers lie above those of organic farmers. This may seem counterintuitive because previous literature has found that organic farming entails higher costs of production vis-à-vis conventional agriculture (Uematsu and Mishra 2012). However, most of the additional cost of organic compared to conventional farming stems from increased costs for external labor (Uematsu and Mishra 2012). Since I do not consider labor as a variable input but a quasi-fixed one, labor costs do not enter MC but are included in the fixed cost share. This is in line with the share of fixed in totals costs with a mean (median) of 53 percent (55 percent) for conventional farmers compared to 65 percent (67 percent) for organic farmers.

Table 3.1 Descriptive Statistics of Marginal Cost of Milk Production and Milk Output

		Mean	Median	1st percentile	99th percentile
Marginal cost [€/kg]	Conventional	0.13	0.08	0.03	1.12
	Organic	0.11	0.07	0.02	0.81
Output [tons]	Conventional	494.66	212.58	0.22	4,555.90
	Organic	331.55	153.60	0.24	2,423.40

Source: Own calculations based on data of the European Farm Accountancy Data Network

[17] Note that the outcome of the test procedure does not change when I first test specialised dairying against mixed farms and then conventional versus organic or first test conventional against organic and thereafter specialised dairying against mixed farms.

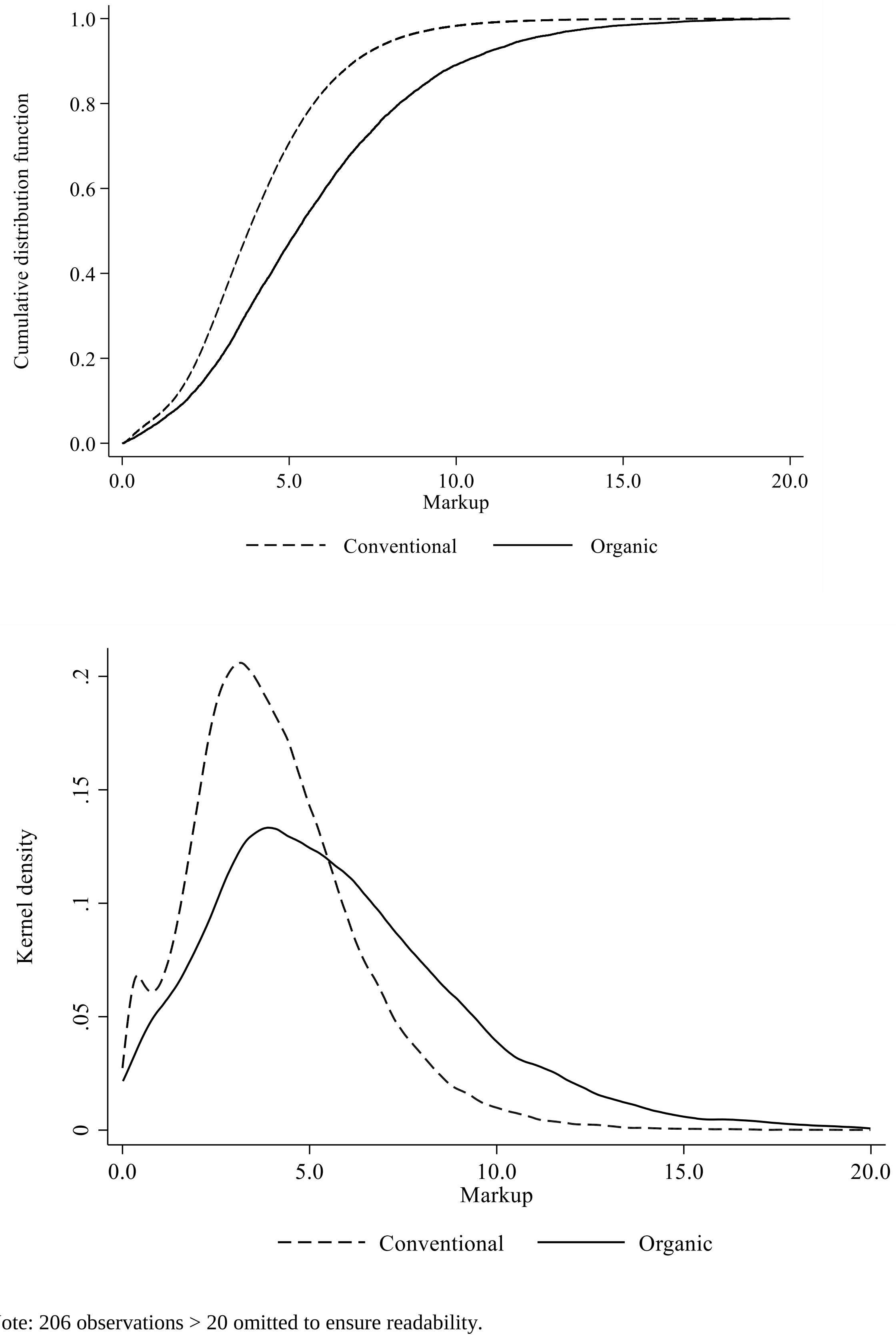
In addition, my MC estimates are in line with those of Wieck and Heckelei (2007) who estimate MC of dairy farmers for selected regions in Denmark, France, Germany, the Netherlands and the UK (1989-2000). Regional averages of MC range from 0.12 €/kg to 0.18 €/kg in 1991 and from 0.084 €/kg to 0.15 €/kg in 1999. Given that my data cover the period from 2004-2017 and farmers realized further technical progress, my MC estimates are plausible.

Next, I compute markups (μ) by dividing the milk price (P) by the estimates of MC, i.e., P/MC, where a value of one indicates marginal cost pricing. Table 3.2 contains the descriptive statistics of markups for conventional and organic farmers. The arithmetic mean of conventional farmers' markups is 4.11, i.e., the milk price exceeds MC by 311 percent (Table 3.2). This value equals 5.95 for organic farmers suggesting a markup premium for organic farmers of 1.84 over conventional farmers without controlling for other factors. This is supported by the difference in median markups between conventional (3.78) and organic (5.27) farmers amounting to 1.49 (Table 3.2). The density and cumulative distribution functions of markups confirm this since markups of organic farmers dominate those of conventional farmers (Figure 3.1).

Table 3.2 Descriptive Statistics of Markups for Conventional and Organic Dairy Farmers

		Mean	**Median**	**Minimum**	**1st percentile**	**99th percentile**	**Maximum**
Markup	Conventional	4.11	3.78	0.00	0.20	10.99	1,205.09
	Organic	5.95	5.27	0.01	0.27	19.12	349.43

Source: Own calculations based on data of the European Farm Accountancy Data Network



Note: 206 observations > 20 omitted to ensure readability.

Source: Own illustration based on data of the European Farm Accountancy Data Network

Figure 3.1 Kernel Density and Cumulative Distribution Function of Markups for Conventional and Organic Farmers

It is noteworthy that my mean and median markup estimates far exceed those of earlier studies estimating markups for other sectors (e.g., Autor et al. 2020; De Loecker et al. 2020).[18] Recent applications in the food sector find mean markups ranging from 1.07 to 2.57 for the food manufacturing industry (Curzi et al. 2021; Jafari et al. 2022; Koppenberg and Hirsch 2022b; Lopez et al. 2018) and from 1.18 to 3.57 for the food retailing sector (Hirsch and Koppenberg 2020; Koppenberg and Hirsch 2022a; Sckokai et al. 2013). However, two pivotal differences between manufacturing and service industries and the farming sector drive this result. First, unlike most of the companies in manufacturing and service industries, the farming sector is characterized by a very large share of sole proprietors running their farms without external work force. In my sample, approximately 62 percent of the observations do not employ any paid labor whereas 93.8 percent deploy unpaid labor of at least one full-time equivalent (assuming an annual workload of 1,600 hours per year and person). Hence, markups do not only compensate for entrepreneurial risk but also for foregone earnings from an alternative employment of the farm family members. Second, the share of quasi-/fixed cost is much larger in farming than in other sectors. While De Loecker et al. (2020) and Koppenberg and Hirsch (2022b) observe a share of fixed in total costs in manufacturing of approximately 30 percent and 20 percent, respectively, the mean share of quasi-/fixed costs in total costs is 54 percent in my sample. Therefore, a comparison of farmers' markups with other industries has little informative value. I provide an in-depth discussion on the relationship between unpaid labor, quasi-/fixed costs and markups when I present the results of the regression analysis.

With respect to differences between countries, Table 3.3 and Figure 3.2 show the descriptive statistics of markups per country and median markups per country for conventional and organic farms, respectively. In general, Eastern European countries yield lower average markups compared to Western and Southern Europe as well as Scandinavia (Table 3.3 and Figure 3.2). Mean markups in Eastern Europe range from 3.36 (Poland) to 1.83 in Slovakia (Table 3.3). Western European countries show the highest mean markups with 7.00 (Netherlands), 5.60 (Austria), 5.24 (France) and 5.06 (Germany) (Table 3.3). This result stems from generally lower milk prices in Eastern Europe as well as MC disadvantages in my sample.

[18] For instance, Autor et al. (2020) as well as De Loecker et al. (2020) find median markups between 1 and 1.6. While Autor et al. (2020) use data on all firms in manufacturing, wholesale trade, retail trade, services, utilities, transportation and finance in the US, De Loecker et al. (2020) only include publicly traded US-firms but without restrictions regarding the sectoral activity.

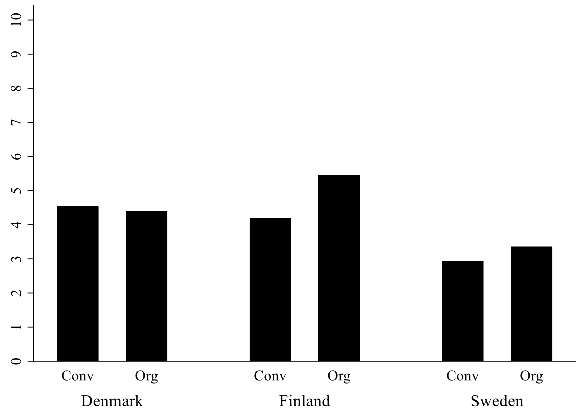
Table 3.3 Descriptive Statistics of Markups per Country

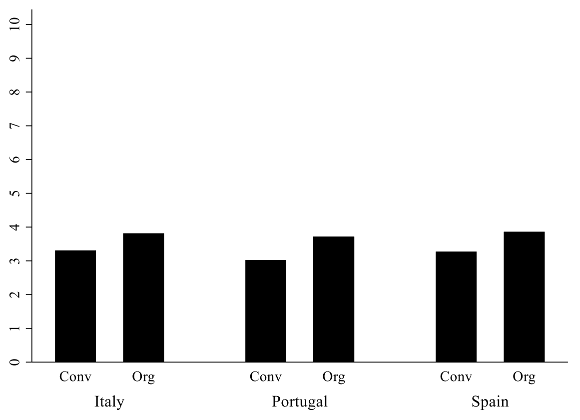
Country	Mean	Median	1st percentile	99th percentile	Observations
Austria	5.60	5.16	1.10	13.70	11,268
Belgium	4.96	4.55	0.27	13.21	5,952
Czechia	2.53	2.31	0.38	6.60	5,419
Denmark	4.66	4.53	1.46	10.63	5,292
Finland	4.55	4.26	1.63	9.81	4,607
France	5.24	4.88	1.42	12.51	22,378
Germany	5.06	4.76	1.04	12.26	36,606
Hungary	2.42	2.22	0.32	6.74	2,176
Italy	4.04	3.32	0.59	14.07	15,612
Latvia	2.36	2.27	0.11	5.74	5,708
Netherlands	7.00	6.46	2.66	15.91	4,496
Poland	3.36	3.17	0.10	10.21	51,412
Portugal	3.89	3.02	0.60	10.44	4,267
Slovakia	1.83	1.70	0.12	4.62	1,896
Slovenia	2.82	2.35	0.37	9.33	3,539
Spain	3.65	3.28	1.35	9.47	9,488
Sweden	3.17	3.01	1.28	10.13	4,986
United Kingdom	4.32	3.96	1.28	10.13	7,258

Note: Markups are defined as the ratio of price over marginal cost and are expressed in levels.

Source: Own calculations based on data of the European Farm Accountancy Data Network

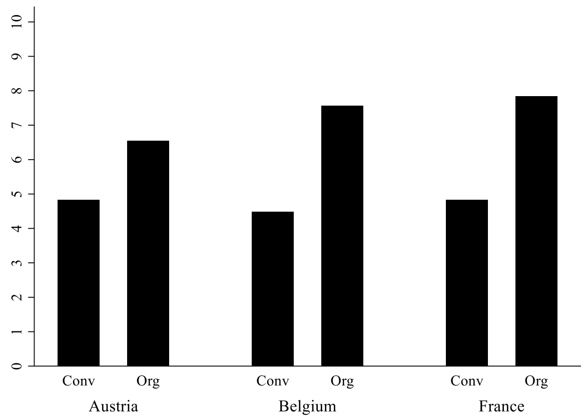
The overall tendency of larger markups for organic farmers (cf. Figure 3.1 and Table 3.2) is robust on the country-level since median markups of organic farms exceed those of conventional farms in all countries but Denmark, Poland, Slovakia and Slovenia (Figure 3.2). As Figure 3.2 indicates, the deviations in median markups of organic and conventional farms is most pronounced in Western Europe in contrast to Scandinavia, Eastern and Southern Europe where median markups are closer to each other for the two farming types.

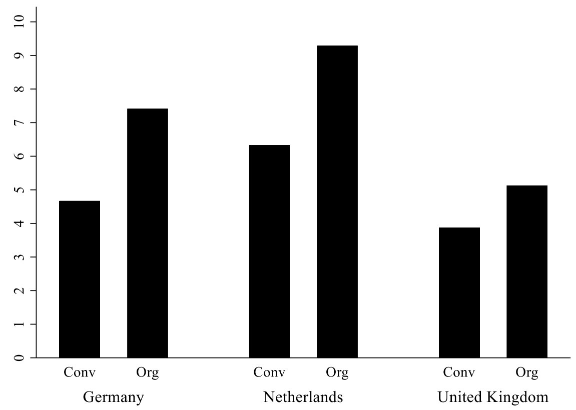




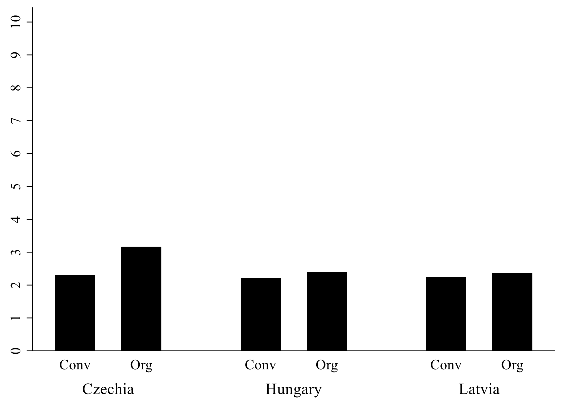
Scandinavia

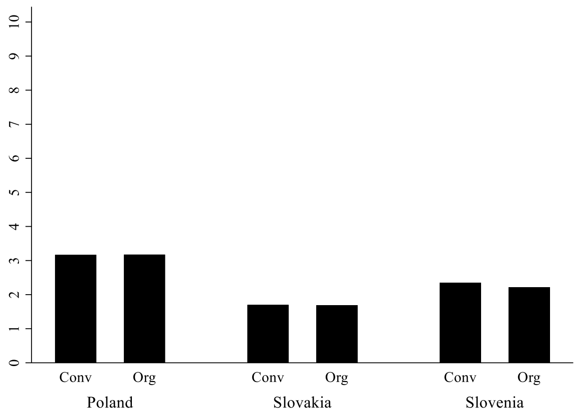
Southern Europe





Western Europe





Eastern Europe

Note: Markups are defined as the ratio of price over marginal cost and are expressed in levels.

Source: Own illustration based on data of the European Farm Accountancy Data Network

Figure 3.2 Median Markups per Country for Conventional (Conv) and Organic (Org) Farms

Turning to the determinants of markups, column 2-3 of Table 3.4 contain the results of the pooled OLS and the FE regression. Since Figure 3.1 and Table 3.2 indicate that the distribution of the markup estimates is skewed and contains some extreme values at its upper end, the results of the linear regressions could be distorted. Therefore, I reestimate the pooled OLS and the FE model once omitting observations below the one percent and above the 99 percent percentile of markups and once omitting observations below the five percent and above the 95 percent percentile of markups. Moreover, I apply a robust median regression, which is well suited in the presence of extreme values (Powell 2022).[19] As a second robustness check, I estimate (8) using pooled OLS, FE and the median regression using all observations but log markup as the dependent variable. The results of the pooled OLS and FE models excluding the bottom and top markup percentiles are shown in column 4-7 of Table 3.4 along with the results of the median regression (column 8 of Table 3.4). The estimations of the models using log markup as the dependent variable are shown in Table 3.A9 in the appendix since they are mostly in accordance with the other regressions.

The results of the pooled OLS using all observations suggest a gross markup premium for organic over conventional dairy farmers of 2.579 ($p<0.01$), i.e., on average markups of organic farmers exceed those of conventional farmers by 257.9 percentage points (cf. column 2 of Table 3.4). However, as stated earlier, pooled OLS will be biased in the presence of unobserved effects specific to each farm that influence the explanatory variables and markup. The FE model using all observations, which accounts for the unobserved farm characteristics, yields a markup premium of 0.924 ($p<0.01$) which is less than half the estimate of the pooled OLS (cf. column 2 and 3 of Table 3.4). Omitting extreme values which potentially distort the linear models, the predicted markup premium of the pooled OLS models shrink to 1.664 ($p<0.01$) and 0.898 ($p<0.01$) for organic over conventional farmers while the FE model estimates amount to 0.778 ($p<0.01$) and 0.586 ($p<0.01$) (column 4-7 of Table 3.4). The robust median regression predicts a premium of 1.034 ($p<0.01$) (column 8 of Table 3.4). Hence, I find evidence in favor of Hypothesis 1, i.e., that organic farmers generate higher markups compared with conventional farmers in European milk production. That is, the supply of organic products allows farmers to drive a larger wedge between output price and MC compared to conventional farmers.

[19] As suggested by a referee, I also estimate the quantile regression at the 10, 25, 75 and 90 percent quantile. The results and their discussion can be found in the appendix.

Table 3.4 Markups and Their Determinants in European Dairy Farming: Pooled OLS, FE and Median Regression

Variables	**Pooled OLS**	**FE**	**Pooled OLS**	**FE**	**Pooled OLS**	**FE**	**Median regression**
			Excluding markups below 1% and above 99% percentile		**Excluding markups below 5% and above 95% percentile**		
ORG	2.579***	0.924***	1.664***	0.778***	0.898***	0.586***	1.034***
	(0.191)	(0.213)	(0.110)	(0.157)	(0.089)	(0.141)	(0.119)
OSHORG	-0.122***	0.018	-0.073***	0.008	-0.027**	0.007	-0.022**
	(0.019)	(0.026)	(0.015)	(0.018)	(0.012)	(0.016)	(0.010)
OSHCON	-0.069***	-0.026***	-0.051***	-0.024***	-0.024**	-0.018**	-0.049***
	(0.013)	(0.010)	(0.011)	(0.009)	(0.010)	(0.008)	(0.004)
ln(MILK)	0.662***	0.773***	0.600***	0.787***	0.431***	0.809***	0.763***
	(0.015)	(0.025)	(0.014)	(0.023)	(0.013)	(0.025)	(0.007)
UNPLAB	0.011***	0.003***	0.010***	0.002***	0.009***	0.002**	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
PRSHM	-0.108***	-0.092***	-0.109***	-0.088***	-0.086***	-0.075***	-0.088***
	(0.009)	(0.005)	(0.006)	(0.004)	(0.005)	(0.004)	(0.004)
PRSHL	0.011***	0.013***	0.014***	0.012***	0.011***	0.008***	0.026***
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
RETSHM	-0.024	0.002	-0.005	0.002	-0.004	-0.003	-0.008***
	(0.018)	(0.006)	(0.007)	(0.006)	(0.006)	(0.005)	(0.003)
RETSHL	0.015**	-0.022***	0.012***	-0.021***	0.011***	-0.019***	-0.011***
	(0.007)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)
SHFC	0.069***	0.096***	0.050***	0.083***	0.039***	0.074***	0.077***
	(0.005)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Constant	2.814***	0.850***	3.521***	1.510***	3.198***	1.968***	
	(0.441)	(0.179)	(0.282)	(0.133)	(0.247)	(0.114)	

	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	No	Yes	No	Yes	No	No
Farm fixed effects	No	Yes	No	Yes	No	Yes	Yes
Observations	81,490	81,490	80,092	80,092	74,622	74,622	81,490
R-squared	0.232	0.200	0.330	0.289	0.264	0.222	

Note: Standard errors clustered by farm in parentheses; Significance indicators: *** p<0.01, ** p<0.05, * p<0.1; definition of variables and descriptive statistics can be found in the appendix (Table 3.A1 and Table 3.A2)

Source: Own calculations based on data of the European Farm Accountancy Data Network

Table 3.5 Markup Determinants: Pooled OLS, FE and Median Regression Controlling for Marginal Costs

Variables	Pooled OLS	FE	Pooled OLS	FE	Pooled OLS	FE	Median regression
			Excluding markups below 1% and above 99% percentile		Excluding markups below 5% and above 95% percentile		
ORG	2.454***	0.915***	1.349***	0.699***	0.867***	0.372***	0.816***
	(0.193)	(0.213)	(0.100)	(0.154)	(0.062)	(0.118)	(0.137)
OSHORG	-0.115***	0.016	-0.065***	-0.008	-0.085***	-0.053***	-0.012
	(0.019)	(0.026)	(0.014)	(0.017)	(0.009)	(0.015)	(0.008)
OSHCON	-0.067***	-0.028***	-0.052***	-0.040***	-0.077***	-0.075***	-0.056***
	(0.013)	(0.010)	(0.011)	(0.009)	(0.007)	(0.006)	(0.004)
ln(MILK)	0.546***	0.693***	0.238***	0.251***	0.040***	-0.198***	0.214***
	(0.036)	(0.039)	(0.018)	(0.058)	(0.012)	(0.025)	(0.021)
UNPLAB	0.011***	0.003***	0.010***	0.003***	0.005***	0.001*	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
PRSHM	-0.106***	-0.090***	-0.103***	-0.080***	-0.065***	-0.057***	-0.091***
	(0.009)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)
PRSHL	0.010***	0.013***	0.015***	0.012***	0.010***	0.008***	0.017***
	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
RETSHM	-0.028	0.001	-0.020***	-0.011**	-0.045***	-0.036***	-0.015***
	(0.018)	(0.006)	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)
RETSHL	0.012*	-0.022***	-0.003	-0.019***	-0.016***	-0.024***	-0.012***
	(0.007)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
SHFC	0.070***	0.094***	0.049***	0.066***	0.023***	0.024***	0.065***
	(0.005)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
MC	-1.316***	-0.611**	-7.834***	-6.993***	-25.088***	-26.883***	-6.979***
	(0.435)	(0.242)	(0.403)	(0.821)	(0.993)	(0.566)	(0.032)

Constant	2.615***	0.918***	3.646***	2.401***	6.971***	6.040***	
	(0.442)	(0.181)	(0.253)	(0.165)	(0.233)	(0.129)	
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	No	Yes	No	Yes	No	No
Farm fixed effects	No	Yes	No	Yes	No	Yes	Yes
Observations	81,490	81,490	80,092	80,092	74,622	74,622	81,490
R-squared	0.247	0.211	0.460	0.425	0.651	0.536	

Note: Standard errors clustered by farm in parentheses; Significance indicators: *** p<0.01, ** p<0.05, * p<0.1; definition of variables and descriptive statistics can be found in the appendix (Table 3.A1 and Table 3.A2).

Source: Own calculations based on data of the European Farm Accountancy Data Network

With respect to the effects of increasing market shares of organic milk in total milk production, the FE model predicts that for an increase in the market share of organic milk of one percentage point, the markup of organic farmers increases by 0.018 which is, however, not significantly different from zero (p=0.48) (column 3 of Table 3.4). This is robust when I exclude extreme markup values (cf. column 5 and 7 of Table 3.4). In contrast, pooled OLS (Table 3.4, column 2, 4 and 6; p<0.05) as well the median regression (Table 3.4, column 8; p<0.05) predict that markups of organic farmers decrease with increasing market shares of organic in total milk production. When using log markup as the dependent variable, only pooled OLS predicts a significantly negative relationship between markup and the share of organic milk whereas the estimates of the FE model and the median regression are not significantly different from zero (cf. Table 3.A9). To look deeper into the mechanisms driving this ambiguous result, I reestimate the models and control for MC to elicit the impact of varying shares of organic milk in overall milk production on the milk price component of markups.

The results in Table 3.5 show that pooled OLS predicts that markups controlled for MC decrease with increasing market shares of organic milk (p<0.01). Accounting for unobserved farm heterogeneity, the FE model excluding markups below the five percent and above the 95 percent percentile identifies a negative and significant relationship between the share of organic milk in total production and the markup controlled for MC (cf. Table 3.5, column 7). However, the other FE models (column 3 and 5 of Table 3.5) as well as the median regression (column 8 of Table 3.5) do not yield a significant relationship between the share of organic in total milk production and markups. That is, increased supply, i.e., increasing market shares of organic in total milk production, seems to be offset by increased demand such that prices do not change, and hence markups are not impacted by varying market shares of organic milk (Willer et al. 2019).[20] Consequently, I do not find clear evidence for Hypothesis 2a (*Markups of organic farms decrease with an increasing market share of organic milk in total milk production).*

For Hypothesis 2b (*Markups of conventional farms decrease with an increasing market share of organic milk in total milk production*), all models yield negative parameter estimates which are significantly different from zero (cf. Table 3.4 and Table 3.A9). Thus, demand for conventional milk decreases and, thereby, entails shrinking markups for conventional farmers. The estimates for $OSHCON$ range from -0.018 for FE excluding markups below the five percent and above the 95 percent percentile to -0.069 for pooled OLS (cf. Table 3.4). Given a mean

[20] Note that for approximately 80 percent of the observations the market shares of organic milk increase. Therefore, my argumentation refers to increasing supply/demand.

increase across countries over the entire sample period in the market share of organic milk of 4.19 percentage points, this would imply a markup decrease of 0.08 and 0.29 for FE excluding the bottom and top five percent and pooled OLS, respectively. Consequently, in addition to the organic markup premium the effect of increasing market shares of organic milk on conventional dairy farmers' markups also incentivizes the conversion to organic farming.

Regarding farm size, the coefficient of log milk output [thousand tons] amounts to 0.787 and is significantly different from zero (cf. Table 3.4, column 5). That is, markups rise by 0.787 for a one percent increment in milk output, which supports the expectation that markups increase with increasing output (Hypothesis 3). The effect size and its significance is robust across all models. It is also interesting to note how the estimates change when I control for MC (Table 3.5). The models excluding upper and lower markup percentiles and controlling for MC predict a markup change between -0.198 and 0.251 when milk output increases by one percent, which points to the presence of substantial economies of scale for conventional as well as organic farmers because farmers with higher output realize a high share of their markup gains from lower MC. My result is in line with other studies who find that marketing cooperatives and producer organizations help farmers to enhance their bargaining power towards downstream companies (e.g., Cakir and Balagtas 2012; Fałkowski et al. 2017; Prasertsri and Kilmer 2008). But, while the previous literature investigates this effect for organizations with multiple farms, I am able to show that the enhancing effect of size on market power is also present at the level of a single farm.

For the concentration in downstream industries, the results are equivocal. For the dairy processing industry, an increase in the market share of medium-sized processors of one percentage point entails a decrease in farmers' markups of 0.108 (pooled OLS; $p<0.01$) and 0.092 (FE; $p<0.01$) (cf. column 2 and 3 of Table 3.4). However, the pooled OLS and the FE models both yield positive estimates for large processors' market share that are significantly different from zero (cf. column 2 and 3 of Table 3.4). The models excluding the lower and upper markup percentiles and the median regression confirm this finding (cf. Table 3.4, column 4-8). A possible explanation for this outcome is the spatial nature of competition in dairy processing (Graubner et al. 2011a; Graubner et al. 2011b; Perekhozhuk et al. 2015). Because milk is highly perishable and costly to transport due to its high water content, it is infeasible for farmers to deliver their milk to far dairy processors (Rogers and Sexton 1994). Therefore, already medium-sized processors may countervail farmers' bargaining power and engage in price discrimination (Graubner et al. 2011a). In contrast, large processors need higher raw milk quantities to exploit their processing capacities, and pay higher prices to ensure raw milk supply. In that regard, Mérel and Sexton (2017) show that high market concentration in the processing sector may not necessarily entail milk prices below the competitive level but the long-run incentive to secure milk supply dominates the short-run incentive to undercut the perfectly competitive milk price which would lead to farm exit in the long-run.

Last, neither pooled OLS nor FE results identify any significant impact of medium-sized retailers' market shares ($RETSHM$) on dairy farmers' markups in the base models (cf. column 2-3 of Table 3.4), even if omitting extreme markup values (cf. column 4-7 of Table 3.4). Only for the median regression, I find a negative coefficient for $RETSHM$ which is also significantly different from zero (p<0.01; Table 3.4 column 8). When controlling for MC and excluding the bottom and top markup percentiles, all models predict a negative relationship between $RETSHM$ and markup (p<0.01; cf. column 4-8 of Table 3.5).

For the market share of large retailers ($RETSHL$), pooled OLS yields a significantly positive estimate (p<0.05) whereas the coefficient for FE is negative as expected (p<0.01) (cf. Table 3.4, column 2-3). This is robust when excluding the bottom and top percentiles of markups (Table 3.4 column 4-7) while the estimate of the median regression is negative and significantly different from zero (p<0.01). Controlling for MC, the results are similar except for the fact the p-values for pooled OLS increase in the base model (p=0.069) and when excluding the bottom and top one percent markup percentile (p=0.41) (Table 3.5). The remaining models (cf. column 3 and 5-8 of Table 3.4) yield negative estimates which are significant (p<0.01). As pooled OLS ignores unobserved farm-specific heterogeneity, its results should be interpreted with caution such that I rely on the outcome of the FE and median regression, which present evidence in favor of Hypothesis 4b (*Dairy farmers' markups decrease with increasing concentration in the food retail sector*). My result is in accordance with studies on the bargaining power of retailers (e.g., Bonnet and Bouamra-Mechemache 2016; Draganska et al. 2010; Richards et al. 2018) which find that multi-/national food retail chains are able to push prices below the competitive level in procurement of food products from processors. Consequently, the processors' marginal value product of raw milk diminishes leading to lower prices of agricultural outputs and, finally, to smaller markups for farmers.

Regarding the relationship between the control variables and markups, all coefficients have the expected signs, i.e., the share of quasi-/fixed costs and the amount of unpaid labor are positively related with markups. An increase in $SHFC$ by one percentage point is associated with an increase in markups of 0.039 to 0.096 depending on the model (cf. Table 3.4). The same accounts to the amount of unpaid labor spent on the farm [hundred hours]. The parameter estimates range from 0.002 to 0.011 and are significantly different from zero in all models (cf. Table 3.4).

As stated earlier, the markups obtained in this study are much larger than those of earlier studies on manufacturing and service sectors. This is mainly driven by the fact that the fixed cost share, i.e., the share of quasi-/fixed in total costs, is much larger in agriculture compared to other sectors. For instance, Koppenberg and Hirsch (2021) investigate markups in three European dairy processing sectors (France, Italy and Spain) where firms have a mean fixed cost share of approximately 20 percent whereas the fixed cost share in my sample amounts to 54 percent. Using the lower (0.039; cf. Table 3.4, column 6) and upper (0.096; cf. Table 3.4, column 3) boundaries of the respective coefficient estimates ($SHFC$), a reduction of the fixed cost share from 54 percent to 20 percent would entail a decrease in markup by 1.33 and 3.26, respectively. Besides, the vast majority of industrial companies does not use unpaid labor in contrast to farmers. Decreasing the amount of unpaid labor from the sample mean (36.10) to zero would lead markups to diminish by further 0.07 or 0.40 depending on whether we use the lower boundary of the coefficient estimate for unpaid labor (0.002; cf. Table 3.4, column 3/7) or the upper boundary (0.011; cf. Table 3.4, column 2). Hence, a large share of the discrepancy in markups between my study and those of earlier studies on industrial and service sectors can be explained by differences in the share of fixed cost and the use of unpaid labor.

3.7 Conclusion

I estimate farm-level markups of output price over marginal cost of milk production for a sample of approximately 40,000 European dairy farmers using a translog cost function. Second, I investigate the role of farm- and country-level characteristics to explain the heterogeneity of markups across farms with particular emphasis on the role of organic farming.

Mean marginal cost are slightly larger for conventional compared to organic farmers while mean output is almost 50 percent larger for conventional farmers. My results indicate that the vast majority of farmers charges markups above one such that milk prices exceed marginal costs of milk production. I observe the largest markups in Western Europe and Scandinavia and the lowest markups in Eastern Europe while Southern European farmers rank in between.

The regressions of markups on farm- and country-level characteristics show a significant markup premium for organic over conventional dairy farmers. When controlling for marginal costs, the advantage is slightly smaller such that organic farmers produce at lower marginal costs and achieve higher prices than conventional farmers do. Interestingly, markups of organic farmers do not vary with increasing market shares of organic milk in total milk production even when I control for marginal costs. Given that market shares of organic milk rise in approximately 90 percent of the cases, potential price decreases for organic milk due to increased supply are offset by rising demand. In contrast, markups of conventional farmers decrease with increasing market shares of organic milk as the demand for conventional milk decreases which is robust across all model specifications.

In addition, markups increase significantly with milk output across all models. This is in line with studies that identify the impact of producer organizations and cooperatives on the milk price bargaining power of farmers, and find that cooperative members achieve significantly higher prices compared to non-members. However, the incline diminishes when I control for marginal costs which points to the presence of economies of scale, i.e., cost advantages that large farms benefit from, thereby boosting their markups.

Regarding the concentration in downstream sectors, the results are not fully conclusive. While the market share of medium-sized food retailers has a negative impact on farmers' markups only in half of the specifications, fixed effects and median regression suggest that the market share of large retailers has a significant negative impact on markups in all cases. A positive association between markups and the market share of large retailers is only drawn by pooled OLS, which, however, ignore farm-specific heterogeneity. Overall, my findings thus point to adverse effects of the presence of large national food retail chains on farm-level markups. For concentration in dairy processing, I find a robust negative relationship between the market share of medium-sized processors and farm-level markups in all models. Contrary, my analysis reveals a positive link between the market share of large dairy processors and farmers' markups, which is consistent across all models. This seems counterintuitive given the large body of literature on the relationship of market structure and conduct predicting that processors will pay below-competitive raw milk prices with rising concentration. But, the assurance of long-run milk supply from farmers may dominate the short-run incentive to exercise bargaining power in raw milk procurement (Mérel and Sexton 2017) such that large dairy processors could pay higher prices than medium-sized processors.

From a farmer's perspective, my results show that the conversion to organic agriculture is highly beneficial when looking at markups as a target measure. Besides, continuously increasing demand for organic milk outweighs potential price decreases due to increasing supply in the past years so that the conversion is still to be considered attractive for conventional farmers. This is even reinforced by the fact that markups of conventional farmers decrease with increasing market shares of organic milk. While my analysis illustrates the case of organic farming and dairy farmers' markups, the outcomes are likely transferable to other niche products such as organic meat production or locally produced plant-based milk. By successfully discovering or creating new niche markets farmers can enhance their bargaining power towards downstream companies, and thereby, sustain long-term competitiveness. For the Common Agricultural Policy, policy makers may contemplate the creation of innovation funds that may help farmers to design new products or redesign the production process to generate price premia in new niche markets.

Further, my analysis indicates that farm growth is beneficial from a cost perspective as well as partly from a price perspective. That is, large dairy farms exploit economies of scale on one hand. On the other hand, they have higher bargaining power towards downstream companies. This is in line with earlier research stating that larger farms are less likely affected by asymmetric price transmission to and from downstream companies compared to smaller farms (Bakucs et al. 2014). Consequently, farm growth is a favorable strategy from a farmer's perspective reinforcing the structural change of European agriculture towards larger farms, which plays an important role in debates on the Common Agricultural Policy of the European Union (European Union 2016).

The robust negative relationship between farmers' markups and the market share of large food retailers, which are mostly driven by the presence of large multi-/national retail chains, raises concerns with respect to adverse effects of the continuing consolidation in food retailing on farmers in Europe. While competition authorities mainly look at the impact of mergers and acquisitions on downstream competition in their evaluation process, my study highlights the need to consider the influence on upstream companies as well.

Despite my study is informative about the differences in markups between organic and conventional farmers, other farm and product characteristics and the potential presence of interactive effects on farm-level markups are worthwhile to examine. For instance, labels of local production or extensive non-organic livestock farming as well as increased transparency rendered by e.g., livestreams of the livestock sheds may also provide synergies in generating a markup premium. With the given data however, it is not possible to elicit such mechanisms so that I encourage future research to investigate this question. Second, milk is, like meat, highly perishable. The effect of organic production on markups might change as international trade of raw products becomes more important when perishability declines, e.g., for cereals. With increased international competition, the markup premia for organic farmers may then abate.

Besides, it would also be valuable to investigate whether different variables affect markups of conventional and organic farms differently. This could reveal interesting insights from a policy-making point of view regarding e.g., the development of antitrust policies for downstream industries. However, such an analysis is beyond the scope of this paper.

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3.8 Appendix

Table 3.A1 Definitions of Variables Used in the Analysis

Category	Variable	Definition	Unit	Source
Cost function estimation				
Outputs	*Milk sales*	Revenue from selling milk	Euro	FADN
	Milk price	Price per kilogram of milk	Euro/kilogram	FADN
	Milk quantity	Quantity of milk produced on the farm	Kilograms	FADN
	Livestock sales	Revenue from selling animals	Euro	FADN
	Livestock price	Price index of animals sold	Percentage (base = 2010)	Eurostat
	Livestock sales quantity	Livestock sales/ Price index of animals sold	Euro	FADN/Eurostat
	Crop sales	Revenue from selling crops	Euro	FADN
	Crop price	Price index of crops	Percentage (base = 2010)	Eurostat
	Crop sales quantity	Crop sales/ Price index of crops	Euro	FADN/Eurostat
Variable inputs	*Feed expenditures*	Expenditures for feed for grazing livestock not produced on farm	Euro	FADN
	Feed price	Price index for animal feedstuff purchases	Percentage (base = 2010)	Eurostat
	Feed quantity	Feed expenditures/ Price index for animal feedstuff purchases	Euro	FADN/Eurostat
	Energy expenditures	Expenditures for energy	Euro	FADN
	Energy price	Price index for energy	Percentage (base = 2010)	Eurostat
	Energy quantity	Energy expenditures/ Price index for energy	Euro	FADN/Eurostat
	Crop input expenditures	Expenditures for seeds + expenditures for fertilizer + expenditures for plant protection products	Euro	FADN
	Crop input price	Composite price index for seeds, fertilizer and plant protection products weighted by expenditure shares	Percentage (base = 2010)	FADN/Eurostat
	Crop input quantity	Expenditures for seeds/ Price index for seeds + expenditures for fertilizer/ price index for fertilizer + expenditures for plant protection products/ price index for plant protection products	Euro	FADN/Eurostat

Quasi-fixed inputs	*Unpaid labor quantity*	Labor deployed on the farm without monetary remuneration	Hours	FADN
	Paid labor quantity	Labor deployed on the farm with monetary remuneration	Hours	FADN
	Land	Land under cultivation	Hectares	FADN
	Capital	Value of fixed assets except land and livestock	Euro	FADN
	Dairy cattle	Average number of dairy cows on the farm	Livestock units	FADN
	Other livestock	Average number of livestock on the farm except dairy cows	Livestock units	FADN
Second stage regression				
	ORG	Dummy variable being equal to one for organic farms and zero for conventional farms		FADN
	OSHORG	Variable capturing the market share of organic milk in total milk production for organic farms and is zero for conventional farms	Percent	Eurostat
	OSHCON	Variable capturing the market share of organic milk in total milk production for conventional farms and is zero for organic farms	Percent	Eurostat
	ln(MILK)	Natural log of milk output	1,000 tons	FADN
	PRSHM	Market share [sales] of medium-sized dairy processors (50-249 employees)	Percent	Eurostat
	PRSHL	Market share [sales] of large dairy processors (>250 employees)	Percent	Eurostat
	RETSHM	Market share [sales] of medium-sized food retailers (50-249 employees)	Percent	Eurostat
	RETSHL	Market share [sales] of large food retailers (>250 employees)	Percent	Eurostat
	UNPLAB	Number of hours of unpaid labor deployed on the farm	100 hours	FADN
	SHFC	Share of quasi-/fixed costs in total costs calculated by subtracting costs of purchased feed, energy, seeds, fertilizer and crop protection products	Percent	FADN

Source: European Farm Accountancy Data Network and Eurostat 2020a, 2020b, 2020c, 2020d

Table 3.A2 Descriptive Statistics of Variables for Cost Function Estimation

Variable	Mean	Standard deviation	Minimum	Maximum
Cost function				
Cost [€]	304,658.4	816,013.6	373.0	26,477,742.0
Milk output [kg]	485,785.7	951,719.2	1,000	33,614,380.0
Livestock output [€]	340.8	928.0	<0.1	88,329.8
Crop output [€]	41,655.9	191,346.6	0.0	11,500,880.0
Feed price	108.3	17.7	68.8	146.8
Energy price	100.0	15.6	51.9	141.4
Maintenance of machinery and buildings price	99.7	10.2	71.3	123.3
Crop input price	105.4	18.3	58.2	155.2
Unpaid labor quantity [hours]	3,651.8	1,823.9	0.0	44,896.0
Paid labor quantity [hours]	5,399.0	25,501.1	0.0	1,006,106.0
Land quantity [hectares]	141.4	385.3	0.3	9,997.5
Capital [€]	337,842.3	827,796.6	0.0	24,125,880.0
Dairy cattle quantity [livestock units]	66.7	113.1	<0.1	3,492.3
Second stage regression				
ORG	0.05	0.22	0.00	1
OSHORG	0.49	2.56	0.00	20.30
OSHCON	5.41	3.53	0.00	20.30
ln(MILK)	-1.51	1.43	-6.91	3.49
PRSHM	4.18	2.31	1.15	13.42
PRSHL	25.55	4.61	5.70	40.67
RETSHM	8.71	4.72	0.00	44.18
RETSHL	13.75	7.53	0.00	22.57
UNPLAB	36.10	16.45	0.01	432.00
SHFC	54.13	14.13	2.69	97.36

Source: European Farm Accountancy Data Network and Eurostat 2020a

Table 3.A3 Representativeness of the Sample Farms for Farming Type "Specialist Milk" by Country (2016)

Country	Farm number (sample)	Farm number (population)	Share of sample in population [%]	Dairy cows (sample) [livestock units]	Dairy cows (population) [livestock units]	Share of sample in population [%]	Difference between dairy cow share and farm number share [percentage points]
Austria	617	26,720	2.31	16,297	861,380	1.89	-0.42
Belgium	358	4,530	7.90	31,501	589,010	5.35	-2.55
Czechia	138	910	15.16	34,994	202,200	17.31	2.14
Denmark	374	2,970	12.59	81,293	875,720	9,28	-3.31
Finland	254	7,280	3.49	14,974	410,550	3.65	0.16
France	969	41,470	2.37	65,343	4,492,870	1.45	-0.88
Germany	2,300	53,010	4.34	230,722	5,802,570	3.98	-0.36
Greece	9	1,850	0.49	Not reported*	112,330	Not reported*	Not reported*
Hungary	96	3,500	2.74	20,569	226,880	9.07	6.32
Italy	620	31,230	1.99	48,339	2,454,300	1.97	-0.02
Latvia	292	10,540	2.77	15,777	186,070	8.48	5.71
Netherlands	349	16,470	2.12	47,748	2,356,080	2.03	-0.09
Poland	2,651	101,060	2.62	70,211	2,457,630	2.86	0.23
Portugal	312	6,590	4.73	10,557	389,510	2.71	-2.02
Slovakia	66	2,080	3.17	18,178	96,580	18.82	15.65
Slovenia	184	6,280	2.93	3,803	161,160	2.36	-0.57
Spain	692	16,180	4.28	57,051	1,168,650	4.88	0.60
Sweden	386	3,650	10.58	35,363	539,950	6.55	-4.03
United Kingdom	443	11,410	3.88	67,531	2,751,700	2.45	-1.43
All countries	10,798	341,140	3.17	859,694**	25,633,200**	3.35**	0.19

Source: FADN and Eurostat 2020c; *not reported due to confidentiality agreement since number of farms is below 15; **excluding Greece.

Table 3.A4 Results of Testing for Technological Differences of Conventional and Organic Farms

	Joint technology	Flexible technology	
Variables	**All farms**	**Conventional**	**Organic**
ln(milk quantity)	-0.333***	-0.336***	-0.217
	(0.045)	(0.055)	(0.154)
ln(livestock output)	0.125***	0.120***	0.177***
	(0.016)	(0.019)	(0.055)
ln(crop output)	0.010***	0.008**	0.040***
	(0.003)	(0.003)	(0.014)
ln(crop input price/energy price)	0.168***	0.159***	-0.048***
	(0.007)	(0.005)	(0.018)
ln(feed price/energy price)	-0.143***	-0.141***	0.085*
	(0.010)	(0.012)	(0.051)
ln(unpaid labor quantity)	-0.089***	-0.089***	-0.054
	(0.019)	(0.022)	(0.058)
ln(paid labor quantity)	0.038***	0.042***	-0.018
	(0.007)	(0.008)	(0.030)
ln(land quantity)	0.655***	0.663***	0.695***
	(0.038)	(0.028)	(0.204)
ln(other livestock)	0.086***	0.091***	-0.105
	(0.033)	(0.029)	(0.115)
ln(capital)	0.002	0.006	-0.021
	(0.020)	(0.018)	(0.087)
ln(dairy cows)	-0.053	-0.047	-0.238
	(0.049)	(0.047)	(0.213)
*ln(milk quantity)*ln(milk quantity)*	0.043***	0.043***	0.030***
	(0.003)	(0.003)	(0.008)
*ln(milk quantity)*ln(crop output)*	-0.003***	-0.003***	-0.003*
	(0.001)	(3.87e-4)	(0.002)
*ln(milk quantity)*ln(livestock output)*	-0.007***	-0.007***	-0.007
	(0.002)	(0.002)	(0.007)
*ln(crop output)*ln(crop output)*	0.001***	0.001***	0.001***
	(8.97e-5)	(7.20e-5)	(3.29e-4)
*ln(crop output)*ln(livestock output)*	-4.05e-4**	-4.99e-4**	0.001*
	(1.70e-4)	(2.17e-4)	(0.001)
*ln(livestock output)*ln(livestock output)*	0.005***	0.005***	0.004**
	(4.57e-4)	(3.73e-4)	(0.002)
*ln(milk quantity)*ln(crop input price/energy price)*	-0.006***	-0.005***	0.002
	(0.001)	(4.12e-4)	(0.002)
*ln(milk quantity)*ln(feed price/energy price)*	0.043***	0.043***	0.040***
	(0.001)	(0.001)	(0.004)
*ln(crop output)*ln(crop input price/energy price)*	0.001***	0.001***	0.001***
	(5.59e-4)	(4.28e-5)	(8.76e-5)
*ln(crop output)*ln(feed price/energy price)*	-0.002***	-0.002***	-0.002***
	(3.74e-5)	(7.58e-5)	(4.05e-4)

*ln(livestock output)*ln(crop input price/energy price)*	-0.001***	-0.001***	-0.001
	(6.45e-5)	(1.83e-4)	(4.97e-4)
*ln(livestock output)*ln(feed price/energy price)*	0.001***	0.001***	0.001
	(1.85e-4)	(2.37e-4)	(0.001)
*ln(milk quantity)*ln(unpaid labor quantity)*	-0.006***	-0.006***	-0.004
	(0.002)	(0.002)	(0.007)
*ln(milk quantity)*ln(paid labor quantity)*	-0.004***	-0.004***	-0.003
	(0.001)	(0.001)	(0.003)
*ln(milk quantity)*ln(land quantity)*	-0.044***	-0.044***	-0.070***
	(0.004)	(0.003)	(0.016)
*ln(milk quantity)*ln(other livestock)*	-0.005	-0.005**	0.011
	(0.003)	(0.002)	(0.011)
*ln(milk quantity)*ln(capital)*	-0.008***	-0.009***	0.010
	(0.002)	(0.002)	(0.009)
*ln(milk quantity)*ln(dairy cows)*	0.014***	0.014***	0.029
	(0.004)	(0.005)	(0.022)
*ln(crop output)*ln(unpaid labor quantity)*	2.52e-4	2.29e-4	-1.11e-4
	(1.67e-4)	(1.87e-4)	(0.001)
*ln(crop output)*ln(paid labor quantity)*	9.79e-6	4.01e-5	-0.000*
	(3.82e-5)	(4.55e-5)	(2.33e-4)
*ln(crop output)*ln(land quantity)*	0.004***	0.004***	0.004***
	(3.41e-4)	(2.93e-4)	(0.001)
*ln(crop output)*ln(other livestock)*	-2.27e-4	-9.88e-5	-1.12e-4
	(3.10e-4)	(3.84e-4)	(0.001)
*ln(crop output)*ln(capital)*	-1.31e-4	-3.60e-5	-0.002***
	(1.59e-4)	(1.65e-4)	(0.001)
*ln(crop output)*ln(dairy cows)*	-0.001	-0.001	0.001
	(0.001)	(4.92e-4)	(0.003)
*ln(livestock output)*ln(unpaid labor quantity)*	-0.001***	-0.001*	-0.003
	(4.25e-4)	(0.001)	(0.003)
*ln(livestock output)*ln(paid labor quantity)*	0.001***	0.001***	3.97e-4
	(2.39e-4)	(2.47e-4)	(0.001)
*ln(livestock output)*ln(land quantity)*	-1.85e-4	1.87e-4	-0.008
	(0.001)	(0.001)	(0.008)
*ln(livestock output)*ln(other livestock)*	0.006***	0.006***	0.018***
	(0.001)	(0.001)	(0.006)
*ln(livestock output)*ln(capital)*	-0.002***	-0.002***	-0.006**
	(0.001)	(0.001)	(0.003)
*ln(livestock output)*ln(dairy cows)*	-0.011***	-0.012***	-0.008
	(0.002)	(0.003)	(0.009)
*ln(crop input price/energy price)*ln(crop input price/energy price)*	-0.006***	-0.005**	-0.039***
	(0.002)	(0.002)	(0.005)
*ln(crop input price/energy price)*ln(feed price/energy price)*	0.004***	0.005***	-0.009***
	(0.001)	(0.001)	(0.003)
ln(feed price/energy price) ln(feed price/energy price)*	-0.034***	-0.036***	0.039***
	(0.003)	(0.003)	(0.013)
*ln(crop input price/energy price)*ln(unpaid labor quantity)*	2.95e-4	0.001**	3.45e-5
	(2.94e-4)	(2.58e-4)	(0.001)

*ln(crop input price/energy price)*ln(paid labor quantity)*	-0.001***	-0.001***	-0.001***
	(5.24e-5)	(4.79e-5)	(1.33e-4)
*ln(crop input price/energy price)*ln(land quantity)*	0.021***	0.022***	0.005***
	(0.001)	(0.001)	(0.001)
*ln(crop input price/energy price)*ln(other livestock)*	-0.005***	-0.005***	-0.002*
	(3.15e-4)	(3.52e-4)	(0.001)
*ln(crop input price/energy price)*ln(capital)*	-0.004***	-0.004***	-0.002***
	(1.69e-4)	(1.16e-4)	(0.001)
*ln(crop input price/energy price)*ln(dairy cows)*	-0.005***	-0.006***	-0.003**
	(0.001)	(4.78e-4)	(0.001)
*ln(feed price/energy price)*ln(unpaid labor quantity)*	0.001*	0.001**	-0.002
	(0.001)	(4.40e-4)	(0.003)
*ln(feed price/energy price)*ln(paid labor quantity)*	-0.003***	-0.003***	-0.002***
	(1.07e-4)	(9.39e-5)	(4.02e-4)
*ln(feed price/energy price)*ln(land quantity)*	-0.005***	-0.006***	0.006*
	(0.001)	(0.002)	(0.003)
*ln(feed price/energy price)*ln(other livestock)*	0.009***	0.009***	0.014***
	(0.001)	(0.001)	(0.003)
*ln(feed price/energy price)*ln(capital)*	-0.011***	-0.011***	-0.016***
	(4.38e-4)	(4.10e-4)	(0.002)
*ln(feed price/energy price)*ln(dairy cows)*	0.008***	0.009***	-0.003
	(0.001)	(0.002)	(0.005)
*ln(unpaid labor quantity)*ln(unpaid labor quantity)*	0.005***	0.005***	0.008***
	(0.001)	(0.001)	(0.002)
*ln(unpaid labor quantity)*ln(paid labor quantity)*	-0.001*	-0.001**	4.41e-4
	(0.001)	(4.22e-4)	(0.002)
*ln(unpaid labor quantity)*ln(land quantity)*	2.04e-4	4.11e-4	0.004
	(0.001)	(0.001)	(0.008)
*ln(unpaid labor quantity)*ln(other livestock)*	0.005***	0.005***	-0.003
	(0.001)	(0.001)	(0.004)
*ln(unpaid labor quantity)*ln(capital)*	0.006***	0.007***	-0.004
	(0.001)	(0.001)	(0.003)
*ln(unpaid labor quantity)*ln(dairy cows)*	0.008***	0.007**	0.018**
	(0.002)	(0.003)	(0.008)
*ln(paid labor quantity)*ln(paid labor quantity)*	0.005***	0.005***	0.006***
	(1.49e-4)	(1.41e-4)	(0.001)
*ln(paid labor quantity)*ln(land quantity)*	-0.003***	-0.003***	0.004**
	(4.33e-4)	(0.001)	(0.002)
*ln(paid labor quantity)*ln(other livestock)*	-0.002***	-0.002***	-0.004*
	(4.88e-4)	(3.66e-4)	(0.002)
*ln(paid labor quantity)*ln(capital)*	-0.001***	-0.001***	0.001
	(2.75e-4)	(2.97e-4)	(0.001)
*ln(paid labor quantity)*ln(dairy cows)*	0.005***	0.005***	2.69e-5
	(0.001)	(0.001)	(0.003)
*ln(land quantity)*ln(land quantity)*	0.028***	0.030***	0.027**
	(0.002)	(0.003)	(0.011)
*ln(land quantity)*ln(other livestock)*	0.003	0.001	0.023**
	(0.002)	(0.003)	(0.010)

*ln(land quantity)*ln(capital)*	-0.012***	-0.011***	-0.020*
	(0.001)	(0.001)	(0.010)
*ln(land quantity)*ln(dairy cows)*	0.001	-0.005	0.072***
	(0.005)	(0.004)	(0.022)
*ln(other livestock)*ln(other livestock)*	0.009***	0.009***	0.015***
	(0.001)	(0.001)	(0.003)
*ln(other livestock)*ln(capital)*	-0.002*	-0.003***	0.006
	(0.001)	(0.001)	(0.005)
*ln(other livestock)*ln(dairy cows)*	-0.018***	-0.016***	-0.065***
	(0.004)	(0.004)	(0.015)
*ln(capital)*ln(capital)*	0.008***	0.008***	0.007***
	(2.10e-4)	(2.11e-4)	(0.001)
*ln(capital)*ln(dairy cows)*	-0.002	1.69e-4	-0.019**
	(0.003)	(0.002)	(0.008)
*ln(dairy cows)*ln(dairy cows)*	0.006**	0.005*	0.003
	(0.003)	(0.003)	(0.015)
2005	-0.016***	-0.017***	0.028***
	(0.002)	(0.003)	(0.007)
2006	-0.011***	-0.013***	0.030***
	(0.003)	(0.002)	(0.010)
2007	0.047***	0.048***	0.043***
	(0.002)	(0.002)	(0.012)
2008	0.011***	0.011***	0.020**
	(0.002)	(0.002)	(0.010)
2009	0.002	0.000	0.051***
	(0.003)	(0.002)	(0.009)
2010	-0.009***	-0.010***	0.014
	(0.002)	(0.002)	(0.008)
2011	-0.029***	-0.029***	-0.027***
	(0.002)	(0.003)	(0.009)
2012	-0.009***	-0.008***	-0.022***
	(0.002)	(0.002)	(0.008)
2013	0.016***	0.016***	0.014
	(0.002)	(0.002)	(0.011)
2014	0.028***	0.028***	0.028***
	(0.003)	(0.002)	(0.007)
2015	0.038***	0.038***	0.048***
	(0.003)	(0.002)	(0.009)
2016	0.058***	0.056***	0.087***
	(0.002)	(0.002)	(0.008)
2017	0.042***	0.039***	0.080***
	(0.002)	(0.002)	(0.010)
Constant	2.936***	2.910***	
	(0.276)	(0.327)	
Observations	203,979	203,979	
Within-R-squared	0.407	0.409	

Note: Standard errors in parentheses; Significance indicators: *** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations based on European Farm Accountancy Data Network

Table 3.A5 Results of Testing for Technological Differences of Mixed Farms and Specialized Dairying (Only Conventional)

	Joint technology	Flexible technology	
Variables	**All conventional farms**	**Mixed farms**	**Specialized dairy**
ln(milk quantity)	-0.338***	-0.233***	-0.522***
	(0.036)	(0.051)	(0.045)
ln(livestock output)	0.120***	0.136***	0.109***
	(0.019)	(0.026)	(0.022)
ln(crop output)	0.007	0.005	
	(0.005)	(0.007)	
ln(crop input price/energy price)	0.178***	0.072***	0.077***
	(0.006)	(0.005)	(0.009)
ln(feed price/energy price)	-0.148***	-0.176***	-0.075***
	(0.010)	(0.008)	(0.021)
ln(unpaid labor quantity)	-0.086***	-0.127***	0.119**
	(0.017)	(0.020)	(0.054)
ln(paid labor quantity)	0.042***	0.008	0.076***
	(0.006)	(0.008)	(0.012)
ln(land quantity)	0.669***	0.596***	0.532***
	(0.046)	(0.037)	(0.059)
ln(other livestock)	0.087**	0.118***	0.206***
	(0.041)	(0.045)	(0.036)
ln(capital)	0.007	-0.017	0.030
	(0.018)	(0.018)	(0.021)
ln(dairy cows)	-0.048	-0.026	-0.021
	(0.041)	(0.054)	(0.071)
*ln(milk quantity)*ln(milk quantity)*	0.043***	0.034***	0.060***
	(0.002)	(0.003)	(0.004)
*ln(milk quantity)*ln(crop output)*	-0.003***	-0.002**	
	(0.001)	(0.001)	
*ln(milk quantity)*ln(livestock output)*	-0.007***	-0.008***	-0.007***
	(0.002)	(0.003)	(0.003)
*ln(crop output)*ln(crop output)*	0.001***	0.001***	
	(9.04e-5)	(9.58e-5)	
*ln(crop output)*ln(livestock output)*	-0.001***	-0.001**	
	(1.80e-4)	(0.001)	
*ln(livestock output)*ln(livestock output)*	0.005***	0.005***	0.005***
	(3.09e-4)	(0.001)	(0.001)
*ln(milk quantity)*ln(crop input price/energy price)*	-0.006***	-0.001**	-0.004***
	(0.001)	(0.001)	(0.001)
*ln(milk quantity)*ln(feed price/energy price)*	0.043***	0.041***	0.056***
	(0.001)	(0.001)	(0.002)
*ln(crop output)*ln(crop input price/energy price)*	0.001***	0.001***	
	(2.80e-5)	(5.58e-5)	

*ln(crop output)*ln(feed price/energy price)*	-0.001***	-0.002***	
	(5.97e-5)	(1.07e-4)	
*ln(livestock output)*ln(crop input price/energy price)*	-0.001***	-0.001***	-1.83e-4
	(1.56e-4)	(2.56e-4)	(1.32e-4)
*ln(livestock output)*ln(feed price/energy price)*	0.001***	0.001***	0.001*
	(2.83e-4)	(4.55e-4)	(4.53e-4)
*ln(milk quantity)*ln(unpaid labor quantity)*	-0.006***	-0.004**	-0.020***
	(0.002)	(0.002)	(0.005)
*ln(milk quantity)*ln(paid labor quantity)*	-0.004***	-0.001	-0.009***
	(0.001)	(0.001)	(0.001)
*ln(milk quantity)*ln(land quantity)*	-0.044***	-0.036***	-0.037***
	(0.005)	(0.005)	(0.004)
*ln(milk quantity)*ln(other livestock)*	-0.004	-0.007	-0.014***
	(0.004)	(0.005)	(0.003)
*ln(milk quantity)*ln(capital)*	-0.009***	-0.007***	-0.010***
	(0.002)	(0.002)	(0.002)
*ln(milk quantity)*ln(dairy cows)*	0.014***	0.019***	0.007
	(0.004)	(0.006)	(0.010)
*ln(crop output)*ln(unpaid labor quantity)*	2.53e-4	1.57e-4	
	(1.78e-4)	(2.12e-4)	
*ln(crop output)*ln(paid labor quantity)*	3.66e-5	1.62e-4*	
	(4.04e-5)	(8.96e-5)	
*ln(crop output)*ln(land quantity)*	0.004***	0.003***	
	(3.60e-4)	(0.001)	
*ln(crop output)*ln(other livestock)*	-9.12e-5	0.001	
	(2.59e-4)	(0.001)	
*ln(crop output)*ln(capital)*	-1.62e-5	7.09e-5	
	(1.32e-4)	(2.27e-4)	
*ln(crop output)*ln(dairy cows)*	-0.001	-0.001	
	(0.001)	(0.001)	
*ln(livestock output)*ln(unpaid labor quantity)*	-0.001*	-0.001**	2.55e-4
	(0.001)	(0.001)	(0.001)
*ln(livestock output)*ln(paid labor quantity)*	0.001***	0.001***	0.001**
	(2.62e-4)	(3.00e-4)	(3.75e-4)
*ln(livestock output)*ln(land quantity)*	2.09e-4	-0.001	-0.001
	(0.001)	(0.002)	(0.002)
*ln(livestock output)*ln(other livestock)*	0.006***	0.007***	0.006***
	(0.002)	(0.002)	(0.002)
*ln(livestock output)*ln(capital)*	-0.002***	-0.003*	-0.001
	(0.001)	(0.002)	(0.001)
*ln(livestock output)*ln(dairy cows)*	-0.012***	-0.010***	-0.015***
	(0.003)	(0.004)	(0.004)
*ln(crop input price/energy price)*ln(crop input price/energy price)*	-0.004*	-0.008**	-0.009***
	(0.002)	(0.003)	(0.003)
*ln(crop input price/energy price)*ln(feed price/energy price)*	0.005***	0.006***	0.013***
	(0.001)	(0.001)	(0.001)
ln(feed price/energy price) ln(feed price/energy price)*	-0.035***	-0.021***	0.009
	(0.004)	(0.004)	(0.006)

*ln(crop input price/energy price)*ln(unpaid labor quantity)*	2.15e-4	0.002***	0.001***
	(2.45e-4)	(3.95e-4)	(3.85e.4)
*ln(crop input price/energy price)*ln(paid labor quantity)*	-0.001***	-0.001***	-0.001***
	(5.66e-5)	(9.21e-5)	(7.10e-5)
*ln(crop input price/energy price)*ln(land quantity)*	0.022***	0.040***	0.012***
	(0.001)	(0.001)	(0.001)
*ln(crop input price/energy price)*ln(other livestock)*	-0.005***	-0.008***	-0.002***
	(3.64e-4)	(4.07e-4)	(3.24e-4)
*ln(crop input price/energy price)*ln(capital)*	-0.004***	-0.005***	-0.003***
	(1.76e-4)	(2.83e-4)	(2.53e-4)
*ln(crop input price/energy price)*ln(dairy cows)*	-0.005***	-0.012***	-0.003***
	(0.001)	(0.001)	(0.001)
*ln(feed price/energy price)*ln(unpaid labor quantity)*	0.001**	0.004***	-0.001
	(0.001)	(0.001)	(0.001)
*ln(feed price/energy price)*ln(paid labor quantity)*	-0.003***	-0.002***	-0.004***
	(1.08e-4)	(8.22e-4)	(2.27e-4)
*ln(feed price/energy price)*ln(land quantity)*	-0.006***	-0.006***	-0.003**
	(0.001)	(0.001)	(0.001)
*ln(feed price/energy price)*ln(other livestock)*	0.009***	0.011***	0.006***
	(0.001)	(0.001)	(4.98e-4)
*ln(feed price/energy price)*ln(capital)*	-0.011***	-0.009***	-0.013***
	(4.79e-4)	(0.001)	(4.84e-4)
*ln(feed price/energy price)*ln(dairy cows)*	0.009***	0.008***	0.005*
	(0.001)	(0.001)	(0.002)
*ln(unpaid labor quantity)*ln(unpaid labor quantity)*	0.005***	0.006***	0.003***
	(4.34e-4)	(0.001)	(0.001)
*ln(unpaid labor quantity)*ln(paid labor quantity)*	-0.001**	-3.27e-4	-3.65e-4
	(4.93e-4)	(0.001)	(0.001)
*ln(unpaid labor quantity)*ln(land quantity)*	4.03e-4	0.002*	0.010***
	(0.001)	(0.001)	(0.002)
*ln(unpaid labor quantity)*ln(other livestock)*	0.005***	0.006***	-0.001
	(0.001)	(0.001)	(0.004)
*ln(unpaid labor quantity)*ln(capital)*	0.007***	0.007***	0.003*
	(0.001)	(0.001)	(0.002)
*ln(unpaid labor quantity)*ln(dairy cows)*	0.006**	0.003	0.009
	(0.003)	(0.003)	(0.006)
*ln(paid labor quantity)*ln(paid labor quantity)*	0.004***	0.004***	0.005***
	(1.53e-4)	(1.48e-4)	(1.79e-4)
*ln(paid labor quantity)*ln(land quantity)*	-0.003***	-0.003***	-0.003***
	(4.27e-4)	(0.001)	(0.001)
*ln(paid labor quantity)*ln(other livestock)*	-0.002***	-0.003***	-0.001*
	(4.69e-4)	(0.001)	(0.001)
*ln(paid labor quantity)*ln(capital)*	-0.001***	-0.001**	-0.001***
	(2.70e-4)	(3.05e-4)	(2.69e-4)
*ln(paid labor quantity)*ln(dairy cows)*	0.005***	0.001	0.010***
	(0.001)	(0.001)	(0.002)
*ln(land quantity)*ln(land quantity)*	0.030***	0.047***	0.011***
	(0.002)	(0.003)	(0.003)

*ln(land quantity)*ln(other livestock)*	0.001	-0.014***	0.012***
	(0.003)	(0.004)	(0.004)
*ln(land quantity)*ln(capital)*	-0.011***	-0.008***	-0.012***
	(0.001)	(0.002)	(0.003)
*ln(land quantity)*ln(dairy cows)*	-0.006	-0.027***	0.011*
	(0.006)	(0.007)	(0.006)
*ln(other livestock)*ln(other livestock)*	0.008***	0.009***	0.011***
	(0.001)	(0.002)	(0.002)
*ln(other livestock)*ln(capital)*	-0.003**	-0.004*	-0.001
	(0.001)	(0.002)	(0.002)
*ln(other livestock)*ln(dairy cows)*	-0.016***	0.001	-0.025***
	(0.005)	(0.007)	(0.005)
*ln(capital)*ln(capital)*	0.008***	0.008***	0.008***
	(1.44e-4)	(2.00e-4)	(2.04e-4)
*ln(capital)*ln(dairy cows)*	0.001	-0.003	0.003
	(0.002)	(0.003)	(0.003)
*ln(dairy cows)*ln(dairy cows)*	0.005**	0.007*	0.004
	(0.002)	(0.004)	(0.005)
2005	-0.016***	-0.031***	-0.010***
	(0.002)	(0.002)	(0.003)
2006	-0.012***	-0.014***	-0.017***
	(0.002)	(0.002)	(0.003)
2007	0.048***	0.045***	0.022***
	(0.003)	(0.003)	(0.003)
2008	0.011***	0.013***	-0.014***
	(0.002)	(0.002)	(0.003)
2009	0.000	-0.009***	-0.008**
	(0.002)	(0.001)	(0.004)
2010	-0.009***	-0.011***	-0.025***
	(0.002)	(0.002)	(0.003)
2011	-0.027***	-0.030***	-0.047***
	(0.002)	(0.002)	(0.003)
2012	-0.007***	-0.012***	-0.024***
	(0.002)	(0.002)	(0.003)
2013	0.017***	0.010***	-0.008***
	(0.002)	(0.002)	(0.003)
2014	0.029***	0.015***	0.018***
	(0.002)	(0.002)	(0.003)
2015	0.038***	0.028***	0.018***
	(0.002)	(0.002)	(0.003)
2016	0.056***	0.052***	0.023***
	(0.002)	(0.002)	(0.003)
2017	0.039***	0.073***	0.052***
	(0.003)	(0.024)	(0.012)
Constant	2.930***	2.700***	
	(0.260)	(0.263)	
Observations	192,601	192,601	

Within-R-squared	0.413	0.418

Note: Standard errors in parentheses; Significance indicators: *** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations based on European Farm Accountancy Data Network

Table 3.A6 Results of Testing for Technological Differences of Mixed Farms and Specialized Dairying (Only Organic)

	Joint technology	Flexible technology	
Variables	**All conventional farms**	**Mixed farms**	**Specialized dairy**
ln(milk quantity)	-0.148	-0.161	-0.356*
	(0.123)	(0.184)	(0.196)
ln(livestock output)	0.182***	0.165	0.165
	(0.070)	(0.111)	(0.100)
ln(crop output)	0.035**	0.025	
	(0.014)	(0.022)	
ln(crop input price/energy price)	0.085***	-0.002	0.082***
	(0.014)	(0.015)	(0.023)
ln(feed price/energy price)	-0.091*	-0.038	-0.155***
	(0.054)	(0.031)	(0.055)
ln(unpaid labor quantity)	-0.092	-0.114	-0.137
	(0.089)	(0.103)	(0.110)
ln(paid labor quantity)	0.007	-0.021	-0.005
	(0.039)	(0.034)	(0.042)
ln(land quantity)	0.557***	0.540**	0.527**
	(0.136)	(0.251)	(0.241)
ln(other livestock)	-0.062	0.083	0.040
	(0.107)	(0.174)	(0.213)
ln(capital)	0.033	-0.093	0.081
	(0.070)	(0.103)	(0.131)
ln(dairy cows)	-0.201	-0.151	0.011
	(0.146)	(0.260)	(0.255)
*ln(milk quantity)*ln(milk quantity)*	0.026***	0.037***	0.025*
	(0.009)	(0.013)	(0.014)
*ln(milk quantity)*ln(crop output)*	-0.003*	-0.002	
	(0.001)	(0.003)	
*ln(milk quantity)*ln(livestock output)*	-0.008	-0.002	-0.009
	(0.008)	(0.013)	(0.014)
*ln(crop output)*ln(crop output)*	0.001**	0.001***	
	(2.70e-4)	(2.65e-4)	
*ln(crop output)*ln(livestock output)*	0.001	-2.51e-4	
	(0.001)	(0.001)	
*ln(livestock output)*ln(livestock output)*	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)
*ln(milk quantity)*ln(crop input price/energy*	-0.004***	4.54e-4	-0.003

price)	(0.001)	(0.002)	(0.002)
*ln(milk quantity)*ln(feed price/energy price)*	0.041***	0.033***	0.052***
	(0.004)	(0.004)	(0.006)
*ln(crop output)*ln(crop input price/energy price)*	3.47e-4***	4.30e-4***	
	(8.03e-5)	(1.38e-4)	
*ln(crop output)*ln(feed price/energy price)*	-0.002***	-0.002***	
	(2.20e-4)	(3.38e-4)	
*ln(livestock output)*ln(crop input price/energy*	-0.001	-1.85e-5	-0.001
price)	(4.94e-4)	(0.001)	(4.38e-5)
*ln(livestock output)*ln(feed price/energy price)*	0.001	-0.001	0.002
	(0.010)	(0.002)	(0.002)
*ln(milk quantity)*ln(unpaid labor quantity)*	0.001	-0.012	0.018
	(0.010)	(0.009)	(0.014)
*ln(milk quantity)*ln(paid labor quantity)*	-0.003	-0.007**	0.005
	(0.004)	(0.003)	(0.005)
*ln(milk quantity)*ln(land quantity)*	-0.050***	-0.083***	-0.020
	(0.015)	(0.027)	(0.021)
*ln(milk quantity)*ln(other livestock)*	-2.85e-4	0.013	-0.022
	(0.011)	(0.020)	(0.026)
*ln(milk quantity)*ln(capital)*	0.002	1.16e-4	0.011
	(0.007)	(0.012)	(0.014)
*ln(milk quantity)*ln(dairy cows)*	0.023	0.011	0.008
	(0.017)	(0.029)	(0.030)
*ln(crop output)*ln(unpaid labor quantity)*	-3.12e-5	3.05e-4	
	(4.12e-4)	(0.001)	
*ln(crop output)*ln(paid labor quantity)*	-3.52e-4*	-4.79e-4	
	(2.06e-4)	(3.63e-4)	
*ln(crop output)*ln(land quantity)*	0.004***	0.003	
	(0.001)	(0.002)	
*ln(crop output)*ln(other livestock)*	-7.35e-5	0.001	
	(0.001)	(0.002)	
*ln(crop output)*ln(capital)*	-0.002***	-0.002*	
	(4.89e-4)	(0.001)	
*ln(crop output)*ln(dairy cows)*	0.001	-3.37e-4	
	(0.002)	(0.004)	
*ln(livestock output)*ln(unpaid labor quantity)*	-0.004*	-0.005***	-0.003
	(0.002)	(0.002)	(0.005)
*ln(livestock output)*ln(paid labor quantity)*	0.001	0.002	3.19e-4
	(0.001)	(0.002)	(0.001)
*ln(livestock output)*ln(land quantity)*	-0.004	-0.018**	0.006
	(0.006)	(0.008)	(0.009)
*ln(livestock output)*ln(other livestock)*	0.016***	0.018**	0.013
	(0.005)	(0.008)	(0.009)
*ln(livestock output)*ln(capital)*	-0.007***	-0.006	-0.007
	(0.003)	(0.005)	(0.005)
*ln(livestock output)*ln(dairy cows)*	-0.011	-0.014	-0.012
	(0.010)	(0.016)	(0.015)
*ln(crop input price/energy price)*ln(crop input*	-0.018***	-0.025***	-0.017***

price/energy price)	(0.007)	(0.010)	(0.005)
*ln(crop input price/energy price)*ln(feed price/energy price)*	-0.001	2.79e-4	0.005
	(0.003)	(0.004)	(0.003)
ln(feed price/energy price) ln(feed price/energy price)*	-0.009	0.024	-0.014
	(0.013)	(0.017)	(0.016)
*ln(crop input price/energy price)*ln(unpaid labor quantity)*	9.23e-5	0.002**	-1.49e-4
	(0.001)	(0.001)	(0.001)
*ln(crop input price/energy price)*ln(paid labor quantity)*	-2.88e-4***	-3.70e-4**	-2.02e-4*
	(1.03e-4)	(1.80e-4)	(1.23e-4)
*ln(crop input price/energy price)*ln(land quantity)*	0.005***	0.014***	0.002**
	(0.001)	(0.002)	(0.001)
*ln(crop input price/energy price)*ln(other livestock)*	-0.001	-0.002	3.34e-4
	(0.001)	(0.002)	(0.001)
*ln(crop input price/energy price)*ln(capital)*	-0.002***	-0.002*	-0.002***
	(0.001)	(0.001)	(0.001)
*ln(crop input price/energy price)*ln(dairy cows)*	0.001	-0.005*	0.001
	(0.002)	(0.003)	(0.002)
*ln(feed price/energy price)*ln(unpaid labor quantity)*	-0.003	-0.004	-0.003
	(0.003)	(0.003)	(0.004)
*ln(feed price/energy price)*ln(paid labor quantity)*	-0.002***	-0.001*	-0.003***
	(4.07e-4)	(0.001)	(4.42e-4)
*ln(feed price/energy price)*ln(land quantity)*	0.005	0.006	0.005
	(0.004)	(0.004)	(0.005)
*ln(feed price/energy price)*ln(other livestock)*	0.013***	0.015***	0.011***
	(0.003)	(0.003)	(0.004)
*ln(feed price/energy price)*ln(capital)*	-0.015***	-0.014***	-0.016***
	(0.002)	(0.003)	(0.002)
*ln(feed price/energy price)*ln(dairy cows)*	-0.003	0.004	-0.010
	(0.005)	(0.005)	(0.008)
*ln(unpaid labor quantity)*ln(unpaid labor quantity)*	0.008***	0.012***	0.004*
	(0.001)	(0.003)	(0.002)
*ln(unpaid labor quantity)*ln(paid labor quantity)*	-0.002	0.007**	-0.007***
	(0.003)	(0.003)	(0.002)
*ln(unpaid labor quantity)*ln(land quantity)*	0.002	-0.001	0.007
	(0.009)	(0.011)	(0.011)
*ln(unpaid labor quantity)*ln(other livestock)*	-0.001	4.62e-4	-0.009
	(0.005)	(0.005)	(0.009)
*ln(unpaid labor quantity)*ln(capital)*	-0.004	0.003	-0.010*
	(0.003)	(0.004)	(0.006)
*ln(unpaid labor quantity)*ln(dairy cows)*	0.017	0.021	0.013
	(0.011)	(0.014)	(0.020)
*ln(paid labor quantity)*ln(paid labor quantity)*	0.006***	0.008***	0.005***
	(0.001)	(0.001)	(0.001)
*ln(paid labor quantity)*ln(land quantity)*	0.004**	0.001	0.005*
	(0.002)	(0.003)	(0.003)
*ln(paid labor quantity)*ln(other livestock)*	-0.003**	-0.004**	-0.002
	(0.001)	(0.002)	(0.003)
*ln(paid labor quantity)*ln(capital)*	-4.30e-4	-0.001	-0.001

	(0.001)	(0.001)	(0.001)
*ln(paid labor quantity)*ln(dairy cows)*	-4.18e-4	0.004	-0.006
	(0.004)	(0.004)	(0.005)
*ln(land quantity)*ln(land quantity)*	0.021**	0.015	0.014
	(0.011)	(0.015)	(0.010)
*ln(land quantity)*ln(other livestock)*	0.024*	0.037***	0.033**
	(0.013)	(0.013)	(0.015)
*ln(land quantity)*ln(capital)*	-0.022***	0.019	-0.047***
	(0.008)	(0.012)	(0.014)
*ln(land quantity)*ln(dairy cows)*	0.048***	0.075**	0.027
	(0.016)	(0.030)	(0.029)
*ln(other livestock)*ln(other livestock)*	0.012**	0.013*	0.010
	(0.006)	(0.007)	(0.007)
*ln(other livestock)*ln(capital)*	0.010**	-0.021**	0.023***
	(0.005)	(0.010)	(0.008)
*ln(other livestock)*ln(dairy cows)*	-0.050***	-0.055**	-0.035
	(0.014)	(0.025)	(0.029)
*ln(capital)*ln(capital)*	0.008***	0.010***	0.007***
	(0.001)	(0.001)	(0.001)
*ln(capital)*ln(dairy cows)*	-0.011	-0.014	-0.016
	(0.007)	(0.014)	(0.013)
*ln(dairy cows)*ln(dairy cows)*	0.010	0.008	0.027
	(0.011)	(0.019)	(0.019)
2005	-0.009	-0.014	-0.052***
	(0.010)	(0.010)	(0.011)
2006	-0.008	-0.041***	-0.033***
	(0.010)	(0.011)	(0.012)
2007	0.024**	0.018	-0.025**
	(0.012)	(0.011)	(0.010)
2008	-0.002	-0.019	-0.044***
	(0.012)	(0.012)	(0.010)
2009	0.024***	0.001	-0.016*
	(0.009)	(0.014)	(0.009)
2010	-0.009	-0.007	-0.058***
	(0.009)	(0.012)	(0.011)
2011	-0.043***	-0.054***	-0.088***
	(0.011)	(0.013)	(0.011)
2012	-0.036***	-0.065***	-0.068***
	(0.011)	(0.010)	(0.009)
2013	0.008	-0.035***	-0.017
	(0.009)	(0.013)	(0.011)
2014	0.009	-0.026***	-0.018*
	(0.011)	(0.009)	(0.010)
2015	0.031**	-0.004	-0.002
	(0.012)	(0.011)	(0.008)
2016	0.069***	0.029***	0.035***
	(0.010)	(0.010)	(0.008)
2017	0.057***	0.073***	0.052***

	(0.010)	(0.024)	(0.012)
Constant	2.001***	2.646***	
	(0.863)	(0.880)	
Observations	11,378	11,378	
Within-R-squared	0.3244	0.3314	

Note: Standard errors in parentheses; Significance indicators: *** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations based on European Farm Accountancy Data Network

Table 3.A7 Final Cost Function Estimates

	Conventional farms		**Organic farms**	
Variables	**Specialized dairying**	**Mixed farms**	**Specialized dairying**	**Mixed farms**
ln(milk quantity)	-0.844***	-0.333***	-0.889***	-0.466**
	(0.052)	(0.038)	(0.231)	(0.237)
ln(livestock output)	0.104***	0.120***	-0.054	0.235**
	(0.022)	(0.020)	(0.101)	(0.114)
ln(crop output)		0.067***		0.217***
		(0.013)		(0.052)
ln(crop input price/energy price)	0.346***	0.561***	0.226***	0.289***
	(0.011)	(0.012)	(0.036)	(0.056)
ln(feed price/energy price)	0.058***	-0.046***	-0.088	-0.153*
	(0.015)	(0.013)	(0.067)	(0.084)
ln(unpaid labor quantity)	0.053	-0.168***	-0.116	-0.261**
	(0.044)	(0.018)	(0.121)	(0.124)
ln(paid labor quantity)	0.033***	-0.003	-0.089**	-0.119***
	(0.010)	(0.008)	(0.038)	(0.041)
ln(land quantity)	0.663***	0.488***	0.345	0.351*
	(0.040)	(0.039)	(0.222)	(0.213)
ln(other livestock)	0.080**	0.060*	-0.112	0.013
	(0.038)	(0.031)	(0.184)	(0.170)
ln(capital)	0.040***	0.006	0.072	-0.381***
	(0.015)	(0.016)	(0.087)	(0.099)
ln(dairy cows)	0.140**	0.101**	0.633**	0.290
	(0.062)	(0.046)	(0.299)	(0.314)
*ln(milk quantity)*ln(milk quantity)*	0.072***	0.038***	0.043***	0.029**
	(0.002)	(0.002)	(0.012)	(0.014)
*ln(milk quantity)*ln(crop output)*		-0.011***		-0.022***
		(0.001)		(0.006)
*ln(milk quantity)*ln(livestock output)*	-0.008***	-0.009***	0.007	-0.015
	(0.002)	(0.002)	(0.011)	(0.013)
*ln(crop output)*ln(crop output)*		0.003***		1.20e-4
		(2.25e-4)		(0.001)
*ln(crop output)*ln(livestock output)*		-0.001		-0.002
		(0.001)		(0.003)

*ln(livestock output)*ln(livestock output)*	0.005***	0.004***	0.003*	0.008***
	(0.001)	(4.56e-4)	(0.002)	(0.002)
*ln(milk quantity)*ln(crop input price/energy price)*	-0.019***	-0.032***	-0.015***	-0.020***
	(0.001)	(0.001)	(0.003)	(0.005)
*ln(milk quantity)*ln(feed price/energy price)*	0.058***	0.055***	0.082***	0.064***
	(0.001)	(0.001)	(0.006)	(0.007)
*ln(crop output)*ln(crop input price/energy price)*		0.010***		0.004***
		(2.59e-4)		(0.001)
*ln(crop output)*ln(feed price/energy price)*		-0.010***		-0.003***
		(2.96e-4)		(0.001)
*ln(livestock output)*ln(crop input price/energy price)*	3.80e-4	-0.001***	-0.002*	-3.67e-4
	(2.97e-4)	(3.67e-4)	(0.001)	(0.002)
*ln(livestock output)*ln(feed price/energy price)*	3.76e-4	0.001***	0.004**	0.001
	(4.05e-4)	(4.19e-4)	(0.002)	(0.003)
*ln(milk quantity)*ln(unpaid labor quantity)*	-0.013***	0.002	0.031***	0.009
	(0.005)	(0.002)	(0.011)	(0.012)
*ln(milk quantity)*ln(paid labor quantity)*	-0.008***	-4.76e-4	0.011***	-0.005
	(0.001)	(0.001)	(0.004)	(0.003)
*ln(milk quantity)*ln(land quantity)*	-0.051***	-0.040***	-0.020	-0.084***
	(0.004)	(0.004)	(0.021)	(0.021)
*ln(milk quantity)*ln(other livestock)*	0.001	0.003	-0.018	0.038**
	(0.004)	(0.003)	(0.020)	(0.019)
*ln(milk quantity)*ln(capital)*	-0.008***	-0.005***	0.015*	0.038***
	(0.001)	(0.002)	(0.008)	(0.011)
*ln(milk quantity)*ln(dairy cows)*	0.005	0.019***	-0.034	0.015
	(0.004)	(0.004)	(0.028)	(0.034)
*ln(crop output)*ln(unpaid labor quantity)*		2.67e-4		0.001
		(4.34e-4)		(0.001)
*ln(crop output)*ln(paid labor quantity)*		1.92e-4		-0.002**
		(1.74e-4)		(0.001)
*ln(crop output)*ln(land quantity)*		0.015***		0.010**
		(0.001)		(0.005)
*ln(crop output)*ln(other livestock)*		-0.003***		1.99e-4
		(0.001)		(0.005)
*ln(crop output)*ln(capital)*		-0.002***		-0.004*
		(0.001)		(0.002)
*ln(crop output)*ln(dairy cows)*		-0.001		0.019**
		(0.002)		(0.008)
*ln(livestock output)*ln(unpaid labor quantity)*	0.002*	-1.91e-4	-0.001	-0.003
	(0.001)	(0.001)	(0.005)	(0.003)
*ln(livestock output)*ln(paid labor quantity)*	4.61e-4	0.001*	0.001	0.002
	(3.58e-4)	(3.13e-4)	(0.001)	(0.002)
*ln(livestock output)*ln(land quantity)*	0.001	-0.002	0.001	-0.026***
	(0.002)	(0.002)	(0.009)	(0.010)
*ln(livestock output)*ln(other livestock)*	0.006***	0.008***	0.018**	0.020**
	(0.002)	(0.001)	(0.008)	(0.008)
*ln(livestock output)*ln(capital)*	-0.002***	-0.001	-4.10e-4	-0.002
	(0.001)	(0.001)	(0.003)	(0.004)

*ln(livestock output)*ln(dairy cows)*	-0.013***	-0.004	-0.027*	0.004
	(0.003)	(0.003)	(0.014)	(0.017)
*ln(crop input price/energy price)*ln(crop input price/energy price)*	-0.036***	0.026***	-0.011	-0.002
	(0.005)	(0.006)	(0.013)	(0.027)
*ln(crop input price/energy price)*ln(feed price/energy price)*	0.023***	0.011***	0.013**	-0.013
	(0.002)	(0.003)	(0.007)	(0.012)
ln(feed price/energy price) ln(feed price/energy price)*	0.039***	0.065***	0.013	0.121***
	(0.007)	(0.007)	(0.027)	(0.040)
*ln(crop input price/energy price)*ln(unpaid labor quantity)*	0.002***	-0.003***	0.001	0.003
	(0.001)	(0.001)	(0.002)	(0.003)
*ln(crop input price/energy price)*ln(paid labor quantity)*	-6.57e-5	-1.02e-4	2.21e-4	-3.43e-4
	(1.29e-4)	(1.34e-4)	(3.42e-4)	(0.001)
*ln(crop input price/energy price)*ln(land quantity)*	0.015***	0.051***	0.004	0.035***
	(0.001)	(0.001)	(0.003)	(0.006)
*ln(crop input price/energy price)*ln(other livestock)*	-0.003***	-0.012***	-0.001	-0.011***
	(0.001)	(0.001)	(0.002)	(0.003)
*ln(crop input price/energy price)*ln(capital)*	-0.001***	-0.004***	-0.001	-0.003
	(3.09e-4)	(4.25e-4)	(0.001)	(0.002)
*ln(crop input price/energy price)*ln(dairy cows)*	-0.007***	-0.016***	0.005	-0.010*
	(0.001)	(0.001)	(0.004)	(0.006)
*ln(feed price/energy price)*ln(unpaid labor quantity)*	-0.006***	0.001**	-0.009***	-0.002
	(0.001)	(0.001)	(0.003)	(0.004)
*ln(feed price/energy price)*ln(paid labor quantity)*	-0.001***	-6.69e-5	-0.002***	0.001
	(1.76e-4)	(1.53e-4)	(0.001)	(0.001)
*ln(feed price/energy price)*ln(land quantity)*	-0.016***	-0.048***	-0.018***	-0.014
	(0.001)	(0.002)	(0.006)	(0.010)
*ln(feed price/energy price)*ln(other livestock)*	-0.026***	0.001	0.016	-0.011
	(0.007)	(0.005)	(0.026)	(0.029)
*ln(feed price/energy price)*ln(capital)*	-0.003	0.002	-0.029***	-0.018**
	(0.002)	(0.002)	(0.007)	(0.009)
*ln(feed price/energy price)*ln(dairy cows)*	0.003*	0.017***	-0.026***	0.010
	(0.002)	(0.001)	(0.007)	(0.009)
*ln(unpaid labor quantity)*ln(unpaid labor quantity)*	0.004***	0.005***	0.002	0.012***
	(0.001)	(0.001)	(0.003)	(0.003)
*ln(unpaid labor quantity)*ln(paid labor quantity)*	0.003***	-4.26e-4	-0.006*	0.015***
	(0.001)	(0.001)	(0.003)	(0.004)
*ln(unpaid labor quantity)*ln(land quantity)*	0.008***	0.002	0.004	-0.007
	(0.002)	(0.002)	(0.013)	(0.013)
*ln(unpaid labor quantity)*ln(other livestock)*	-0.003	0.005***	-0.005	-0.002
	(0.003)	(0.001)	(0.009)	(0.006)
*ln(unpaid labor quantity)*ln(capital)*	0.004***	0.007***	-0.018***	0.001
	(0.001)	(0.001)	(0.005)	(0.004)
*ln(unpaid labor quantity)*ln(dairy cows)*	-0.007	-0.006***	-0.008	-0.010
	(0.006)	(0.002)	(0.015)	(0.014)
*ln(paid labor quantity)*ln(paid labor quantity)*	0.002***	0.002***	0.004***	0.007***
	(2.59e-4)	(1.89e-4)	(0.001)	(0.001)
*ln(paid labor quantity)*ln(land quantity)*	-0.001	-0.002***	0.008***	-2.93e-4
	(0.001)	(0.001)	(0.002)	(0.003)

*ln(paid labor quantity)*ln(other livestock)*	0.001	-0.002***	-0.004*	-0.004
	(0.001)	(4.78e-4)	(0.002)	(0.003)
*ln(paid labor quantity)*ln(capital)*	3.83e-4	0.001***	-2.94e-4	0.002
	(2.66e-4)	(2.72e-4)	(0.001)	(0.001)
*ln(paid labor quantity)*ln(dairy cows)*	0.007***	-2.02e-4	-0.012***	0.002
	(0.001)	(0.001)	(0.004)	(0.004)
*ln(land quantity)*ln(land quantity)*	0.010***	0.047***	0.028**	0.046***
	(0.002)	(0.002)	(0.013)	(0.014)
*ln(land quantity)*ln(other livestock)*	-3.22e-4	-0.013***	0.057***	0.031**
	(0.003)	(0.003)	(0.015)	(0.015)
*ln(land quantity)*ln(capital)*	-0.008***	-0.004**	-0.039***	0.028***
	(0.001)	(0.002)	(0.008)	(0.009)
*ln(land quantity)*ln(dairy cows)*	0.017***	-0.032***	0.011	0.043*
	(0.005)	(0.005)	(0.025)	(0.026)
*ln(other livestock)*ln(other livestock)*	0.013***	0.007***	0.009	0.018***
	(0.001)	(0.001)	(0.006)	(0.007)
*ln(other livestock)*ln(capital)*	0.003**	-0.003*	0.026***	-0.034***
	(0.001)	(0.001)	(0.005)	(0.008)
*ln(other livestock)*ln(dairy cows)*	-0.038***	-0.009**	-0.051**	-0.074***
	(0.004)	(0.004)	(0.023)	(0.025)
*ln(capital)*ln(capital)*	0.004***	0.004***	0.005***	0.006***
	(1.98e-4)	(2.05e-4)	(0.001)	(0.001)
*ln(capital)*ln(dairy cows)*	0.002	-0.004*	-0.018**	-0.042***
	(0.002)	(0.002)	(0.008)	(0.014)
*ln(dairy cows)*ln(dairy cows)*	0.009***	0.009***	0.069***	0.016
	(0.003)	(0.002)	(0.018)	(0.024)
2005	0.038***	0.053***	0.002	0.057***
	(0.004)	(0.003)	(0.014)	(0.016)
2006	0.036***	0.078***	0.020	0.036**
	(0.004)	(0.003)	(0.014)	(0.017)
2007	0.054***	0.105***	0.013	0.080***
	(0.003)	(0.002)	(0.012)	(0.015)
2008	0.006*	0.056***	-0.002	0.047***
	(0.003)	(0.002)	(0.012)	(0.014)
2009	0.006*	0.023***	0.019	0.049***
	(0.003)	(0.002)	(0.012)	(0.014)
2010	0.016***	0.068***	-0.006	0.069***
	(0.004)	(0.003)	(0.013)	(0.016)
2011	-0.009**	0.044***	-0.044***	0.010
	(0.004)	(0.003)	(0.012)	(0.015)
2012	0.016***	0.063***	-0.024**	0.007
	(0.004)	(0.003)	(0.012)	(0.014)
2013	0.026***	0.071***	0.016	0.024*
	(0.003)	(0.002)	(0.012)	(0.014)
2014	0.052***	0.081***	0.021*	0.033**
	(0.004)	(0.003)	(0.012)	(0.015)
2015	0.036***	0.065***	0.025**	0.044***
	(0.003)	(0.002)	(0.012)	(0.014)

2016	0.036***	0.079***	0.056***	0.071***
	(0.003)	(0.002)	(0.011)	(0.014)
2017	0.043***	0.081***	0.044***	0.076***
	(0.004)	(0.003)	(0.012)	(0.014)
Constant	4.544***	3.379***	5.789***	5.983***
	(0.376)	(0.253)	(1.492)	(1.476)
Observations	81,890	110,711	6,756	4,622
Within-R-squared	0.425	0.426	0.354	0.307

Note: Standard errors in parentheses; Significance indicators: *** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations based on European Farm Accountancy Data Network

Table 3.A8 Check of the Properties of the Cost Function

	Number of observations violating property…			
Farms	**Monotonicity in output**	**Monotonicity in input prices**	**Concavity in input prices**	**Number of observations violating any property (share)**
Conventional; specialized dairying	459	0	0	459 (2.93%)
Conventional; mixed	801	0	0	801 (2.22%)
Organic; specialized dairying	29	0	0	29 (3.81%)
Organic; mixed	90	0	0	90 (1.93%)

Source: Own calculations based on European Farm Accountancy Data Network

Table 3.A10 depicts the results of the median regression (baseline) and the quantile regression at the 10, 25, 75 and 90 percent quantiles. For $OSHCON$, $ln(MILK)$, $UNPLAB$ and $SHFC$ the set of results of the quantile regressions does not deliver any new insights. Despite the impact of $PRSHM$ and $PRSHL$ is not significantly different from zero at all quantiles of the markup distribution, the direction of the effect is consistent across all models.

Interestingly, the difference between organic and conventional farmers' markups decreases to 0.304 when considering the 90 percent quantile compared to lower quantiles (cf. Table 3.A10). That is, the advantage of organic over conventional farming in terms of markup is smaller for farmers that already have high markups. This may be due to the fact that high markup farmers already engage in direct marketing to consumers which allows for high prices by skipping the processing and retailing stages of the supply chain.

Regarding the effect of an increasing share of organic milk in total milk production on the markups of organic farmers, the results are still ambiguous. For the effect appears to be positive for quantiles at the lower (ten percent, p<0.1) and upper (90 percent, p<0.01) of the markup distribution, the models predict a negative effect when using quantiles closer to the median though only partly significantly different from zero (25 percent, p=0.349; 75 percent, p<0.01).

Table 3.A9 Markup Determinants: Pooled OLS, FE and Median Regression Using Log Markup

Variables	**Pooled OLS**	**FE**	**Median regression**
ORG	0.543***	0.168***	0.123**
	(0.027)	(0.031)	(0.055)
OSHORG	-0.033***	0.002	-0.005
	(0.004)	(0.004)	(0.007)
OSHCON	-0.021***	-0.004**	-0.019***
	(0.003)	(0.002)	(0.005)
ln(MILK)	0.293***	0.371***	0.383***
	(0.006)	(0.010)	(0.003)
UNPLAB	0.002***	2.94e-4	4.40e-4
	(3.87e-4)	(2.02e-4)	(2.92e-4)
PRSHM	-0.020***	-0.017***	-0.006**
	(0.002)	(0.001)	(0.003)
PRSHL	0.002***	0.002***	0.003***
	(0.001)	(4.42e-4)	(0.001)
RETSHM	-0.004*	-0.001	0.002*
	(0.002)	(0.001)	(0.001)
RETSHL	0.007***	-0.006***	-0.002***
	(0.001)	(0.001)	(0.001)
SHFC	0.985***	2.200***	2.268***
	(0.046)	(0.030)	(0.021)
Constant	1.807***	0.879***	
	(0.079)	(0.032)	
Year fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	No	No
Farm fixed effects	No	Yes	Yes
Observations	81,490	81,490	81,490
R-squared	0.424	0.375	

Note: Standard errors clustered by farm in parentheses; Significance inditcators: *** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations based on European Farm Accountancy Data Network

When it comes to the impact of the market share of medium-sized retailers on markups, the effect is not significantly different from zero for the upper quantiles of the markup distribution (cf. Table 3.A10). In contrast, the market share of large retailers does have a negative and significant impact only for the upper quantiles (50, 75 and 90 percent; cf. Table 3.A10). Hence, the presence of large, multinational retail chains does not affect the markups of farmers which already have low markups but forces high markup farmers to decrease their markups, and will therefore ceteris paribus lead to a denser markups distribution.

Table 3.A10 Determinants of Markups: Quantile Regression at Different Markup Quantiles

Variables	Median regression	10% quantile regression	25% quantile regression	75% quantile regression	90% quantile regression
ORG	1.034***	0.957***	0.892***	1.538***	0.304***
	(0.119)	(0.040)	(0.345)	(0.224)	(0.103)
OSHORG	-0.022**	0.011*	-0.067	-0.075***	0.082***
	(0.010)	(0.006)	(0.072)	(0.026)	(0.016)
OSHCON	-0.049***	-0.020***	-0.041***	-0.038***	-0.029***
	(0.004)	(0.003)	(0.006)	(0.004)	(0.003)
ln(MILK)	0.763***	0.811***	0.743***	0.674***	0.740***
	(0.007)	(0.019)	(0.049)	(0.036)	(0.021)
UNPLAB	0.004***	-0.002	-0.001	0.003***	0.006*
	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)
PRSHM	-0.088***	-0.010	-0.020	-0.124***	-0.198***
	(0.004)	(0.014)	(0.013)	(0.007)	(0.020)
PRSHL	0.026***	0.015***	0.009*	0.021***	0.016
	(0.003)	(0.001)	(0.005)	(0.004)	(0.012)
RETSHM	-0.008***	-0.009***	0.014	-0.001	-0.011
	(0.003)	(0.002)	(0.011)	(0.003)	(0.008)
RETSHL	-0.011***	0.003	-0.008	-0.032***	-0.039***
	(0.003)	(0.004)	(0.008)	(0.002)	(0.005)
SHFC	0.077***	0.081***	0.075***	0.094***	0.108***
	(0.002)	(0.001)	(0.007)	(0.003)	(0.005)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Country fixed effects	No	No	No	No	No
Farm fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	81,490	81,490	81,490	81,490	81,490

Note: Standard errors clustered by farm in parentheses; Significance inditcators: *** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations based on European Farm Accountancy Data Network

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4 Output Market Power and Firm Characteristics in Dairy Processing: Evidence from Three EU Countries

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Abstract

The dairy processing industry is the largest subsector in the EU food industry and is characterized by high concentration. We investigate the extent of output market power exerted in EU dairy processing applying the advanced stochastic frontier approach to estimate firm-level markups of price over marginal cost using the example of France, Italy and Spain from 2008 to 2017. We further relate markups to firm characteristics to identify what type of dairy processors possess the highest power in the sector. Our findings only reveal small average deviations from perfect competition but we find considerable heterogeneity of markups within and between the three countries. With respect to firm characteristics, we identify a strong positive relationship between markup and profitability pointing towards the presence of welfare decreasing market power. In addition, we find firm size and markups to be inversely related such that small firms operating in differentiated niche markets are able to charge higher markups, thereby enhancing their profitability. This result can serve EU dairy processors for future strategic alignment, and is particularly interesting from a policy perspective as large firms are mostly blamed in the exercise of market power in public and policy debates.

4.1 Introduction

While it is advantageous for firms to possess market power, the functioning of competition in food supply chains is desirable for consumers to minimize food expenditures as well as for farmers to facilitate price transmission to and from downstream sectors (Assefa et al. 2014; Assefa et al. 2017; McCorriston 2002; Sheldon 2017). Cakir and Balagtas (2012) for instance, estimate a welfare loss from market power exercised by U.S. dairy cooperatives of $636 million dollars per year. The EU dairy processing sector also serves as a good example of an industry where firms are suspected to exhibit market power, since it is characterized by high concentration (OECD 2014; Ramírez et al. 2006; Wijnands et al. 2007).[21] Moreover, dairy processing constitutes the largest subindustry in EU food manufacturing with 13,605 enterprises generating a turnover of €151 billion in 2016 (Eurostat 2019a). Hence, anticompetitive behavior in this industry would have considerable consequences in terms of welfare losses for farmers and consumers. In addition, the sector has recently been affected by a series of political events that potentially affect the dynamics in market power such as the stepwise abandonment of the milk quota until 2015 (Giles 2015; Kapelko et al. 2017) and the Russian import ban for food products from the EU in 2014 (Boulanger et al. 2016; Hirsch et al. 2020).

In this paper, we provide new insights on the degree of output market power and its relationship to firm characteristics in EU food processing using the example of three economically important and diverse dairy processing sectors which represent a composite market share of 40.79 percent in the EU dairy processing sector (2018): France, Italy and Spain (Eurostat 2019a).[22] Our analysis is based on an advanced stochastic frontier approach (SFA) that allows generating markups of output price over marginal cost based on different technologies across sectors. Moreover, we tackle problems of endogeneity resulting from the frequent use of deflated revenue/expenditures in estimation of the technology's parameters using a two-stage control function approach. We go beyond previous work by relating markups to firm characteristics such as size and age, which can be of interest for dairy processors' strategic alignment to countervail bargaining power of food retailers (Anders 2008; Gohin and Guyomard 2000; Iozzi and Valletti 2014) as well as for policy makers to introduce targeted competition policy

[21] The four firm concentration ratio is above 50 percent when considering Europe as a whole market (Bukeviciute et al. 2009). When we look at each country separately, the five firm concentration ratios are approximately 70 percent (Cotterill 1999).

[22] We also considered to include Germany, the Netherlands and the United Kingdom in our study but the data availability was insufficient.

measures. We employ firm-level panel data over the years 2008 to 2017, which enables us to identify potential changes in market power due to the abolishment of the EU milk quota system and the Russian import ban.

A substantial amount of research has been dedicated to examine the presence of market power in food industries and retailing as there are hints for deviations from competitive behavior, e.g., asymmetric price and price volatility transmission along the chain (Assefa et al. 2017), excessive prices charged by U.S. dairy cooperatives towards dairy processors (Cakir and Balagtas 2012) or the exertion of market power by retailers towards consumers (Hirsch and Koppenberg 2020; McCorriston 2014). The majority of studies on market power investigates pricing above marginal cost in output markets (markup), or below the marginal value product in procurement (markdown) representing common definitions of market power (Bonanno et al. 2018; Sheldon and Sperling 2003; Simeone et al. 2017). Concerning input market power in dairy processing, a fundamental issue with regards to markdowns in raw milk procurement is spatial competition between dairy processors as noted by previous studies (Graubner et al. 2011a; Graubner et al. 2011b; Perekhozhuk et al. 2015). While our data set represents the population concerning the size distribution of firms well, our information on the firms' location is restricted to their headquarters. Hence, we do not observe whether the companies operate several plants or only one, where the plants are located, and how large each single plant is.[23] In addition, we do not observe firm-level raw milk prices. However, this information is crucial to model spatial competition correctly. Therefore, we abstain from estimating markdowns.

Despite an extensive number of articles based on the New Empirical Industrial Organization (NEIO) approach to identify market power, the method involves substantial drawbacks concerning the set of underlying assumptions regarding 1) ex-ante choice of functional forms for demand and cost (Mei and Sun 2008; Perekhozhuk et al. 2017; Sexton 2000), 2) perfect competition in upstream and downstream markets (Sexton 2000), and 3) the game that is played by the market actors such as Bertrand or Cournot oligopolies (Corts 1999; Sheldon 2017). Therefore, market power estimates stemming from methods imposing fewer restrictive assumptions are desirable. The SFA is an advanced approach that avoids estimation of the conduct parameter and does not require data on input prices (Kumbhakar et al. 2012; Sexton

[23] This is also the reason why most empirical studies estimate markdowns for entire regions using aggregate data. Examples for the milk processing industry are Grau and Hockmann (2018), Panagiotou and Stavrakoudis (2017) and Perekhozhuk et al. (2015). For an analysis using plant-level data, we refer the reader to Perekhozhuk et al. (2013).

and Xia 2018). Other promising approaches to estimate markups are the demand system approach (Berry et al. 1995; Nevo 2001) which avoids the estimation of cost parameters but estimates demand and vertical relationships in supply chains based on price data, which however, is unavailable in our case. Another example is the production function approach introduced by Hall (1988) and recently applied in various studies such as De Loecker and Warzynski (2012), De Loecker et al. (2020) or Koppenberg and Hirsch (2022). However, the approach has been criticized due to issues with respect to recovering parameters of the technology in the primal problem (e.g., Bond et al. 2021; Gandhi et al. 2020). That is why we refrain from using the production function approach.

We contribute to the market power literature by estimating firm-level output market power in three important EU dairy processing sectors (France, Italy, Spain) which differ significantly with respect to production technologies and market structures, making it an interesting case study (Wijnands et al. 2007). We overcome weaknesses of earlier studies using deflated revenues and input expenditures in markup estimation causing issues of endogeneity. We use the SFA avoiding any assumptions of the game played between the market actors yielding high flexibility with respect to the outcomes. On top of that the SFA allows us to examine markup heterogeneity within the industries in contrast to the NEIO approach. Moreover, we are the first study relating markups to firm characteristics in the food industry providing the basis for developing and analyzing targeted competition policy measures as well as firms' strategic orientation.

Our objective is twofold: First, we assess output market power on the firm-level by determining price markups and Lerner indices using the SFA approach. We subsequently investigate how markups vary over time, between different countries and different firms within the countries. Moreover, we analyze how firm-specific characteristics are related to market power in terms of markups.

The remainder of the article is structured as follows. The second section displays the theoretical and empirical background. Next, we describe the SFA approach to estimate markups and Lerner indices on the firm-level. Thereafter, the data and empirical framework for the estimation of the degree and the relationship with firm characteristics of markups are described. We continue with the presentation of the results and their discussion. Lastly, we end by concluding our research and deriving implications.

4.2 Theoretical and Empirical Background on Market Power

In the Structure-Conduct-Performance Paradigm, Mason (1939) and Bain (1954) argue that firms operating in concentrated industries exploit higher profits given that they do not engage in competition (Bain 1954; Viaene and Gellynck 1995). Empirical applications of this approach interpret a significantly positive relationship between concentration and profitability as an indicator of market power. Hence, these studies do not estimate a direct parameter of market power but use indirect measures (e.g., Bain 1954).

In turn, the NEIO approach (e.g., Appelbaum 1982; Bresnahan 1982) builds on the measurement of cost and conduct parameters, and the estimation of conjectural elasticities of industries or firms. Conjectural elasticities proxy the expected change in total industry output as a reaction to changes in a firm's output by estimating a system of supply, output demand and factor demand equations (Azzam and Pagoulatos 1990; Geneseove and Mullin 1998; Wann and Sexton 1992). The conjectural elasticity divided by the absolute value of elasticity of demand yields the Lerner index[24] of monopoly price-setting power, a proxy for market power that indicates how closely a firm's or industry's price aligns to that of a monopoly.

As regards empirical applications of the NEIO framework, Katchova et al. (2005) find for the U.S. potato processing industry a Lerner index of below 0.01 for output and input market power, whereas Morrison Paul (2001) finds similar values for the output market of the U.S. beef-packing industry. Schroeter (1988) estimates an industry Lerner index on the output market for the same sector of 0.08 in 1951 that decreases to 0.036 in 1983, and recently, Chung et al. (2018) reveal values from 0.010 to 0.091 for the period of 1980-2011. The Californian pear processing sector is characterised by larger Lerner index estimates of 0.066 and 0.164 for canned pears and fruit cocktails, respectively (Wann and Sexton 1992). In contrast, Bhuyan and Lopez (1998) estimate an average industry-level Lerner index of 0.330 for U.S. food processing output markets from 1972 through 1987, whereas Buschena and Perloff (1991) find the U.S. coconut oil market to be even less competitive with a Lerner index of 0.609.

On average, estimates for European countries are smaller compared to U.S. markets. The strongest deviation from perfect competition is found by Gohin and Guyomard (2000) for French retailers' buyer power for 1977-1993 (Lerner index = 0.20). Examining the German food retailing sector (1995-2000), Anders (2008) finds Lerner indices of 0.103 and 0.026 (0.033

[24] The index takes on values between zero (no price-setting power) and one (full monopolistic price-setting power). It can also be calculated as the difference between price and marginal cost over price.

and 0.005) for beef and pork procurement (sales), respectively. Studying the Austrian dairy value chain, Salhofer et al. (2012) report that retailers' purchase prices of dairy products would be 12.43 percent larger in the absence of buyer power in the retailer-processor relationship (1997-2008). Millàn (1999) investigates the degree of market power in output markets of Spanish food processing industries. The maximum value he obtains lies below 0.1 for the period 1978-1991 assuming constant returns to scale. Mérel (2009)'s estimates for the French Comté cheese market are not even significantly different from zero (1985-2005). Similarly, while Cavicchioli (2018) finds some evidence for market power in the Italian fluid milk value chain for the period from 2000-2008, he fails to reject the Nullhypothesis of perfect competition for 1996-2003. In summary, results from previous literature for the European food processing sector do not point to the presence of high degrees of market power as the reported Lerner indices are generally not close to one while the results of food retailer buyer power investigations suggest some degree of market power in procurement.

While the NEIO approach, on which the above evidence is based, has the advantage of allowing the researcher to model counterfactual competitive market structures, it involves substantial drawbacks concerning the set of underlying assumptions. First, the outcomes are based on ex ante choices of functional forms for supply, demand and production technology which strongly influence estimation results (Mei and Sun 2008; Perekhozhuk et al. 2017; Sexton 2000). Second, the models implicitly assume perfect competition at upstream and downstream market stages, an assumption not usually fulfilled in real markets (Sexton 2000). Third, NEIO studies require assumptions regarding a game, e.g., Bertrand or Cournot oligopoly, that is played by the market actors to identify parameters resulting in biased estimates when these assumptions are inaccurate (Corts 1999; Sheldon 2017).

Kumbhakar et al. (2012) have introduced a method overcoming most of the aforementioned drawbacks of the NEIO approach by using an SFA to estimate market power without estimating conduct but only cost function parameters. In their study on the Norwegian saw milling industry, they apply frontier technique to estimate deviations from marginal cost pricing and not cost or input use in-/efficiency. So far, only a few studies employ the SFA to identify the degree of market power in the food sector. For example, Lopez et al. (2018) investigate output market power in the U.S. food industries and find considerable deviations from competitive behaviour with an average industry-level Lerner index of 0.17. Panagiotou and Stavrakoudis (2017) examine the degree of buyer power in the U.S. cattle industry and find a Lerner index of 0.2289. Scalco et al. (2017) identify the degree of both, buyer and seller power in the

Brazilian milk market. Their results yield that the deviation from competitive behaviour of retailers amounts to 8 percent of the wholesale price and that 75 percent of the retailers' market power stems from oligopsony power. To our knowledge, Čechura et al. (2015) is the only SFA study focusing explicitly on the firm-level. They cover the European dairy processing industry over the period 2003 to 2012 and find markups ($(P - MC)/MC$) of output price (P) over marginal cost (MC) of 0.121. However, in contrast to our article, Čechura et al. (2015) do not investigate the impact of firm-specific factors that are potentially related to the degree of market power.

4.3 The Stochastic Frontier Approach to Estimate Market Power

In line with the largest body of literature, we define the market power of a firm as charging a markup on output price (P) so that it exceeds marginal cost (MC) (e.g., Berry et al. 2019; De Loecker et al. 2020; Kumbhakar et al. 2012). Our methodology builds primarily on the SFA developed by Kumbhakar et al. (2012), which is based on the inequality $P > MC$ multiplied on both sides by the ratio of output (Y) over variable cost (C):

$$P\frac{Y}{C} > MC\frac{Y}{C} = \frac{\partial C}{\partial Y}\frac{Y}{C} = \frac{\partial lnC}{\partial lnY} = CE \quad (1)$$

where CE denotes cost elasticity with respect to output (Kumbhakar et al. 2012). The inequality defined by (1) can be altered to an equality by adding a markup term (u) capturing the difference between the revenue-total cost ratio and cost elasticity (CE):

$$\frac{PY}{C} = CE + u, \qquad u \geq 0 \quad (2)$$

To define CE, we choose a translog form for the cost function since it provides the most flexible functional form imposing only few a priori restrictions (Christensen et al. 1973; Kumbhakar et al. 2012; Perekhozhuk et al. 2017):

$$\begin{aligned} lnC = {} & \beta_0 + \sum_{j=1}^{J}\beta_j lnW_j + 0.5\sum_{j=1}^{J}\sum_{k=1}^{J}\beta_{jk} lnW_j lnW_k + \sum_{j=1}^{J}\sum_{q=1}^{Q}\beta_{jq} lnW_j lnK_q + \\ & \sum_{q=1}^{Q}\beta_q lnK_q + 0.5\sum_{q=1}^{Q}\sum_{r=1}^{R}\beta_{qm} lnK_q lnK_r + \beta_Y lnY + 0.5\beta_{YY}(lnY)^2 + \\ & \sum_{j=1}^{J}\beta_{jY} lnW_j lnY + \sum_{q=1}^{Q}\beta_{qY} lnK_q lnY + 0.5\beta_{TT}T^2 + \sum_{j=1}^{J}\beta_{jT} lnW_j lnT + \\ & \sum_{q=1}^{Q}\beta_{qT} lnK_q lnT + \beta_{YT} TlnY \end{aligned} \quad (3)$$

where W are the prices of the J variable inputs, T reflects a technology term, and β are the parameters to be estimated. K denotes the quantities of the Q quasi-fixed inputs. The resulting first derivative with respect to log output yields:

$$\frac{\partial lnC}{\partial lnY} = CE = \beta_Y + \beta_{YY} lnY + \sum_{j=1}^{J} \beta_{jY} lnW_j + \sum_{q=1}^{Q} \beta_{qY} lnK_q + \beta_{YT} T \tag{4}$$

Inserting (4) into (2) and adding a symmetric two-sided error term v which captures stochastic noise leads to:

$$\frac{PY}{C} = \beta_Y + \beta_{YY} lnY + \sum_{j=1}^{J} \beta_{jY} \, lnW_j + \sum_{q=1}^{Q} \beta_{qY} \, lnK_q + \beta_{YT} T + u + v = CE + u + v \tag{5}$$

The percentage markup (θ) by which price exceeds marginal cost is then calculated as the markup component u over the estimated cost elasticity (CE).

Information on input prices (W) is usually not available. However, using duality between the cost and transformation function, we can estimate the same markups using an input distance function (IDF) approach (Diewert 1971; Färe and Primont 1995; Kumbhakar et al. 2012). From the Envelope theorem, it follows that the first order condition of the Lagrangian for cost minimization is given by (Kumbhakar et al. 2012):

$$\frac{\partial lnC}{\partial lnY} = -\frac{\partial \, ln \, h(\cdot)}{\partial \, ln \, Y} \div \sum_j \frac{\partial \, ln \, h(\cdot)}{\partial \, ln \, X_j} \tag{6}$$

where h is the transformation function. Imposing homogeneity of degree one in inputs on the transformation function simplifies (6) to (Kumbhakar 2011):[25]

$$\frac{\partial lnC}{\partial lnY} = \frac{\partial \, ln \, h(\cdot)}{\partial \, ln \, Y} \tag{7}$$

Further, we can express h as an input distance function (IDF).[26] Imposing a translog form for the transformation function, we obtain the following IDF (Kumbhakar 2011):

$$\begin{aligned} lnX_1 = {} & \alpha_0 + \sum_{j=2}^{J} \alpha_j ln(X_j/X_1) + 0.5 \sum_{j=2}^{J} \sum_{k=2}^{J} \alpha_{jk} ln(X_j/X_1) ln(X_k/X_1) + \\ & \sum_{j=2}^{J} \sum_{q=1}^{Q} \alpha_{jq} ln(X_j/X_1) lnK_q + \sum_{q=1}^{Q} \alpha_q lnK_q + 0.5 \sum_{q=1}^{Q} \sum_{r=1}^{R} \alpha_{qr} lnK_q lnK_r + \\ & \alpha_Y lnY + 0.5 \alpha_{YY} (lnY)^2 + \sum_{j=2}^{J} \alpha_{jY} ln(X_j/X_1) lnY + \sum_{q=1}^{Q} \alpha_{qY} lnK_q lnY + 0.5 \alpha_{TT} T^2 + \\ & \sum_{j=2}^{J} \alpha_{jT} ln(X_j/X_1) lnT + \sum_{q=1}^{Q} \alpha_{qT} lnK_q lnT + \alpha_{YT} T lnY \end{aligned} \tag{8}$$

[25] Homogeneity of degree one in inputs is equivalent to $\sum_j \frac{\partial \, ln \, h(\cdot)}{\partial \, ln \, x_j} = -1$

[26] The IDF is an alternative transformation function that we obtain when solving the transformation function for X_j

X are the quantities of the J inputs and α the parameters to estimate. Note that we applied the necessary normalisations[27] to the underlying transformation function (see Coelli et al. 2005; Kumbhakar 2011 for details). Taking the first derivative of (8) with respect to log output leads to the following formulation for CE, which resembles (4) when replacing normalised input prices by normalised inputs quantities:

$$\frac{\partial lnC}{\partial lnY} = \frac{\partial \ln X_1}{\partial \ln Y} = CE = \alpha_Y + \alpha_{YY} lnY + \sum_{j=2}^{J} \alpha_{jY}\, ln(X_j/X_1) + \sum_{q=1}^{Q} \alpha_{qY}\, lnK_q + \alpha_{YT} T \tag{9}$$

Inserting (9) into (2), we arrive at the following estimable equation from which markups can be derived:

$$\frac{PY}{C} = \alpha_Y + \alpha_{YY} lnY + \sum_{j=2}^{J} \alpha_{jY}\, ln\left(\frac{X_j}{X_1}\right) + \sum_{q=1}^{Q} \alpha_{qY}\, lnK_q + \alpha_{YT} T + u + v \tag{10}$$

To adhere to theoretical properties, the IDF (8) must be non-decreasing and concave in variable inputs and non-increasing in output and quasi-fixed inputs (Coelli et al. 2005). Note that we can only test whether the IDF is non-increasing in output because we estimate its first derivative with respect to log output (10) and not the IDF itself. For this purpose, it suffices that the predicted values of the cost elasticity are larger than or equal to zero as we specify u as positive deviations from the frontier (Coelli et al. 2005). The estimation of (10) allows to derive firm-level values of markup and Lerner index. The markup of price over marginal cost is given by (Kumbhakar et al. 2012):

$$\hat{\theta} = \frac{\hat{u}}{\widehat{CE}} = \frac{P - MC}{MC} \tag{11}$$

The Lerner index ($\hat{L}$) can then be computed as:

$$\hat{L} = \frac{\hat{\theta}}{1 + \hat{\theta}}, \qquad \hat{L} \in [0,1] \tag{12}$$

4.4 Empirical Implementation

We now turn to the estimation of (10) and how we deal with price biases of our output measure and one of the inputs as the first step of our empirical analysis using a two-stage approach to estimate the stochastic frontier (section 4.4.1). Thereafter (section 4.4.2), we describe the firm

[27] The normalizations are applied to the underlying transformation function which can be found in Kumbhakar (2011). Homogeneity of degree one in inputs implies that $\sum_{j=2}^{J} \alpha\,\mathrm{j} = -1, \sum_{j=2}^{J} \alpha_{jk} = 0 \;\forall\, k, \sum_{j=2}^{J} \alpha_{jY} = 0$ and symmetry implies that $\alpha_{jk} = \alpha_{kj}$ (Baños-Pino et al. 2002).

characteristics which we relate to markups in the second step of our analysis, and elucidate how we address potential endogeneity of firm characteristics in this second step.

4.4.1 Markup Estimation

Since our dataset is of panel nature, our empirical implementation is based on:

$$\frac{P_{it}Y_{it}}{C_{it}} = \alpha_Y + \alpha_{YY} lnY_{it} + \sum_{j=2}^{J} \alpha_{jY} ln(X_{jit}/X_{1it}) + \sum_{q=1}^{Q} \alpha_{qY} lnK_{qit} + \alpha_{YT}T + u_{it} + v_{it} \qquad (13)$$

The subscripts i and t represent firm and year, respectively. Deflated operating revenue serves as the output measure (Y) (Hirsch et al. 2020; Soboh et al. 2012). The variable inputs comprise labor (X_1) and materials (X_2), while capital is a quasi-fixed input (K). We use the number of employees as a measure for labour, while deflated material costs contain all variable input purchases ahead of processing and mainly consist of raw milk purchases (Wijnands et al. 2007). Capital is defined as the book value of fixed assets (Asker et al. 2014; Gopinath et al. 2017; Hirsch et al. 2020). Finally, T is approximated by a set of year dummies (Hirsch et al. 2020). We assume that $u \sim N^+(0, \sigma_u^2)$, where N^+ indicates a half-normal distribution truncated at zero from below, and $v \sim N(0, \sigma_v^2)$ (Kumbhakar et al. 2012; Lopez et al. 2018). u is estimated following Jondrow et al. (1982):

$$E[u_{it}|\varepsilon_{it}] = \frac{\sigma\lambda}{1+\lambda^2}\left(\frac{\phi(a_{it})}{1-\Phi(a_{it})} - a_{it}\right) \qquad (14)$$

where $\varepsilon_{it} = u_{it} + v_{it}$, $\sigma = (\sigma_u^2 + \sigma_v^2)^{0.5}$, $\lambda = \sigma_u/\sigma_v$, $a_{it} = \varepsilon_{it} \cdot \lambda/\sigma$ while $\phi(a_{it})$ and $\Phi(a_{it})$ denote the standard normal density and cumulative distribution function evaluated at a_{it}, respectively (Greene 2005). We are aware that the half-normal distribution imposes that only positive markups are possible. However, we assume that negative markups occur in exceptional cases only and not systematically as the dairy industry is mature.[28]

It has to be noted that the specification defined in equation (13) is potentially affected by endogeneity of two variables due to the input price bias and output price bias incurred by using industry-wide price deflators to obtain physical quantities (e.g., Bond et al. 2021; Morlacco 2020). If material prices deviate from industry averages, the coefficient estimates of the frontier will be biased. We suppose two possible sources of material price deviations from industry averages: First, firm specific deviations might be caused by differences by time-invariant

[28] The market for electric vehicles is a popular example of industries where negative markups are observed frequently since the companies heavily invest in research and development activities, and therefore have negative price cost margins (e.g., Tesla).

effects. For instance, dairy processors who only process organic milk will generally pay a higher milk price due to the organic price premium (e.g., Crowder and Reganold 2015). The same accounts for dairy processors that consist of a cooperative (e.g., Hanisch et al. 2013). Second, market power in raw milk procurement may enable processors to hold the milk price below the competitive level. This would clearly violate the assumption of exogenous input prices, and consequently input quantities in the cost minimization framework.

To account for deviations of firm specific milk input prices from the industry average due to unobserved factors such as processing organic milk only or being organized in a cooperative along with other regional effects, we use a firm-fixed effects specification (see e.g., De Loecker et al. 2016). With respect to input market power in raw milk procurement exercised by dairy processors, we rely on insights from literature on spatial competition. Since raw milk is bulky and characterized by a high water content, transportation costs are relatively high compared to the product value (Rogers and Sexton 1994). This enables buyers of agricultural commodities to apply spatial price discrimination (Graubner et al. 2011a; Kawaguchi et al. 1997). Hence, it is strategically advantageous for dairy processors to be located further away from other processors to increase the degree of spatial price discrimination. The larger the catchment area of a dairy processor, the larger can be the wedge between actual milk prices paid to farmers and milk prices under perfect competition (Graubner et al. 2011a; Kawaguchi et al. 1997). We assume that the catchment area, and ultimately, a processor's bargaining power in raw milk procurement is positively related with firm size. Therefore, we create an additional variable based on the company's total assets, the total quantity of raw milk produced in each country and the share of revenue generated by the firms in the sample in the overall industry:

$$X_{2it}^{*} = \frac{Totass_{it}}{\sum_{i=1}^{I} Totass_{it}} \cdot \frac{\sum_{i=1}^{I} Revenue_{it}}{PopRevenue_{t}} \cdot PopMilk_{t} \qquad (15)$$

X_{2it}^{*} is our instrument for each dairy processor (i) in year t. $Totass$ and $Revenue$ are the value of a firm's total assets and its revenue, respectively. $PopRevenue_t$ is the revenue generated by the population in year t (Eurostat 2019a). $PopMilk_t$ is the quantity of raw milk produced in the country in year t (FAO 2019) purged from raw milk imports and exports (Eurostat 2019b). Hence, $PopMilk_t$ is the total milk input for the population of dairy processors in year t in the respective country. The intuition behind our proxy rests upon the assumption that the share of our sample's revenue in the population corresponds to the share of our sample's raw milk consumption in the population, i.e., $\frac{\sum_{i=1}^{I} Revenue_{it}}{PopRevenue_{t}} = \frac{\sum_{i=1}^{I} Milk_{it}}{PopMilk_{t}}$. This is fulfilled as long as our sample is representative for the population which we check in Table 4.A1 of the manuscript. X_2^* is used as an instrument to pick up all input price differences that are due to market power in the reduced form regression (see Table 4.A4). However, we use $ln(X_2/X_1)$ on the left hand side of the reduced form regression (see Table 4.A4) and $ln(X_2^*/X_1)$ such that we do not have to divide the residual of the reduced form by X_1 in the estimation of the input distance function.

The output price bias stems from the use of deflated revenue, which will be an inaccurate estimate of output in the presence of firm-specific output price deviations from industry averages. Potential causes of such deviations are differences in output quality, product varieties or output market power (see e.g., De Loecker et al. 2016). Again, we use a set of firm-fixed effects to account for time-invariant deviations between firms. We use the values of stock and debtors to proxy the remaining output price variation between firms. We assume that stock is related to output quality such that firms with higher quality products will have lower stocks compared to firms with lower quality products as they sell their products faster. Debtors, on the other hand, are assumed to be related to output price deviations resulting from output market power. Firms with higher output market power will also be able to force their customers to pay faster such that firms with market power in the output market have lower values of debtors.

We address the price biases by using a control function approach equivalent to a two-stage estimation (Amsler et al. 2016; Joshi and Wooldridge 2019; Karakaplan and Kutlu 2017).[29] Following Joshi and Wooldridge (2019), we first formally check for the necessity of applying an instrumental variable approach (i.e., whether a price bias exists) by testing the fixed effects two-stage estimation (FE2SE) against a fixed effects model (FE) with the robust Hausman variable addition test (Joshi and Wooldridge 2019). If we do not reject FE, we will test FE against random effects (RE) with a Hausman test. The result of the test will show whether unobserved time-persistent firm characteristics, i.e., firm heterogeneity, are correlated with the independent variables of the IDF and markup leading to inconsistent estimates of the RE model. In case FE is rejected in favor of FE2SE, we will further test FE2SE against a random effects two-stage estimation (RE2SE), i.e., check for endogeneity of the instruments and the exogeneous independent variables with respect to the firm-specific fixed effects. Last, we test whether strict exogeneity of our instruments is violated following Joshi and Wooldridge (2019).

Moreover, we test for a common technology of the three countries while expecting differences between dairy processing in France, Italy and Spain that cannot be captured by a shift of the

[29] A detailed description of all testing procedures and the results is given in the appendix.

distance function, i.e., by estimating a meta-frontier (Hirsch et al. 2020). The French dairy sector is the most diverse one in the world with more than 1,500 different products (CNIEL 2015). In Italy, consumers can choose between a large variety of regional milk and cheese products as well (Cassandro 2003; De Gregorio and Tugnolo 2015) while Spanish dairy processors mostly focus on drinking milk and fresh dairy products with low incentives outside the central production segment (Sineiro and Vázquez 2014). Due to these differences in product varieties and types, we expect that the technologies are too different to be estimated jointly. We apply the dummy variable procedure of Triebs et al. (2016) to test whether the countries are operating under the same technology.[30]

The stochastic frontiers are estimated with maximum likelihood (ML) using Stata 16. For the RE model, we use the sfpanel command developed by Belotti et al. (2013), which estimates the coefficients based on the true random effects model (Greene 2005). For the fixed effects model, Greene (2005) points towards the incidental parameters problem of increasing i with fixed T. Therefore, we apply the consistent fixed effects model following Chen et al. (2014), which eliminates the individual fixed effects to obtain consistent parameter estimates using within-differencing.

4.4.2 Markups and Firm Characteristics

In a second step, we examine the relationship of markups and firm-specific characteristics. Knowing which firms exercise the strongest market power is important for policy makers so they can implement targeted measures that foster competition. For firms, the analysis provides interesting insights in possible strategic moves to sustain or increase their markups, and thereby, margins.[31] Note however, that for some of the firm characteristics, we discuss in the following, we do not assume a one-way causal relationship but markups may also influence firm characteristics. We illustrate how we address potential issues of endogeneity due to reverse causality in our econometric specification.

[30] For this purpose, we estimate one model pooling the observations from the three sample countries such that all observations have the same parameters for the IDF. Another model using all observations includes interactions of country dummies with the explanatory variables of the IDF leading to country-specific parameter estimates. Thereafter, we test the model with the joint parameters against the model with country-specific parameters with a likelihood-ratio test. We explain the procedure and report the results in detail in the appendix.

[31] Lopez et al. (2018) explain markups using industry characteristics. However, their analysis suggests that only half of estimated markup magnitude stems from industry factors. Therefore, we argue that a substantial share of the remaining variability in markups is attributed to firm characteristics. As previous literature on firm-performance has shown, industry effects do not drive intra-industry firm performance (Hawawini et al. 2003; Hirsch and Schiefer 2016). Therefore, we focus on firm-specific characteristics and abstract from industry effects.

The most discussed factor influencing markups, i.e., market power, is the size of a firm in relation to its competitors. Oftentimes, large internationally operating enterprises ("superstar firms") are expected to exercise high degrees of market power, and hence, yield high markups (e.g., Autor et al. 2020; Barla 2000). In addition, the food industry faces strong downstream bargaining power by retailers that large firms might countervail more easily compared to smaller companies, thereby making firm size an important asset in this sector (e.g., Wijnands et al. 2007). Oppositely, the theory of niche markets suggests higher margins, i.e., higher markups, in niche markets in which small specialized firms typically operate (Ilbery and Kneafsey 1999; Smallbone Shaw et al. 1999). Draganska et al. (2010) argue that unique product characteristics of niche firms can improve the bargaining power in price negotiations vis-à-vis retailers due to a lack of available substitutes. This is supported by the results of Bonnet and Bouamra-Mechemache (2016), who find stronger bargaining power of milk manufacturers in price negotiations with retailers for the niche product (organic milk) compared to the mass commodity (conventional milk). The same accounts for the product attribute of local production, which has experienced an increasing importance in consumers' food purchase decisions in recent years (e.g., Jensen et al. 2019; Watts et al. 2005). Therefore, the link between firm size and markups can be either positive, negative or U-shaped. We measure firm size using the natural logarithm of the firms' total assets to allow for nonlinear relationships with markups (e.g., Hirsch et al. 2014).

As De Loecker et al. (2020) as well as Berry et al. (2019) point out, markups do not necessarily originate from market power but can also be a result of a company's share of fixed costs being larger in comparison to its competitors not resulting in higher profits. Reasons for dispersed fixed cost shares are firms undertaking investments in R&D activities, advertisement, procurement of information technology and capital costs (Berry et al. 2019). A company with comparatively larger fixed cost should therefore also generate higher markups to cover these fixed costs. De Loecker et al. (2020) observe a strong correlation between markups and the share of capital and overheads in total costs. While a markup increase due to increased fixed costs without implying increments in profitability definitely has distributional effects, it does not entail decreases in overall welfare (De Loecker et al. 2020). Therefore, we do not consider such markup changes as abuse of market power. To control for changes in fixed costs, we assess the relationship of markups and the share of fixed in total cost, where fixed costs contain the firms' capital costs and overheads (De Loecker et al. 2020).

In addition, the previous literature has investigated the relationship between markups and capital structure. The findings indicate that the share of equity financing correlates negatively with markups (e.g., Campello 2003; Chevalier and Scharfstein 1995, 1996). Financial constraints in terms of restricted access to equity, i.e., low share of equity financing, incentivize firms to boost short term profits leading to increased markups (Chevalier and Scharfstein 1996). Another stream of literature argues that firms exposed to financial constraints are more likely to engage in price wars leading to smaller markups (e.g., Amountzias 2018; Bottasso and Sembenelli 2001; Busse 2002). The intuition behind this strategic move is the assurance of market shares, and thereby, long run profits.[32] We use the share of equity in total assets as a measure of capital structure and assess its relationship with estimated markups. Based on the empirical findings, we expect a negative or a positive relationship between the equity share and markups.

Besides, De Loecker et al. (2020) find evidence for a reallocation effect, where consumers shift to high markup firms due to superior product quality or unique product characteristics offered by high markup firms.[33] This implies that companies charging a high markup generate above average increases in revenue. We test for the presence of a consumer reallocation effect in our sample by assessing the relationship of markups and the percentage growth of revenue from period t to period $t + 1$ for each firm.

Another factor that is potentially related to markups is the age of a firm. Usually, costs should decrease with firm age due to learning effects (Hirsch et al. 2014; Loderer and Waelchli 2010). Assuming that firms do not adjust prices, this mechanism will result in higher markups for older companies. However, older firms are prone to organizational rigidities, outdated assets and lower ability to adapt to changing economic conditions (Loderer and Waelchli 2010; Majumdar 1997). Some studies report younger firms to outperform their older competitors as they employ state-of-the-art technology resulting in cost reductions (Hill and Kalirajan 1993; Lundvall and Battese 2000). Accordingly, previous literature finds evidence for a negative relationship between age and firm profits in the EU food industry (e.g., Hirsch and Gschwandtner 2013) and

[32] Along these lines, previous research on the food processing sector examining the link between profitability and the source of financing finds evidence for the 'risk-return paradox' (Bowman 1980), i.e., a negative relationship between the share of debt and profitability (e.g., Chaddad and Mondelli 2013; Hirsch et al. 2014).
[33] This is not necessarily an implication of consumer choice but might also be due to attrition of firms charging low markups leading to market exit.

we assume that this also holds for the relationship of markup and age, which we measure as the years since a firm's incorporation.

Finally, we investigate the link between markups and profitability. De Loecker and Eeckhout (2017) find a strong relationship between markup and profitability in their sample of U.S. companies from 1950 until 2014. Along these lines, Berry et al. (2019) argue that particularly firms facing inelastic demand, a fact which likely holds for the food industry[34], charge higher markups leading to increased rents. Therefore, we expect a positive relationship between markups and profitability measured by return on total assets.[35]

We evaluate the relationship between markups and firm-specific characteristics using a second step regression following Renner et al. (2014), Hirsch et al. (2014) and Wimmer and Sauer (2020). Note that we also tried to combine both steps, i.e., identification of the distance function and correlation of markups with firm-specific characteristics, in the estimation of the frontier but the maximum likelihood function showed a ridge in all specifications making it impossible to converge. Moreover, since we do not interpret all of our second step variables having a one-way causal relationship with markup, a one-stage procedure would in turn raise concerns of endogeneity due to reverse causality in the estimation of the frontier. Even firm characteristics for which a one-way causal relationship is assumed may be endogenous, which must be tested ex-post analysis (Bellemare et al. 2017). This is, however, not possible in the framework of a stochastic frontier, and would again require a two-stage approach.

In our second step, we use two-stage least squares (2SLS) estimation to account for the potential endogeneity of firm characteristics (Hirsch et al. 2020; Renner et al. 2014; Wimmer and Sauer 2020). We identify the variables to be treated as being endogenous based on the Davidson and MacKinnon (1993) test for exogeneity of independent variables. If the null hypothesis of exogeneity for all independent variables cannot be rejected, we use standard FE estimation as 2SLS is less efficient when exogenous independent variables are incorrectly treated as endogenous (Wooldridge 2010). We incorporate the first three lags of each independent variable as instruments in the 2SLS regression (Hirsch et al. 2020; Li et al. 2019) and assess their validity and strength using the minimum eigenvalue statistic (Cragg and Donald 1993). The critical values are retrieved from Stock and Yogo (2005). In addition, we have to check for first-order autocorrelation of the residuals since the use of lagged explanatory variables does

[34] In their literature review, Bouamra-Mechemache et al. 2008 find the EU demand for dairy products to be relatively price inelastic providing the basis for increased rent seeking.
[35] We calculate the return on assets by dividing profit before interest and taxes by the amount of total assets.

not solve the endogeneity problem in the case of serially correlated errors (Bellemare et al. 2017; Betz et al. 2018). Therefore, we apply the test for autocorrelation proposed by Arellano and Bond (1991). The Sargan test for the validity of over identifying restrictions is used to assess the exogeneity of the instruments (Sargan 1958). To evaluate whether unobserved time invariant firm heterogeneity influences the firm characteristics and markup, thereby causing endogeneity, we test the FE against a random effects (RE) model with a Hausman-test (Hausman 1978). If we fail to reject the Nullhypothesis, we use RE as it will be efficient. Given that we reject the Nullhypothesis on every reasonable level of significance, we use FE since RE would be inconsistent, if unobserved firm heterogeneity were correlated with the firm characteristics and markup. We estimate the model for each country separately including year dummies to control for year effects such as macroeconomic fluctuations or the evolution of retailer concentration.

Moreover, we apply the robust quantile panel data regression proposed by Powell (2022) as a robustness check. Previous literature finds markups to be non-normally distributed and addresses this by using log markups (e.g., De Loecker and Warzynski 2012; Mariuzzo et al. 2003). The quantile regression estimator does not impose assumptions on the distribution of the dependent variable and is hence less sensitive to extreme values compared to the 2SLS FE estimator. The robust quantile estimator allows one to consider endogeneity similar to the 2SLS FE estimation, and the same variables are assumed to be endogenous, as for the 2SLS FE model.

4.5 Data

We use the AMADEUS database containing financial data on firms in all European countries and economic sectors. The analysis includes three countries fundamentally different with regards to geography, production technology, market structure and product variety (Wijnands et al. 2007): France, Italy and Spain. For instance, Spain has a much larger consumption of drinking milk than the other two countries, whereas cheese consumption is higher in France and Italy compared to Spain. In addition, Italy is a net exporter of dairy products in contrast to France and Spain, where the trade balance is just slightly above zero (Wijnands et al. 2007). We expect different patterns in competition between these countries due to the aforementioned heterogeneity of the three sectors. Our data set yields information on EU dairy processors from 2008-2017 identified by their operation in NACE code 10.5.[36]

[36] The NACE is the official statistical classification of economic activities in the European Community where group 10.5 defines “Manufacture of dairy products” (Eurostat 2008).

We also considered to investigate Germany, the Netherlands and the United Kingdom in our study since they belong to the five largest milk processing countries in the EU (2018) (Eurostat 2019a; see also Table 4.A2), but the data availability was insufficient. For Germany, the AMADEUS database contains 57 firms in 2016 while the population contains 645 firms resulting in a share of only 8.8 percent (Eurostat 2019a) and an underrepresentation of small firms rendering inference from the sample to the population impossible.[37] This is caused by weaker disclosure obligations for small compared to large companies in Germany (IHK Berlin 2021). For the Netherlands and the United Kingdom, there is no legal requirement forcing firms to publish their material costs but they only provide the costs of goods sold which does not allow us to disentangle material costs from labor costs to construct our input measures. Nevertheless, France, Italy and Spain comprise 40.79 percent of the revenue in the total EU dairy processing sector (2018), thereby representing an important part of the market (Eurostat 2019a; cf. Table 4.A2).

After deleting unreasonable observations that contain negative values for costs, inputs and revenue[38], the samples contain 421, 1,095 and 686 firms comprising 2,020, 7,208 and 4,945 observations for France, Italy and Spain from 2008 to 2017, respectively.[39] Table 4.A1 shows the representativeness of our sample compared to the population with respect to firm size (Eurostat 2019a). This is important, as 99 percent of food industry firms in the EU are small- and medium-sized enterprises (Eurostat 2019a). In total, the sample includes 25.85 percent of all companies in the three countries analyzed. Small firms are slightly underrepresented in Italy and Spain, and clearly underrepresented in France. In contrast to Italian and Spanish individual entrepreneurs, French individual companies are not obligated to publish accounts which explains the stronger underrepresentation of small firms in France compared with Italy and Spain (Bureau van Dijk 2011).

Regarding the estimation of the IDF, while we observe revenue, the dataset does not provide information on variable cost, i.e., the denominator on the left-hand side of (13), such that we calculate them by summing the costs of employees and costs of materials, which are the

[37] See the data appendix for details on the size distribution and details on legal requirements to publish accounts in Germany.
[38] This leads to the exclusion of 244, 782 and 161 firm/year observations for France, Italy and Spain, respectively.
[39] One observation refers to a legal entity publishing its accounts. This is, we do not observe plant-level data but one observation may also include subsidiaries such that resulting markups will be a weighted average across subsidiaries in these cases.

expenditures for the variable inputs in (13). We deflate revenue by the industrial producer price index for the dairy processing industry to obtain a measure of physical output (Eurostat 2019d) which we correct for the potential output prices bias using the value of stock and the value of debtors in the reduced form regressions as described in section 4.4.1. For the variable inputs, the number of employees depicts the labor input quantity (X_1). We calculate the quantity of material input (X_2) by deflating the material expenditures by the agricultural milk price index (Eurostat 2019c) and correct it for the potential input price bias using the measure (X_2^*) derived in section 4.4.1 building on a firm's total assets in the second reduced form regression. For the creation of X_2^*, we retrieve the revenue of the dairy processors' population ($PopRevenue$) and the total milk production in a country ($PopMilk$) from Eurostat (2019a) and FAO (2019), respectively.[40] We define the quasi-fixed input capital (K) as the book value of fixed assets deflated by the output price index of the industry of investment good producers (Eurostat 2019d) following previous literature (e.g., Asker et al. 2014; Gopinath et al. 2017; Hirsch et al. 2020).

With respect to the firm characteristics that we relate to markups in the second step of our analysis, we define firm size ($lnTA$) as the log of a firm's total assets (Hirsch et al. 2020; Werner 2017). We obtain the fixed cost share (FCS) by dividing all costs that are not subject of the firm's optimisation problem in period t by the total cost incurred in period t. We compute total cost by subtracting earnings before interest and taxes from revenue to avoid the measure being distorted by the firms' financing strategies and tax optimization. Fixed costs are calculated by subtracting costs of employees and material costs, i.e., variable costs, from total cost as derived above. Hence, FCS contains costs of capital and the firms' overheads (De Loecker et al. 2020).

To measure the equity share (ES), we divide shareholders' funds by a firm's total assets, i.e., the balance sheet total. Revenue growth (RG) is calculated as the firm's growth in revenue from period t to period $t+1$, and we depict firm age as the years since incorporation. Last, we generate our variable for firm profitability (ROA) by dividing the firms' earnings before interest and taxes by total assets. We are aware of potential biases in accounting profits caused by, e.g., profit-smoothing, cross-subsidisation or different depreciation methods (e.g., Barlev and Levy 1979; Fisher and McGowan 1983; Long and Ravenscraft 1984). However, Long and Ravenscraft (1984) find differences between accounting and economic profits to be

[40] Note that we purged total milk production from imports and exports to obtain the raw milk quantity processed in each country using Eurostat (2019b).

insignificant. Besides, AMADEUS data are generated based on harmonized accounting standards which make accounting profits a suitable proxy for economic profits (Danielson and Press 2003). Therefore, we assume that the accounting data from AMADEUS are appropriate to use in our context. The descriptive statistics of all variables are included in the appendix (Table 4.A3).

To avoid extreme values driving the results concerning the analysis of the relationship between markups and firm characteristics in the linear models, we use the bacon algorithm to detect multivariate outliers before performing the 2SLS analysis (Billor et al. 2000). It identifies outliers based on Mahalanobis distances (Weber 2010), and leads to the exclusion of 5, 50 and 9 observations for France, Italy and Spain, respectively. For the robust quantile estimator, we do not exclude these extreme values.

4.6 Results and Discussion

4.6.1 Markup Estimation

The results of the FE2SE model are shown in Table 4.A6 in the appendix.[41] The results of the robust Hausman variable addition test to assess the endogeneity due to the price biases of using deflated revenue and material costs are reported in Table 4.1 and reveal that exogeneity must be rejected for both variables for all countries. Therefore, we use FE2SE in all cases, i.e., implement our control functions for firm-specific deviations from industry wide price averages (cf. Table 4.1). The third part of Table 4.1 shows the results for testing endogeneity of the control functions and the exogeneous independent variables with respect to individual FE, i.e., FE2SE against RE2SE. We find that a zero correlation for Spain is to be rejected ($p<0.01$). For France and Italy, we do not achieve convergence of the likelihood estimation. However, since FE yields consistency in any case (Wooldridge 2010), we sacrifice potential efficiency gains of RE and use the results of the FE model. Moreover, we fail to reject strict exogeneity of the instruments controlling for between firm price variation in all cases, which implies their adequacy (cf. Table 4.1). As expected, the test for a common technology across the three countries rejects that they operate under the same technology such that we stay with the results

[41] Note that we also conduct a general identification test of our instruments for Y. The test reveals that our instruments are valid in all countries, i.e., $p < 0.01$ (Table 4.A5).

of our separate estimations (see Table 4.A9 for the estimation results). With respect to the functional properties of the IDF, none of the observations violates monotonicity in outputs.[42]

An issue arising in the calculation of markups is the treatment of the individual FE (Greene 2005). The first option consists in assigning the FE to the predicted value of the cost elasticity (CE). Another option is the inclusion of the individual effects in the numerator of (11). This is equivalent to interpreting the FE as a firm-specific time invariant markup component. In the third option, the FE is ignored in the markup calculation because we cannot disentangle whether FE are caused by pricing decisions of the firm or represent firm-specific cost components. As regards the previous literature, Čechura et al. (2015) attribute the FE to the markup component while Lopez et al. (2018) assign the FE to the estimated cost elasticity values. We consider all three options but focus on the results generated by leaving out the FE in markup calculation as we cannot identify their cause exactly.[43]

Table 4.2 presents the descriptive statistics of markups and Lerner indices.[44] We observe the highest average markup in Spain (0.195), i.e., the average Spanish firm charges a price exceeding marginal cost by 19.5 percent, followed by Italy (0.125) and the lowest in France (0.073). Accordingly, competition, on average, is most severe in France and weakest in Spain. Nevertheless, minimum markups are below one percent in all countries suggesting the presence of firms being close to marginal cost pricing. Even for the maximum values for French (0.657) dairy processors, the pricing strategy is closer to that under perfect competition compared to a monopoly since the Lerner index is below 0.5. Only for Italy and Spain, we find a maximum Lerner index of 0.539 and 0.719, which is relatively closer to monopoly pricing compared to perfect competition. The third quartiles of markups (Lerner indices) amount to 0.081 (0.075), 0.144 (0.126) and 0.233 (0.189) for France, Italy and Spain, respectively (Table 4.2). Hence, the vast majority of food processors in the analyzed countries deviates weakly from perfect competition. That is, only few firms possess some oligopolistic price setting power, particularly in France and Italy, but are still far away from a perfect monopoly, i.e., when $L = 1$.

[42] As stated earlier, we can only test whether the IDF is non-increasing in output since we estimate its first derivative with respect to output and not the IDF itself.
[43] We include the probability density functions of markups generated when using the other two options in the appendix (Figure 4.A1 and Figure 4.A2). The results for including the fixed effects in the predicted value of the cost elasticity do not differ considerably from the results in Figure 4.1. When we treat the fixed effects as a time-invariant markup component, we do observe negative markups and more dispersed distributions (Figure 4.A2).
[44] We focus on the results for markups since they also hold for Lerner indices due to the relationship between the two ($L = \theta/(1+\theta)$).

Table 4.1 Results of Model Specification Tests

Results of the robust Hausman variable addition test for endogeneity of revenue and material costs		
Country	**Wald statistic (H_0: Deflated revenue is exogeneous)**	**p-value**
France	8.69	<0.01
Italy	52.50	<0.01
Spain	36.71	<0.01
	Wald statistic (H_0: Deflated material costs are exogenous)	
France	13.81	<0.01
Italy	86.74	<0.01
Spain	58.45	<0.01
Results of the robust Hausman variable addition test comparing FE2SE and RE2SE		
	Wald statistic (H_0: RE2SE is consistent)	
France	-	-
Italy	-	-
Spain[a]	162.33	<0.01
Test for strict exogeneity of the instruments		
	χ^2 (H_0: The instruments are exogenous)	
France	0.45	0.93
Italy	4.45	0.22
Spain	4.88	0.18
Test for common technology across countries		
	χ^2 (H_0: The technology parameters are equal across countries)	
-	707.57	<0.01

Note: [a]Model convergence not achieved

Source: Own calculations based on data from AMADEUS

Further, the interquartile range (Table 4.1) as well the probability density functions (Figure 4.1) show that the markup distribution in Spain is the most dispersed followed by Italy, whereas the French distribution is much denser. In addition, as we find median markups to be smaller than mean markups, we conclude that their distributions exhibit a right skew in all countries, which is corroborated by the probability distributions presented in Figure 4.1.[45] Moreover, the

[45] The skewness measures for France, Italy, and Spain are 4.55, 5.28 and 36.16 implying a positive skew for all countries.

Shapiro-Wilk test confirms that the density functions do not display a normal distribution as the null hypothesis of normally distributed markups is rejected for all countries ($p<0.01$; see Table 4.A10) (Shapiro and Wilk 1965).[46] These results confirm the necessity of applying the robust quantile regression to check the robustness of our results from the fixed effects two-stage least squares regression of markups on firm characteristics.

Table 4.2 Descriptive Statistics of Markups ($\hat{\theta}$) and Lerner Indices ($\hat{L}$)

	France		Italy		Spain	
	$\hat{\theta}$	$\hat{L}$	$\hat{\theta}$	$\hat{L}$	$\hat{\theta}$	$\hat{L}$
Mean	0.073	0.067	0.125	0.108	0.195	0.157
Median	0.065	0.061	0.115	0.103	0.181	0.153
1st quartile	0.055	0.052	0.091	0.083	0.135	0.119
3rd quartile	0.081	0.075	0.144	0.126	0.233	0.189
Minimum	0.005	0.005	0.003	0.003	0.003	0.003
Maximum	0.657	0.397	1.168	0.539	2.563	0.719
Standard deviation	0.037	0.028	0.068	0.046	0.118	0.069

Source: Own calculations based on data from AMADEUS

The generally mild departures from perfect competition are likely to be due to high concentration in the retail sector forcing dairy processors into price competition (e.g., OECD 2014; Rudinskaya 2019).[47] Nevertheless, there are some firms in all countries that circumvent retailers' bargaining power, as suggested by the right skew of the markup distribution (cf. Figure 4.1). We look deeper into the kind of firms that are able to exercise market power in the section on markups and firm characteristics. Based on our estimates, the Spanish dairy processing sector is characterized by the weakest competition among all countries in the sample in terms of average markup and France by the highest competition. This result is surprising due to the high diversity of the French and Italian dairy sectors. We would expect that diverse markets offer the possibility to achieve a superior position in single differentiated segments allowing these firms to charge higher markups. This would finally result in higher average markups on the country-level, and imply the highest markups for France and the lowest for Spain. But the retail sector in France is also characterized by the highest concentration with a market share of the five largest retailers being ten percentage points larger compared to Spain (USDA 2017, 2019a, 2019b). Accordingly, the bargaining power of retailers is likely to be

[46] We do not conduct any test of equality of means since the Bartlett test rejects variance homogeneity.
[47] Note that we have not included retailer concentration as an explanatory variable in our second stage regression since the variation in food retail concentration within a country over our sample period was too small.

highest in France leading markups to decrease for food processors, a fact that might outweigh potential markup gains from differentiation.

Our results are mainly in line with previous literature regarding mean markup estimates and Lerner indices. While Mérel (2009) does not find Lerner indices to be significantly different from zero for the French Comté cheese market, we estimate an average of 0.067 for French dairy processing, which is also not far off from the minimum possible value of zero. This result might be driven by a considerable amount of buyer power in French food retailing (Gohin and Guyomard 2000). In the Spanish case, Millàn (1999) obtains different estimates for the Lerner index in the dairy processing industry of 0.072, 0.69 and 0.92 in different model specifications relying on the NEIO approach. He points out that estimation results depend heavily on assumptions on economies of scale or identification of demand equations. Since our methodology does not require any assumptions on scale economies or identification of demand, we argue that our results are more reliable.[48] The study which is closest to ours with respect to methodology (Čechura et al. 2015) yields average firm-level markups of 0.138, 0.136 and 0.126 for French, Italian and Spanish dairy processing sectors, respectively. They also estimate an input distance function with stochastic frontier technique but assume the same distance function for all countries, which seems to homogenize markups across countries.[49] As argued previously, assuming the same technology, cost structures and market conditions for the different countries in our sample are unlikely to adequately reflect market structures (Wijnands et al. 2007). Moreover, we account for price biases in our econometric design, which is ignored by Čechura et al. (2015) potentially leading to biased estimates of the frontier, and consequently, biased markup estimates (Mutter et al. 2013).

Figure 4.2 shows mean markups and revenue weighted markups[50] over time. Weighted markups are of special interest when it comes to evaluating the consequences of market power for consumers. A weighted markup larger than the average markup in an industry implies that the major part of revenue is generated by high markup firms, which indicates a higher welfare loss[51] for consumers compared to the weighted markup being smaller than the average markup. Moreover, looking at the development of average and weighted markups over time allows us

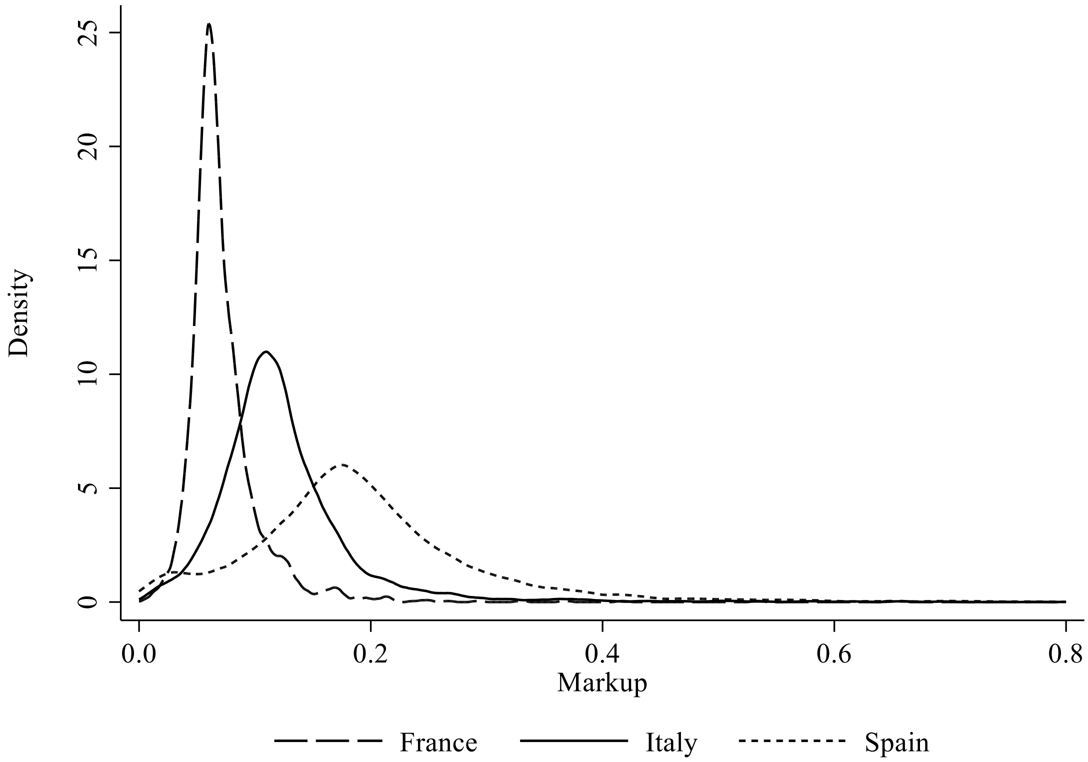
[48] In addition, Millàn (1999) finds values for the Lerner index in some industries that are below zero, i.e., outside the theoretically possible range which is not the case in our analysis.

[49] We retrieve our data from the same source as Čechura et al. (2015) such that the differences in markup estimates are likely not caused by the data generating process.

[50] We assign the weights by the revenue share of a firm in the sample.

[51] This does only hold if retailers passed markups on to consumers.

to identify the effects of the Russian import ban for food products in 2014 or the stepwise abandonment of the EU milk quota until 2015. For France, we find weighted markups to be larger than the unweighted averages throughout the entire period (Figure 4.2). That is, firms charging markups above the mean generally generate the major shares of revenue in France. In contrast, weighted markups are larger than the unweighted average in Italy in 2008, 2009 and 2013 but smaller in the remaining years (Figure 4.2). Similarly, the weighted average markup in Spain is larger than the unweighted average in 2009 but falls short of the unweighted average in the other time periods (Figure 4.2). This indicates that the biggest companies in terms of market share face stronger competition than those with smaller revenue shares in Spain and partly in Italy. We discuss this issue more in-depth in the next section where we relate markups to firm characteristics.



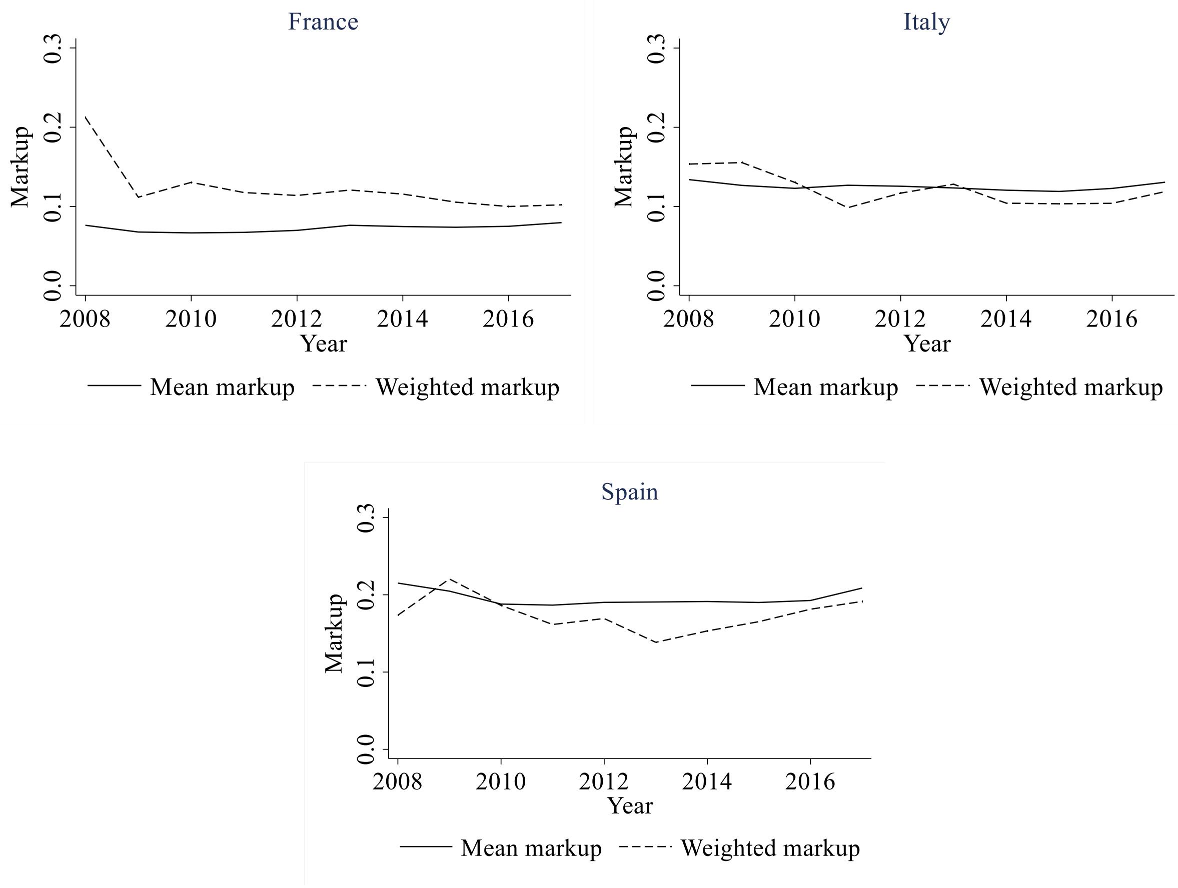
Note: 23 observations > 0.8 omitted to ensure readability

Source: Own calculations based on data from AMADEUS

Figure 4.1 Probability Density Functions of Markups per Country (2008-2017)

Concerning dynamics in the time dimension, we cannot identify any clear patterns of mean or weighted markups in any country. This might be surprising given the potential dynamics in the market caused by the abandonment of the milk quota until 2015 and the Russian import ban for EU food products in 2014. In the aftermath of the abolishment of the milk quota, France is expected to be one of the countries exhibiting the highest increases in output volumes (17.7

percent from 2013-2030) and strongest decreases in prices (-14.5 percent in the same period) in its dairy industry compared to most other EU countries (Philippidis and Waschlik 2019). In Italy and Spain, the estimates are much smaller, i.e., below (-)10 percent for quantity (price) changes. However, these effects will probably evolve over a longer time period such that we cannot identify any trend, yet (Philippidis and Waschlik 2019). Moreover, in- and output prices will likely change proportionally such that dairy processors might be able to sustain their markups (Philippidis and Waschlik 2019). Regarding the Russian import ban, the revenue share of exports to Russia in total exports of dairy products has already been below two percent before the export ban such that dairy processors in the analyzed countries have only been affected slightly by the Russian measure (Eurostat 2019b).[52]



Note: Weights assigned according to the share of revenue generated by a company in the sample

Source: Own calculations based on data from AMADEUS

Figure 4.2 Mean and Weighted Markups Over Time

[52] This picture might change for countries, which had much higher export shares to Russia such as Germany or the Netherlands (Eurostat 2019b). Unfortunately, as discussed earlier for these countries either i) the data availability was low (e.g., the Netherlands) or ii) the sample was not representative (e.g., Germany).

Our finding concerning markup dynamics is in contrast to De Loecker et al. (2020) who observe a strong positive trend of both mean and weighted markups over time. However, they base their analysis solely on large publicly traded U.S. firms operating in many different sectors. The vast majority of the firms included in our sample reflects the EU dairy industry in that they are not publicly traded and small such that a one-to-one comparison of results would be inappropriate.

4.6.2 Markups and Firm Characteristics

Table 4.3 presents the results of the 2SLS fixed effects (FE) instrumental variable (IV) regression for the relationship of markups and firm-level characteristics. The Davidson-MacKinnon test confirms the necessity of the IV approach in France and Italy (Table 4.A11). For Spain, we do not reject exogeneity of any explanatory variable, and hence, use FE for estimation. In France, we reject exogeneity of the equity share, the fixed cost share and revenue growth and use the first lag of the fixed cost share, the equity share, revenue growth and return on assets as well as the third lag of return of assets as instrument. For Italy, the test indicates the necessity to treat the equity share, revenue growth and return on assets as endogenous (cf. Table 4.A11). We use the second lags of the equity share and return on assets as well as the first lag of revenue growth, log total assets and the fixed cost share as instruments.[53] The tests for identification suggest that the instruments are not weak according to their eigenvalues, and the residuals are not significantly serially correlated indicating the suitability to use lags as instruments (cf. Table 4.3). Last, we do not reject the validity of the over identifying restrictions based on the Sargan test. The Hausman test to choose between (2SLS) RE and FE rejects RE in all cases (Table 4.3). That is, we must reject the Nullhypothesis that firm-specific heterogeneity is uncorrelated with markups and firm characteristics implying inconsistent estimates of RE. Therefore, we use the FE model accounting for firm-fixed effects yielding consistent estimates.

Regarding the relationship of firm size and markups, we find a negative and significant relationship for all countries in the 2SLS FE models as well as the quantile regression (Table 4.3). Hence, we cannot confirm the theory of superstar firms as proposed by other authors (e.g., Autor et al. 2020; Barla 2000; De Loecker and Eeckhout 2017), as already revealed by the comparison of average and revenue-weighted markups (cf. Figure 4.2).[54] Instead, our findings

[53] We have used different variables and lags thereof as instruments and have chosen the model yielding the largest eigenvalue without suffering from autocorrelation and invalid over identifying restrictions.

[54] Autor et al. (2020) investigate all sectors jointly in the U.S. economy, Barla (2000) look at the U.S. airline industries and De Loecker and Eeckhout (2017) only investigate publicly traded firms.

support Bouamra-Mechemache et al. (2008) and the theory of niche markets, which suggests that small firms in the dairy processing sector offer unique product attributes such as regional production enabling them to increase their margins either in negotiations with retailers or via direct marketing. Richards et al. (2017) find that retailers are able to increase their margins when offering local food products. Hence, they might be willing to incur a higher markup charged by the producers of the local dairy product in procurement of niche products, which are usually offered by small firms. Large firms that produce high quantities of standardized quality commodities seem to have problems with circumventing retailers' bargaining power in the European dairy processing sector as their products can be substituted easily. For instance, Nestlé or Unilever have their products in very many supermarket shelves across Europe. To avoid losing profits by getting delisted from the big retail chains' assortment, these multinationals probably have to make concessions in price negotiations. Along these lines Mariuzzo et al. (2003), in their analysis of the Irish carbonated soft drinks market, detected that smaller firms offer unique product attributes in differentiated markets to increase their margins. Given the size of the coefficients, we find the negative relationship between size and markups not only to be statistically significant but also economically relevant as a one percent increase in total assets measured in thousand euros leads to a decrease in markups by 0.045 (France), 0.130 (Italy) and 0.112 (Spain), respectively.[55]

In addition, we find a uniform link between markups and the share of fixed costs in total cost in our models across the three countries. As argued by previous studies (e.g., Berry et al. 2019; Chevalier and Scharfstein 1995; De Loecker and Eeckhout 2017; Hall 2018; Jaimovich and Floetotto 2008), firms will charge larger markup whenever they face increasing fixed costs. Thus, markups should not be linked directly to market power but must be put into the fixed cost perspective. The FE model predicts that an increment of one percentage point in the fixed cost share entails a markup increase of 0.653 and 0.845 percentage points in France and Italy, respectively. In Spain, we observe an almost one-to-one relationship between the two measures (cf. Table 4.3). Hence, we can confirm earlier studies with respect to the relationship between markups and fixed costs.

With respect to capital structure measured as the share of equity in total assets (ES), there is neither evidence for the strategy of boosting short-term profits implying a negative correlation between markup and ES nor that firms engage in price wars to sustain market shares, i.e., a

[55] We do not find evidence of a U-shaped relationship. Therefore, we do not present the results here.

positive relationship between markup and ES in the FE models in France and Italy. The quantile regression however, shows a highly significant positive relationship between ES and markups for France and Italy, which points towards price wars due to financial constraints in these countries.[56] Oppositely, we find that Spanish dairy processors seem to boost short term profits as a reaction to declining access to equity as the negative coefficients of ES in the FE and quantile regression model indicate ($p<0.01$; cf. Table 4.3).

Concerning the reallocation of revenues towards high markup firms, we cannot confirm De Loecker et al. (2020). In France and Italy, revenue growth is smaller for firms with higher markups in both the FE as well as the quantile regression models holding everything else constant. Hence, firms with lower markups are able to grow faster in terms of revenue than firms with higher markups. In Spain, we cannot identify any significant link between markup and revenue growth (cf. Table 4.3). This finding may partially explain why the Spanish dairy processing sector is characterized by the highest markups across the three countries. While French and Italian consumers seem to prefer to buy from low markup firms, thereby forcing them into more intense competition, if firms wanted to increase their market shares (grow faster in revenue), Spanish consumers do not seem to do so such that Spanish dairy processing companies charge higher average markups as they are not pushed into more fierce competition by consumers.

Regarding firm age, our analysis reveals that the years since incorporation of the firm and markup are significantly positively related in Italy in the FE model and France and Italy for the quantile regression (cf. Table 4.3), which points towards the theory of learning effects, i.e., firms are able to decrease their cost with increasing operational experience without having to adjust their prices (Hirsch et al. 2014). In Spain, we find a negative and significant relationship between markup and age in the quantile regression model. This may partly be explained by looking at the sectoral characteristics. As stated earlier, the French and Italian dairy industries have a long history of differentiated products (Cassandro 2003; CNIEL 2015; De Gregorio and Tugnolo 2015) whereas the Spanish focus lies on drinking milk and fresh milk products (Sineiro and Vázquez 2014). While old French and Italian dairies in differentiated product segments can also benefit from consumers' preferences for these products, this is not the case in Spain leading to smaller markups.

[56] We have also estimated the models including the cross product of ES and log total assets to examine whether the strategic choice depends on the size of the corporation. However, this does not provide any explanatory power so we do not report the results here.

Table 4.3 Markups and Firm Characteristics

	Fixed effects two stage least squares			Quantile (0.5) regression for panel data		
Variable	**France**	**Italy**	**Spain**	**France**	**Italy**	**Spain**
Log total assets (*lnTA*)	-0.045***	-0.130***	-0.112***	-0.052***	-0.132***	-0.105***
	(0.008)	(0.009)	(0.018)	(0.005)	(8.89e-5)	(0.003)
Fixed cost share (*FCS*)	0.653***	0.845***	1.031***	0.578***	0.931***	0.228***
	(0.085)	(0.039)	(0.27)	(0.081)	(0.001)	(0.033)
Equity share (*ES*)	0.029	0.033	-0.072***	0.056***	0.021***	-0.026**
	(0.039)	(0.067)	(0.015)	(0.015)	(0.001)	(0.010)
Revenue growth (*RG*)	-0.046***	-0.042*	4.23e-4	-0.021**	-0.050***	0.006
	(0.017)	(0.022)	(0.007)	(0.010)	(1.79e-4)	(0.010)
Age	0.002	0.010***	8.94e-4	0.002***	0.008***	-0.001***
	(0.003)	(0.003)	(0.001)	(8.88e-5)	(6.81e-6)	(3.32e-4)
Return on assets (*ROA*)	0.206***	0.910***	0.468***	0.204***	0.901***	0.319***
	(0.040)	(0.107)	(0.024)	(0.018)	(0.004)	(0.016)
Endogenous variables	*FCS*, *ES*, *RG*	*ES*, *RG*, *ROA*	None	*FCS*, *ES*, *RG*	*ES*, *RG*, *ROA*	None
Instruments (lags) used	*FCS* (1), *ES* (1), *RG* (1), *ROA* (1,3)	*ES* (2), *RG* (1), *lnTA* (1), *FCS* (1), *ROA* (2)	None	*FCS* (1), *ES* (1), *RG* (1), *ROA* (1,3)	*ES* (2), *RG* (1), *lnTA* (1), *FCS* (1), *ROA* (2)	None
Wald χ^2 [a]	9,684.63	33,874.53	170.91			
p-value	<0.01	<0.01	<0.01			
Hausman test						
Chi^2	56.28	859.45	1,516.65			
p-value	<0.01	<0.01	<0.01			
First stage statistics						
Minimum eigenvalue statistic	6.26	8.02				
Critical value	4.30	4.30				
Arellano and Bond z-	-0.94	0.10				

statistic						
p-value	0.35	0.92				
Testing overidentifying restrictions						
Sargan χ^2	1.29	1.77				
p-value	0.53	0.41				
Observations	270	3,255	3,349	1,063	5,439	3,358

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; [a]For Spain, the F-statistic is reported since we do not reject exogeneity for any variable.

Source: Own calculations based on data from AMADEUS

Last, we examine the relationship between profitability in terms of return on assets and markup. The relationship is highly significant across all model specifications and countries, which is in line with previous research on markups in general economic literature (e.g., De Loecker and Eeckhout 2017; Mazumder 2014). Since markups and profits are positively related, it is likely that firms charging higher markups exercise market power to boost their profitability, which is evidence for increased rent seeking in the investigated dairy processing industries (Berry et al. 2019). This result implies a consumer welfare loss, which is generally undesirable from a policy maker's point of view. However, combining this result with the model outcomes regarding the relationship of markups and firm size, our analysis suggests that small and medium sized enterprises are able to compete in the highly concentrated sector (i.e., achieve higher markups compared to large companies) and remain profitable. Hence, while consumers may incur welfare losses, larger markups (and profits) for small and medium enterprises compared to large companies can be desirable when it comes to distributional considerations of profits among producers in the industry from a policy making perspective. Besides, our models suggest that consumers shift away from buying products of high markup companies towards low markup companies as suggested by the negative link between revenue growth and markups in France and Italy. Thereby, dairy processors are forced to engage in competition further questioning the need for policy interventions in the sector.

Note that one may be concerned about selection bias due to the loss of observations from our first step, i.e., the estimation of markups, to the second step regression of markups on firm characteristics. This is driven by different causes. First, the second step requires more variables than the first step estimations. Second, the inclusion of revenue growth and the use of the lagged variables as instruments in the second step leads to a further reduction in observations and a higher underrepresentation of small firms. One could argue that only those firms should be included in the first step which also enter the second step. As we aim for a high presence of small firms in order to achieve a representative depiction of the population in the markup estimation, we abstain from excluding the observations not entering the second step regressions in the estimation of the IDF. Nevertheless, we rerun the estimation of the IDF and the second step regressions and present the results in the appendix. Since the findings are very similar to those in Table 4.3, we do not discuss them in further detail here.

4.7 Conclusions

We estimate firm-level markups of output price over marginal cost applying the stochastic frontier approach using input distance functions. The analysis includes data on the French, Italian and Spanish dairy processing industries and accounts for price biases missing input and output price data in the estimation of the input distance function. In a second step, we relate markups to firm characteristics to understand firm characteristics that are related to heterogeneity in markups across firms.

Our results in terms of average markups and Lerner indices show only small deviations from marginal cost pricing, and are hence within the range of previous findings. However, we find considerable heterogeneity across countries and firms. Spanish dairy processors drive the largest wedge between price and marginal cost followed by Italian companies, while the French sector exhibits the smallest values. We expect retailers' bargaining power to partly drive this result since the French food retailing sector exhibits the highest concentration among the three countries.[57] Hence, the need for policy makers to introduce pro-competitive measures in the EU dairy processing sector is questionable given our results.

Moreover, we do not find evidence for an effect of the abandonment of the milk quota or the Russian import ban of EU food products on markups. However, Russia had not been an important trade partner for dairy processors before the ban in any of the three countries, which explains the lack of any impact of the Russian embargo on markups. The picture could change, however, for dairy sectors that have exported considerable amounts of their production to Russia such as Germany. With respect to the abandonment of the EU milk quota, effects will probably evolve over a larger time horizon as previous literature suggests (Philippidis and Waschlik 2019).

Examining the relationship between markup and firm size reveals an inverse correlation. This is particularly interesting since large firms are usually accused to exercise market power. In our context, however, large firms are those that engage in competition most intensively – at least in the output market. Moreover, we find markups and profits to be significantly related in a positive way, which points towards increased rent seeking by EU dairy processors, i.e., markups seem to be connected to market power. However, even though increased rent seeking, i.e., higher markups and profitability, of small firms results in consumer welfare losses, it can be

[57] Hirsch and Koppenberg (2020) study markups in the French retail sector and find significantly larger markups for food retailers, i.e., market power as well as significantly larger markups for the top six retailers.

desirable from a policy maker's point of view since it entails survivorship of small and medium sized enterprises ensuring a certain distribution of profits within the industry. In addition, we find that low markup companies grow faster in terms of revenue as is indicated by a negative link between markups and revenue growth in France and Italy while we do not identify such a tendency for Spain. Hence, fast growing firms engage more in competition, i.e., charge lower markups, than slowly growing firms in two of the three investigated sectors, such that policy interventions to foster competition are further queried.

Looking at our results from the firm perspective, because small firms usually offer highly specialized products in niche markets and are able to charge higher markups translating into increased profitability, product differentiation appears to be a more attractive firm strategy in the EU dairy processing sector than cost leadership in undifferentiated product markets. Due to the heterogeneity of the analyzed dairy sectors, we are confident that this relationship is transferable to other contexts, i.e., countries as well as food industries. Unfortunately, our data do not allow us to shed further light on the type of product, which is a limitation of our study. But, since our results suggest that markups and revenue growth are negatively related holding everything else constant, also small firms are forced to engage in competition by decreasing their prices (markups), if they wanted to increase their market shares. This will, however, induce decreases in profitability.

With respect to the limitations of our study, we have only looked at the output market of the EU dairy processing sector. As another big concern with respect to competition in the dairy sector regards the abuse of buyer power in raw milk procurement (Grau and Hockmann 2018), we encourage future studies to look at the farmer-processor relationship and power dynamics in raw milk markets. This may lead to a different conclusion when evaluating the relationship between (input) market power and firm size as the theory on spatial competition clearly points towards stronger bargaining power in raw milk markets for large dairy processors (e.g., Graubner et al. 2011a; Graubner et al. 2011b).

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4.8 Appendix

4.8.1 Testing Procedure for Endogeneity

The testing procedure follows Joshi and Wooldridge (2019) and starts with estimating the reduced form of the FE2SE which is given as:

$$V_{it} = \psi_i + \sum_{l=1}^{L} \gamma_l X_{lit}^E + \sum_{m=1}^{M} \delta_m Z_{mit} + \eta_{it} \tag{16}$$

where V is the endogenous variable, ψ are the individual fixed effects for each firm, X^E is the vector of exogenous variables from (13), Z is the vector of instruments, and γ and δ are the parameters to estimate. The idiosyncratic error η is assumed to follow a normal distribution with zero mean and uniform variance, i.e., $\eta \sim N\,(0, \sigma_\eta^2)$. We estimate the reduced form for all endogenous variables such that we obtain $D = 2$ vectors of reduced form errors where $d = 1$ denotes the deflated revenue equation and $d = 2$ denotes the deflated material costs equation. In the second stage, we use the $\hat{\eta}_{dit}$ as a control function in (13) (Amsler et al. 2016; Karakaplan and Kutlu 2017):

$$\frac{P_{it}Y_{it}}{C_{it}} = \alpha_{Y(IV)} + \alpha_{YY(IV)} lnY_{it} + \sum_{j=1}^{J-1} a_{jY(IV)} ln(X_{jit}/X_{Jit}) + \sum_{q=1}^{Q} \alpha_{qY(IV)} lnK_{qit} + \alpha_{YT(IV)} T + u_{it} + v_{it} + \sum_{d=1}^{D} \rho_d \hat{\eta}_{dit} \tag{17}$$

where the subscripts IV denote that we obtain the instrumental variable estimates of the coefficients included in (17). ρ is the coefficient of the idiosyncratic error estimates of the reduced forms (16). Rejecting $H0{:}\ \rho = 0$ with a Wald test on a reasonable level of significance (10 percent), implies that we reject exogeneity of the respective variable. We stay with FE2SE as defined in (17) if we reject exogeneity for at least one of the potentially endogeneous variables. Note that the inclusion of $\hat{\eta}_{dit}$ in (17) is equivalent to using the predicted values of the reduced form from (16) (Amsler et al. 2016; Joshi and Wooldridge 2019).

If we fail to reject exogeneity for all potentially endogenous variables, (13) can be estimated without using a two-stage approach, and we assess FE vs. RE based on a procedure similar to the one proposed by Hausman (Hausman 1978; Joshi and Wooldridge 2019). The test is very closely related to (17). The only difference is the exclusion of the $\overline{Z_{mi}}$ and the inclusion of the individual means of lnY, $ln(X_j/X_1)$ and lnK_q. If we reject FE in favour of FE2SE, we will check whether the RE two-stage approach (RE2SE) or FE2SE is preferable with a variable addition test (Joshi and Wooldridge 2019). For this purpose, we estimate:

$$\frac{P_{it}Y_{it}}{C_{it}} = \alpha_{Y(VAT)} + \alpha_{YY(VAT)}lnY_{it} + \sum_{j=1}^{J-1} a_{jY(VAT)}ln(X_{jit}/X_{Jit}) + \sum_{q=1}^{Q} \alpha_{qY(VAT)}lnK_{qit} + \alpha_{YT(VAT)}T + \sum_{l=1}^{L} \gamma_l \overline{X_{li}^*} + \sum_{m=1}^{M} \delta_m \overline{Z_{mi}} + u_{it} + v_{it} \quad (18)$$

where we include the mean values of the L exogenous variables (X^E) and the mean values of the M instruments (Z) for each individual as explanatory variables. VAT denotes that the estimated parameters belong to the variable addition test. We then test the null hypothesis that all γ_l and δ_m are jointly equal to zero. The resulting Wald statistic is χ^2_{L+M}-distributed. When we reject H_0 on a reasonable level of significance (10 percent), RE2SE is inconsistent and we use FE2SE (Joshi and Wooldridge 2019).

Lastly, we test whether strict exogeneity of our instruments is violated following Joshi and Wooldridge (2019). The idea is to estimate (17), and add the leads of our instruments to the set of independent variables:

$$\frac{P_{it}Y_{it}}{C_{it}} = \alpha_{Y(IVEXO)} + \alpha_{YY(IVEXO)}lnY_{it} + \sum_{j=1}^{J-1} a_{jY(IVEXO)}ln(X_{jit}/X_{Jit}) + \sum_{q=1}^{Q} \alpha_{qY(IVEXO)}lnK_{qit} + \alpha_{YT(IVEXO)}T + \sum_{m=1}^{M} \lambda_m Z_{mi,t+1} \sum_{d=1}^{D} \rho_d \, \hat{\eta}_{dit} + u_{it} + v_{it} \quad (19)$$

where λ are the parameters of interest and $IVEXO$ denotes that we obtain the parameter estimates of the test for the exogeneity of our instruments. If the H_0 that all λ_m are jointly equal to zero is to be rejected, the instruments cannot be seen as strictly exogenous. Hence, when rejecting H_0, it must be concluded that at least one of the instruments is endogenous and both FE2SE and RE2SE are inconsistent. In this case, we would have to look for other instruments.

4.8.2 Testing Procedure for Common Technology Across the Countries

To test for a common technology between the dairy processing sector in the three countries, we follow the dummy variable procedure from Triebs et al. (2016) after we have accounted for endogeneity and chosen between the fixed effects and random effects model. The general idea is to estimate a joint model for all countries (joint technology) and one model where we allow the coefficients of the frontier to vary across the countries (separate technologies). We illustrate the estimation strategy at the general distance function used in the main text since additional variables and parameters can be included in the same fashion without changing the test mechanics. The joint technology model is the same as in (10):

$$\frac{PY}{C} = \alpha_Y + \alpha_{YY}lnY + \sum_{j=2}^{J} \alpha_{jY}ln(X_j/X_1) + \sum_{q=1}^{Q} \alpha_{qY}lnK_q + \alpha_{YT}T + u + v \quad (20)$$

We omit the subscripts for i and t to ensure notational simplicity at this point. To allow the coefficients to be country specific, we will estimate (Triebs et al. 2016):

$$\frac{PY}{C} = F \cdot (\alpha_Y^F + \alpha_{YY}^F lnY + \sum_{j=2}^{J} \alpha_{jY}^F ln(X_j/X_1) + \sum_{q=1}^{Q} \alpha_{qY}^F lnK_q + \alpha_{YT}^F)$$
$$I \cdot (\alpha_Y^I + \alpha_{YY}^I lnY + \sum_{j=2}^{J} \alpha_{jY}^I ln(X_j/X_1) + \sum_{q=1}^{Q} \alpha_{qY}^I lnK_q + \alpha_{YT}^I)$$
$$S \cdot (\alpha_Y^S + \alpha_{YY}^S lnY + \sum_{j=2}^{J} \alpha_{jY}^S ln(X_j/X_1) + \sum_{q=1}^{Q} \alpha_{qY}^S lnK_q + \alpha_{YT}^S)$$
$$+ u + v \tag{21}$$

where F is a dummy with value one for French firms and zero otherwise, I is a dummy with value one for Italian firms and zero otherwise and S is a dummy with value one for Spanish firms and zero otherwise. By doing so, we will obtain country specific coefficient estimates. The hypothesis that all firms operate under the same technology translates into the following parametric restrictions (Triebs et al. 2016):

H_0 : $\alpha_Y^F = \alpha_Y^I = \alpha_Y^S$

$$\alpha_{YY}^F = \alpha_{YY}^I = \alpha_{YY}^S$$
$$\alpha_{jY}^F = \alpha_{jY}^I = \alpha_{jY}^S \forall\ j$$
$$\alpha_{YT}^F = \alpha_{YT}^I = \alpha_{YT}^S$$
$$\alpha_{qY}^F = \alpha_{qY}^I = \alpha_{qY}^S$$

To test whether the parametric restrictions are valid, we conduct a simple likelihood ratio test of the model estimated according to (10)/(20) against the model from (21) (Triebs et al. 2016).

4.8.3 Data

For Germany, the AMADEUS database contains 57 firms in 2016 while the population contains 645 firms resulting in a share of only 8.8 percent (Eurostat 2019). The share of small firms, i.e., <50 employees, in the sample (population) amounts to 19.30 percent (81.71 percent) and the share of large firms, i.e., ≥ 250 employees, is 43.86 percent (6.82 percent). Hence, large firms are heavily overrepresented and small firms are strongly underrepresented to an extent which we perceive as inacceptable to draw inference from the sample to the population. The poor data availability for Germany is caused by weaker disclosure obligations for small compared to large companies in Germany. While all corporations and companies without a natural person being liable must disclose their financial statements, sole traders and partnerships with a natural person being liable only have to disclose their financial statements as soon as they fulfil two of the three following criteria: 1) more than €65 million of total assets; 2) more than €130 million of revenue in the fiscal year; 3) an average of more than 5,000 employees in the fiscal year (IHK Berlin 2021).

Table 4.A1 Comparison of the Sample With the Population (2016)[a]

	France	**Italy**	**Spain**	**All**	***Germany***
Number of firms in the sample	218	829	572	1,619	*57*
Number of firms in the population	1,222	3,535	1,507	6,264	*645*
Percentage shares by size class[b]					
Large firms					
Sample	10.09	2.05	2.80	3.40	*43.86*
Population	2.70	0.42	1.19	1.05	*6.82*
Medium firms					
Sample	28.90	10.98	8.56	12.54	*36.84*
Population	6.71	3.25	3.65	4.02	*11.47*
Small firms					
Sample	61.01	86.97	88.64	84.06	*19.30*
Population	90.59	96.32	95.16	94.91	*81.71*

Notes: [a]Note that the sample is unbalanced so that the overall number of firms in the sample differs from the number of firms in 2016. [b]Size classification based on European Commission. 2013: small: < 50 employees; medium: ≥ 50 and < 250 employees; large: ≥ 250 employees.

Source: Own calculations based on AMADEUS; shares for the population are derived from Eurostat (2019).

Table 4.A2 Major EU Milk Producing and Dairy Processing Countries (2018)

	Dairy processing (revenue)[a]		**Raw milk production (tonnes)[b]**	
Rank	**Country**	**Market share (%)**	**Country**	**Market share (%)**
1	France	23.35	Germany	19.86
2	Germany	18.18	France	15.04
3	Italy	11.70	United Kingdom	9.19
4	Netherlands	7.91	Poland	8.50
5	United Kingdom	6.39	Netherlands	8.46
6	Spain	5.74	Italy	7.41
7	Poland	4.99	Ireland	4.70
8	Belgium	2.69	Spain	4.40
9	Austria	1.68	Denmark	3.37
10	Sweden	1.57	Belgium	2.55

[a]Market shares based on Eurostat (2019); [b]Market shares based on FAO (2019)

Table 4.A3 Descriptive Statistics of In-/Output Measures and Firm Characteristics (2008-2017)

	Mean (standard deviation)		
	France	**Italy**	**Spain**
Frontier			
Number of observations	2,020	7,208	4,945
Revenue (PY) [€1,000]	48,472.11 (157,080.10)	22,922.78 (197,315.70)	15,782.71 (75,490.92)
Total variable costs (C) [€1,000]	36,686.43 (112,445.20)	16,809.06 (129,332.80)	11,916.38 (50,695.09)
$\frac{Revenue}{Total\ variabe\ cost}$ $(\frac{PY}{C})$	1.38 (0.40)	1.30 (0.31)	1.34 (0.33)
Deflated revenue (Y)	452.35 (1,460.11)	219.92 (1,896.98)	152.72 (730.97)
Number of employees (X_1)	99.51 (305.97)	51.43 (606.20)	37.80 (141.06)
Deflated material costs (X_2)	297.58 (908.60)	131.05 (949.38)	96.69 (412.16)
Deflated fixed assets (K)	86.50 (303.71)	87.80 (854.37)	48.88 (206.55)
Total assets [€1,000]	21,781.20 (63,890.06)	20,457.83 (176,806.00)	9,974.51 (42,856.72)
Revenue of population [€1,000,000]	29,179.11 (4,401.25)	18,040.31 (1,194.58)	9,477.38 (587.06)
Milk production of population [1,000 tons]	23,694.35 (720.45)	12,805.68 (292.82)	6,600.62 (276.11)
X_2^* *[tons]*	38,344.15 (114,647.70)	16,663.30 (144,712.30)	10,931.43 (46,672.36)
Debtors [€1,000]	4,689.71 (15,177.51)	3,632.06 (20,047.46)	2,072.75 (8,777.39)
Stock [€1,000]	3,835.89 (10,175.72)	3,529.72 (19,956.52)	1,265.63 (5,075.98)
Markup-related firm characteristics			
Number of observations	1,063	5,439	3,358
Total assets [€1,000]	25,988.46 (65,754.65)	22,491.78 (185,934.40)	12,089.72 (48,078.40)
Return on assets	0.06 (0.08)	0.04 (0.08)	0.04 (0.08)
Revenue growth[a]	0.06 (1.23)	0.09 (1.34)	0.09 (1.29)
Age [years]	31.69 (24.09)	28.18 (22.16)	17.47 (10.97)
Equity share	0.39 (0.21)	0.25 (0.19)	0.44 (0.25)
Fixed cost share	0.21 (0.11)	0.19 (0.11)	0.22 (0.15)

Notes: [a]For revenue growth, we report the geometric mean and geometric standard deviation.

Source: Own calculations based on AMADEUS

4.8.4 Estimation Results

Table 4.A4 Reduced Form Regression with Deflated Revenue and $\ln(X_2/X_1)$ as the Dependent Variables

	France	**Italy**	**Spain**
Dependent variable: deflated revenue			
ln Stock	0.179***	0.124***	0.089***
	(0.013)	(0.006)	(0.007)
ln Debtors	0.129***	0.196***	0.096***
	(0.009)	(0.006)	(0.006)
$\ln(X_2^*/X_1)$	-0.053***	-0.008	-0.205***
	(0.014)	(0.011)	(0.013)
lnK	0.134***	0.120***	0.131***
	(0.011)	(0.008)	(0.010)
2009	0.073***	0.014	-2.74e-4
	(0.019)	(0.018)	(0.021)
2010	0.096***	0.004	0.057***
	(0.018)	(0.019)	(0.021)
2011	0.093***	-0.050***	0.053***
	(0.018)	(0.017)	(0.020)
2012	0.121***	-0.043***	0.056***
	(0.019)	(0.017)	(0.020)
2013	0.123***	-0.018	0.057***
	(0.019)	(0.016)	(0.021)
2014	0.124***	0.015	0.093***
	(0.018)	(0.017)	(0.021)
2015	0.152***	0.043**	0.149***
	(0.019)	(0.017)	(0.021)
2016	0.179***	0.088***	0.150***
	(0.019)	(0.017)	(0.020)
2017	0.142***	0.101***	0.195***
	(0.022)	(0.017)	(0.021)
Constant	2.019***	1.377***	2.246***
	(0.112)	(0.069)	(0.070)
Observations	2,020	7,208	4,945
R-squared	0.426	0.290	0.195
Dependent variable: $\ln(X_2/X_1)$			
ln Stock	0.001	0.042***	-0.028***
	(0.016)	(0.007)	(0.008)
ln Debtors	0.059***	0.085***	0.009
	(0.011)	(0.007)	(0.007)
$\ln(X_2^*/X_1)$	0.711***	0.856***	0.607***
	(0.017)	(0.012)	(0.015)
lnK	-0.161***	-0.104***	-0.145***
	(0.013)	(0.009)	(0.011)

2009	0.119***	-0.016	0.076***
	(0.023)	(0.021)	(0.024)
2010	0.129***	-0.029	0.070***
	(0.022)	(0.021)	(0.024)
2011	0.069***	-0.052***	0.139***
	(0.022)	(0.019)	(0.024)
2012	0.136***	-0.150***	0.040*
	(0.024)	(0.019)	(0.024)
2013	0.102***	-0.134***	-0.097***
	(0.023)	(0.019)	(0.024)
2014	0.079***	-0.148***	-0.123***
	(0.022)	(0.019)	(0.024)
2015	0.195***	-0.121***	-0.021
	(0.023)	(0.019)	(0.024)
2016	0.210***	-0.010	0.031
	(0.024)	(0.019)	(0.024)
2017	0.445***	-0.050**	0.018
	(0.027)	(0.020)	(0.024)
Constant	-3.833***	-4.505***	-3.078***
	(0.136)	(0.079)	(0.082)
Observations	2,020	7,208	4,945
R-squared	0.565	0.507	0.294

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; lnx2* denotes the instrument for log material costs.

Source: Own calculations based on AMADEUS

Table 4.A5 General Identification Test of the Instruments in the Reduced Form Regressions

Country	**Wald statistic**	**p-value**
Dependent variable: deflated revenue		
France	148.52	<0.01
Italy	520.07	<0.01
Spain	159.20	<0.01
Dependent variable: ln(X_2/X_1)		
France	596.12	<0.01
Italy	1,884.42	<0.01
Spain	532.99	<0.01

Source: Own calculations based on AMADEUS

Table 4.A6 Fixed Effects Two-Stage Stochastic Frontier

		France	Italy	Spain
Frontier				
	lnY	-0.159*	-0.011	0.012
		(0.085)	(0.030)	(0.057)
	$\hat{\eta}_{Deflated\ revenue}$	0.209***	0.358***	0.382***
		(0.071)	(0.049)	(0.063)
	lnK	0.039*	0.009	0.043
		(0.023)	(0.010)	(0.027)
	$ln(X_2/X_1)$	-0.173***	-0.373***	-0.391***
		(0.047)	(0.040)	(0.051)
	$\hat{\eta}_{ln(X2/X1)}$	0.025	0.017*	-0.006
		(0.017)	(0.010)	(0.013)
	2009	0.012	0.025***	-0.002
		(0.014)	(0.009)	(0.011)
	2010	0.010	0.009	0.010
		(0.023)	(0.007)	(0.011)
	2011	0.001	-0.004	-0.008
		(0.018)	(0.008)	(0.013)
	2012	-0.001	0.007	-0.010
		(0.022)	(0.008)	(0.013)
	2013	0.019	-0.005	-0.007
		(0.027)	(0.008)	(0.012)
	2014	0.012	0.004	-0.028**
		(0.027)	(0.008)	(0.013)
	2015	0.046	0.017**	-0.014
		(0.031)	(0.008)	(0.015)
	2016	0.055	0.019**	-0.009
		(0.037)	(0.009)	(0.017)
	2017	0.039	-0.004	-0.013
		(0.041)	(0.011)	(0.019)
Sigma2	Constant	0.024***	0.040***	0.079***
		(0.008)	(0.007)	(0.014)
Lambda	Constant	1.132	2.588***	4.811***
		(0.975)	(0.464)	(1.332)
	Observations	2,020	7,208	4,945
	Log-likelihood	-14.563	-133.34	-1,119.95

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations based on AMADEUS

Table 4.A7 Testing RE2SE Against FE2SE

	France	Italy	Spain
Frontier			
lnY	-	-	0.197***
			(0.028)
lnK	-	-	-0.037***
			(0.010)
$ln(X_2/X_1)$	-	-	-0.146***
			(0.017)
2009	-	-	0.015
			(0.013)
2010	-	-	0.050***
			(0.011)
2011	-	-	0.024*
			(0.013)
2012	-	-	0.026**
			(0.011)
2013	-	-	0.007
			(0.012)
2014	-	-	-0.016
			(0.012)
2015	-	-	0.007
			(0.012)
2016	-	-	0.015
			(0.013)
2017	-	-	-0.006
			(0.015)
$\overline{2008}$	-	-	0.137
			(0.128)
$\overline{2009}$	-	-	0.084
			(0.191)
$\overline{2010}$	-	-	-0.531
			(0.391)
$\overline{2011}$	-	-	0.331
			(0.430)
$\overline{2012}$	-	-	-0.251
			(0.424)
$\overline{2013}$	-	-	0.235
			(0.436)
$\overline{2014}$	-	-	-0.314
			(0.366)
$\overline{2015}$	-	-	0.564
			(0.544)
$\overline{2016}$	-	-	-0.827
			(0.568)
$\overline{2017}$	-	-	0.771***

				(0.273)
	$\overline{lnK}$	-	-	-0.025*
				(0.014)
	$\overline{ln(X_2^*/X_1)}$	-	-	0.150***
				(0.036)
	$\overline{ln\ Stock}$	-	-	-0.061***
				(0.015)
	$\overline{ln\ Debtors}$	-	-	-0.050***
				(0.013)
	Constant	-	-	0.296**
				(0.121)
Usigma	*Constant*	-	-	-2.283***
				(0.174)
Vsigma	*Constant*	-	-	-5.854***
				(0.448)
Theta	*Constant*	-	-	0.222***
				(0.025)
	Observations	-	-	4,945
	Log-likelihood	-	-	641.85

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations based on AMADEUS

Table 4.A8 Testing the Exogeneity of Instruments

		France	Italy	Spain
Frontier				
	lnY	-0.163*	0.010	0.080
		(0.086)	(0.033)	(0.056)
	$\hat{\eta}_{Deflated\ revenue}$	0.228***	0.351***	0.328***
		(0.078)	(0.052)	(0.060)
	$lnStock_{t+1}$	0.001	-0.003	-0.004
		(0.004)	(0.003)	(0.005)
	$lnDebtors_{t+1}$	0.001	-0.005	-0.001
		(0.005)	(0.005)	(0.005)
	$(lnx_2*-lnx1)_{t+1}$	-0.002	0.011*	0.001
		(0.005)	(0.007)	(0.006)
	$lnx3-lnx1$	0.039***	0.018*	-0.008
		(0.012)	(0.011)	(0.012)
	$lnx2-lnx1$	0.064**	0.008	0.068**
		(0.025)	(0.010)	(0.027)
	$\hat{\eta}_{ln(X2/X1)}$	-0.215***	-0.386***	-0.416***
		(0.056)	(0.044)	(0.052)
	2009	0.010	0.026***	-0.004
		(0.014)	(0.009)	(0.011)
	2010	0.007	0.009	0.004
		(0.022)	(0.007)	(0.011)

	2011	-0.001	-0.006	-0.016
		(0.019)	(0.008)	(0.013)
	2012	-0.006	0.006	-0.016
		(0.022)	(0.008)	(0.012)
	2013	0.014	-0.007	-0.011
		(0.026)	(0.008)	(0.012)
	2014	0.005	-0.001	-0.037***
		(0.026)	(0.009)	(0.012)
	2015	0.034	0.012	-0.033**
		(0.029)	(0.009)	(0.015)
	2016	0.043	0.008	-0.037**
		(0.036)	(0.010)	(0.017)
Sigma2	*Constant*	0.024***	0.039***	0.070***
		(0.008)	(0.007)	(0.015)
Lambda	*Constant*	1.278	2.473***	4.406***
		(1.017)	(0.561)	(1.370)
	Observations	1,864	6,387	4,413
	Log-likelihood	4.723	-104.51	-801.345

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations based on AMADEUS

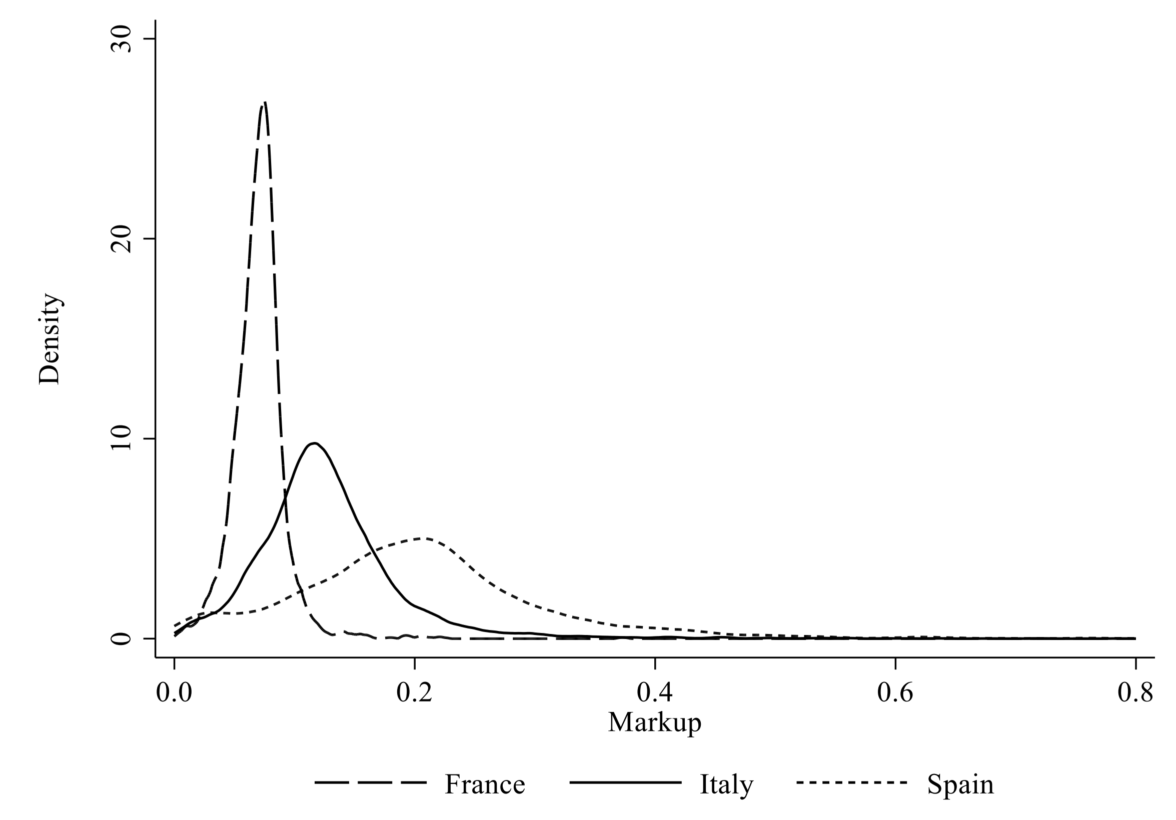
Table 4.A9 Estimation Results of Joint and Separate Technology

		Joint technology	France	Italy	Spain
Frontier					
	lnY	0.020	-0.115	0.014	0.056
		(0.042)	(0.079)	(0.042)	(0.094)
	$\hat{\eta}_{Deflated\ revenue}$	0.314***	0.133	0.331***	0.339***
		(0.048)	(0.092)	(0.056)	(0.106)
	lnk	0.007	0.017	0.017	-0.007
		(0.012)	(0.022)	(0.013)	(0.019)
	lnx2-lnx1	0.014	0.034	0.013	0.040
		(0.016)	(0.022)	(0.011)	(0.038)
	$\hat{\eta}_{ln(X2/X1)}$	-0.320***	-0.124**	-0.357***	-0.378***
		(0.026)	(0.049)	(0.037)	(0.076)
	2009	0.022	0.055*	0.035**	0.003
		(0.019)	(0.029)	(0.014)	(0.024)
	2010	0.022	0.061***	0.021	0.022
		(0.018)	(0.005)	(0.016)	(0.023)
	2011	0.008	0.051*	0.016	0.001
		(0.016)	(0.028)	(0.016)	(0.023)
	2012	0.016	0.058*	0.025	0.002
		(0.017)	(0.034)	(0.023)	(0.027)
	2013	0.015	0.068***	0.014	0.007
		(0.017)	(0.026)	(0.017)	(0.022)
	2014	0.005	0.056*	0.023	-0.017
		(0.017)	(0.032)	(0.017)	(0.025)

	2015	0.019	0.094***	0.034**	-0.007
		(0.018)	(0.030)	(0.016)	(0.028)
	2016	0.023	0.100***	0.028*	-0.003
		(0.019)	(0.032)	(0.017)	(0.030)
	2017	-0.001	0.074*	0.001	-0.016
		(0.023)	(0.039)	(0.019)	(0.033)
Usigma	*Constant*	-2.853***		-2.903***	
		(0.112)		(0.109)	
Vsigma	*Constant*	-45.942***		-46.590***	
		(0.012)		(0.014)	
	Observations	14,173		14,173	
	Likelihood	9,931		10,284	

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

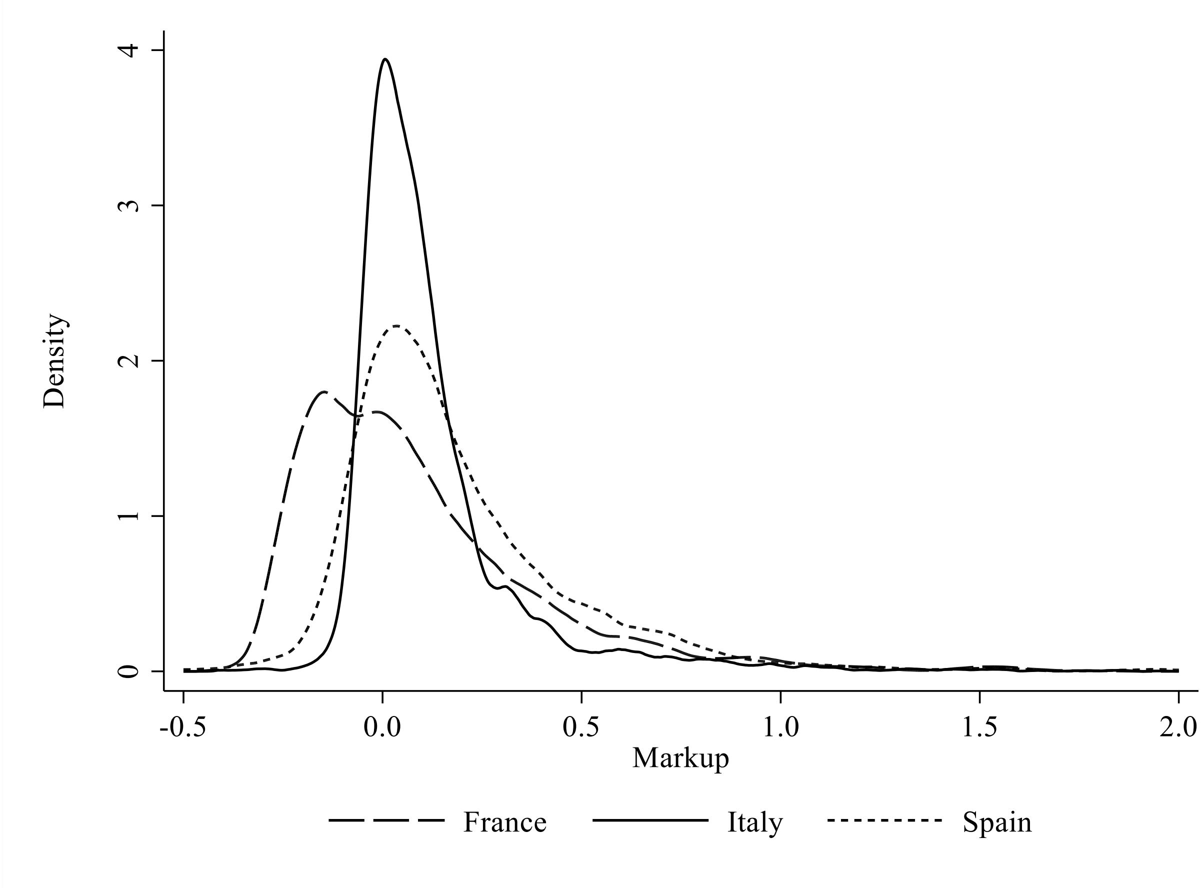
Source: Own calculations based on AMADEUS



Note: 16 observations > 0.8 omitted to ensure readability

Source: Own calculations based on AMADEUS

Figure 4.A1 Probability Density Functions of Markups Including Fixed Effects in the Predicted Value of the Cost Elasticity



Note: 11 observations < -0.5 and 48 observations > 2.0 omitted to ensure readability

Source: Own calculations based on AMADEUS

Figure 4.A2 Probability Density Functions of Markups Treating Fixed Effects as a Time-Invariant Markup Component

Table 4.A10 Results of the Shapiro-Wilk Test for Normal Distribution of Markups

Country	Number of observations	Test statistic (W)	z	p-value
France	2,020	0.623	15.553	<0.001
Italy	7,208	0.729	18.368	<0.001
Spain	4,945	0.776	16.784	<0.001

Source: Own calculations based on AMADEUS

Table 4.A11 Davidson-MacKinnon Test Results for Fixed Effects Two-Stage Least Squares

Variable	France	Italy	Spain
Return on assets (ROA)	0.007	21.204***	0.037
	(0.935)	(<0.001)	(0.848)
Log total assets (lnTA)	0.004	0.002	0.647
	(0.947)	(0.968)	(0.421)
Fixed cost share (FCS)	3.887**	0.087	0.006
	(0.049)	(0.768)	(0.937)
Equity share (ES)	6.053**	3.110*	1.970
	(0.014)	(0.078)	(0.160)
Revenue growth (RG)	5.027**	7.119***	2.449
	(0.025)	(0.008)	(0.118)

Notes: Null hypothesis is exogeneity. χ^2 statistics reported including p-values in parentheses; *** p<0.01, ** p<0.05, * p<0.1

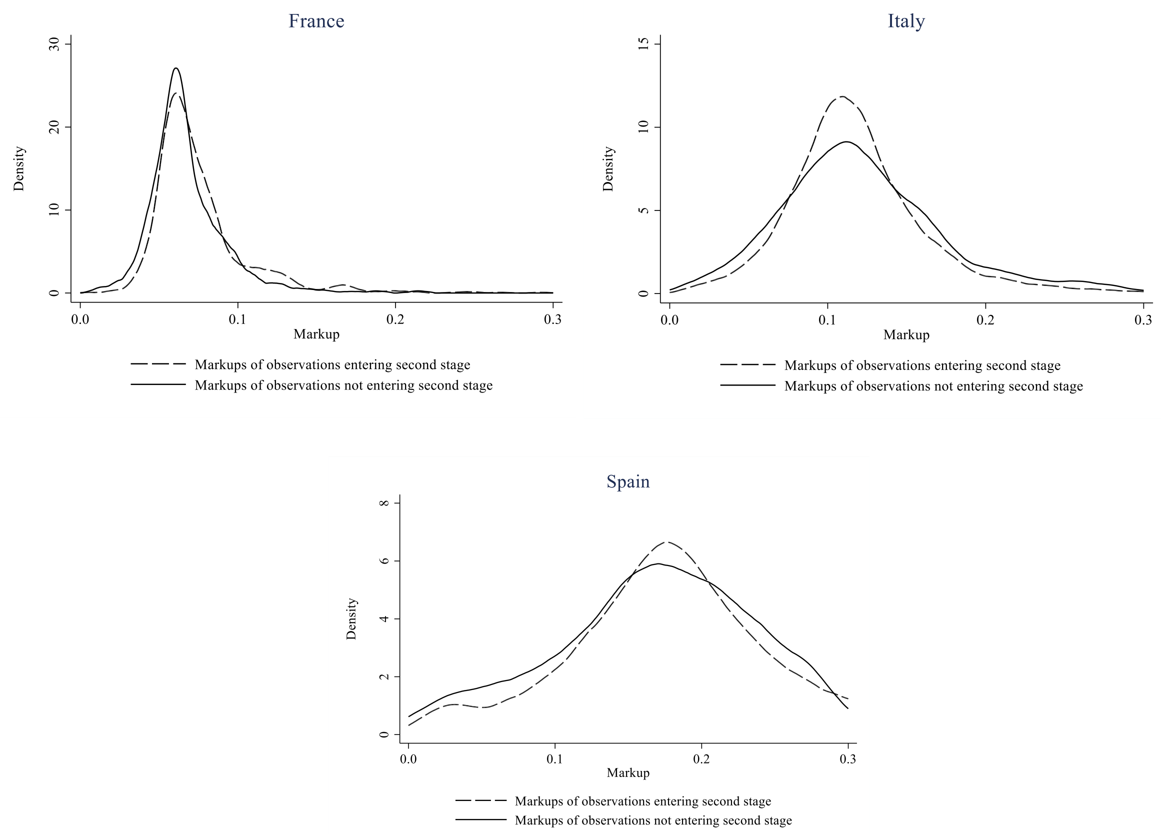
Source: Own calculations based on AMADEUS

One may be concerned about selection bias due to the large loss in terms of observations between our first step, i.e., the estimation of markups, and the second step regression, i.e., the relationship of markups and firm characteristics. This is driven by different causes. First, the second step requires more variables than the first step estimations. Some of these variables such as the date of incorporation and the equity share are not available for all firms that are included in the first step. Second, the inclusion of revenue growth from period t to $t + 1$ in the second step implies that we lose the last period of our sample, and requires that data for each firm are available in two consecutive periods. This leads to a reduction to 1,063, 5,439 and 3,358 observations representing a change of -47.38 percent, -24.54 percent and -32.09 percent for France, Italy and Spain, respectively (see Table 4.A3). Moreover, the use of the lagged variables as instruments in the second step (France and Italy), implies the loss of the first three periods for these two countries, and requires that each firm in the analysis has four consecutive observations. Thereby, we end up with 270, 3,255, 3,349 observations being equal to a share of 13.36 percent, 45.16 percent, 67.72 percent of the original number of observations for France, Italy and Spain, respectively.

One could argue that only those firms should be included in the first step which also enter the second step. However, we aim for a high presence of small firms in order to achieve a representative depiction of the population in the markup estimation. In that regard, we compare the firm size distribution of our sample firms with the distribution in the population in Table 4.A1. Even for our original sample we see that small firms are slightly underrepresented in Italy and Spain and clearly underrepresented in France (cf. Table 4.A1). Therefore, excluding firms not entering the second step in the first step would further bias the sample towards the overrepresentation of large firms as the second stage firms, on average, are larger in terms of total assets (cf. Table 4.A3).

To assess whether our findings are affected by the inevitable reduction in observations we compare markups of those observations entering the second step analysis and those that do not enter the second step. Figure 4.A3 contrasts the distributions of markups for observations entering and observations not entering the second step regressions. We see that median markups between the two groups are very similar in all countries. In Italy and Spain, markups of those observations not entering the second step regressions are slightly more dispersed than those observations entering the second step regressions. Hence, this does not present any indication of a selection bias. Nevertheless, we have re-estimated the IDFs using only those observations that enter the second step regressions and contrast the markup distributions of our original models with those we obtain when we only include those observations entering the second step regressions below (cf. Table 4.A12). We see that the means and medians are slightly different for the two estimations in France and Italy whereas the difference is rather substantial in Spain (cf. Table 4.A12). This is, however, consistent with our analysis given the fact that Spanish firms entering the second step regression are approximately 21 percent larger in terms of total assets (€12,089.72 thousand vs. €9,974.51 thousand; see Table 4.A3) and we observe a strong negative link between firm size and markup (cf. Table 4.3).

Finally, we also run the fixed effects second step regression for the $\hat{\theta}_{SND}$ and present the results along with our original models in Table 4.A13 below. Except for age in Spain, all coefficients that are significant in the $\hat{\theta}_{ORI}$-models are also significantly different from zero in the $\hat{\theta}_{SND}$ with the same signs. In addition, the size of the coefficients in Italy and Spain are very similar across both models. Only in France, we observe considerable differences in the absolute values of the significant coefficient estimates between the two models with the $\hat{\theta}_{SND}$-model showing larger absolute values compared to the original model (cf. Table 4.3). Hence, using only those observations entering the second step regression in the estimation of markups does not produce different results in the second step regression.



Source: Own calculations based on AMADEUS

Figure 4.A3 Probability Density Functions of Markups for Observations Entering vs. Observations Not Entering the Second Stage Regressions

Table 4.A12 Markup Estimates of Original Models (ORI) and Only Including Observations Entering the Second Stage (SND) in the Estimation of the Input Distance Function

	France		**Italy**		**Spain**	
	$\hat{\theta}_{ORI}$	$\hat{\theta}_{SND}$	$\hat{\theta}_{ORI}$	$\hat{\theta}_{SND}$	$\hat{\theta}_{ORI}$	$\hat{\theta}_{SND}$
Mean	0.073	0.092	0.125	0.104	0.195	0.122
Median	0.065	0.084	0.115	0.100	0.181	0.107
1st quartile	0.055	0.070	0.091	0.076	0.135	0.076
3rd quartile	0.081	0.102	0.144	0.120	0.233	0.147
Minimum	0.005	0.003	0.003	0.003	0.003	0.004
Maximum	0.657	1.259	1.168	1.145	2.563	1.058
Standard deviation	0.037	0.060	0.068	0.056	0.118	0.080

Source: Own calculations based on AMADEUS

Table 4.A13 Second Step Regressions for Markup Estimates of Original Models ($\hat{\theta}_{ORI}$) and Only Including Observations Entering the Second Step ($\hat{\theta}_{SND}$) in the Estimation of the Input Distance Function

	France		Italy		Spain	
Dependent variable	$\hat{\theta}_{ORI}$	$\hat{\theta}_{SND}$	$\hat{\theta}_{ORI}$	$\hat{\theta}_{SND}$	$\hat{\theta}_{ORI}$	$\hat{\theta}_{SND}$
Log total assets (lnTA)	-0.045***	-0.082***	-0.130***	-0.119***	-0.112***	-0.081***
	(0.008)	(0.013)	(0.009)	(0.009)	(0.018)	(0.005)
Fixed cost share (FCS)	0.653***	1.174***	0.845***	0.843***	1.031***	0.925***
	(0.085)	(0.151)	(0.039)	(0.081)	(0.27)	(0.021)
Equity share (ES)	0.029	0.049	0.033	0.032	-0.072***	-0.047***
	(0.039)	(0.062)	(0.067)	(0.065)	(0.015)	(0.012)
Revenue growth (RG)	-0.046***	-0.058**	-0.042*	-0.046**	4.23e-4	-0.005
	(0.017)	(0.027)	(0.022)	(0.021)	(0.007)	(0.005)
Age	0.002	-0.004	0.010***	0.015***	8.94e-4	0.003***
	(0.003)	(0.005)	(0.003)	(0.003)	(0.001)	(6.19e-4)
Return on assets (ROA)	0.206***	0.400***	0.910***	0.904***	0.468***	0.442***
	(0.040)	(0.061)	(0.107)	(0.104)	(0.024)	(0.019)
Endogenous variables	FCS, ES, RG	FCS, ES, RG	ES, RG, ROA	ES, RG, ROA	None	None
Instruments (lags) used	FCR (1), ES (1), RG (1), ROA (1,3)	FCR (1), ES (1), RG (1), ROA (1,3)	ES (2), RG (1), lnTA (1), FCS (1), ROA (2)	ES (2), RG (1), lnTA (1), FCS (1), ROA (2)	None	None
Wald $\chi^{2\,a}$	9,684.63	5,559.56	33,874.53	26,114.78	170.91	215.00
p-value	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
Observations	270	270	3,255	3,255	3,349	3,349

Source: Own calculations based on AMADEUS

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5 Markup Estimation: A Comparison of Contemporary Methods at the Example of European Food Retailers

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Abstract

We compare the economic and econometric assumptions of two contemporary procedures for the estimation of markups, the stochastic frontier approach (SFA) and the production function approach (PFA), and apply them to EU food retailing over the period 2010-2018. Although, the estimates of the underlying technology of the two methods are similar, our results suggest that the PFA leads to significantly larger markups, yielding approximated excess consumer expenditures 58.14 to 313.33 percent larger than predicted by the SFA. In addition, the correlation of markups between the two methods is low. This can have implications for the consistency of policy recommendations based on the SFA and the PFA as they yield different outcomes with respect to the state of competition in a market. Last, we find a link between market concentration and markups for the PFA pointing towards adverse effects of further concentration on consumer welfare, whereas our results show no evidence for a relationship between SFA markups and market concentration.

5.1 Introduction

Firms' output market power is commonly defined as price markups which are deviations of output prices from marginal cost (Bonanno et al. 2018). Researchers in applied economics often use price markups to estimate welfare implications stemming from output market power, and finally, to derive policy recommendations for competition authorities (e.g., Lavergne et al. 2001; Maudos and Fernández de Guevara 2007; Wang and Zhao 2007). However, recent reviews show (e.g., Perekhozhuk et al. 2017; Sexton and Xia 2018) that, as the various methods to estimate price markups are based on different assumptions, the resulting estimates can also differ significantly. Given that these assumptions are potentially inaccurate, estimates for market power and the resulting predicted welfare effects can be biased and recommendations for policy makers may be ill-advised. Sexton and Xia (2018) consider that, in contrast to commonly used NEIO approaches, the most promising methods to obtain reliable estimates avoid either estimation of conjectural elasticities and market conduct, or estimating cost parameters.

We contribute to the market power literature by reviewing two methods that do not require the estimation of conduct parameters. We then apply both approaches to EU food retailing as a case study. The first is the comparatively new stochastic frontier approach (SFA) established by Kumbhakar et al. (2012) which applies techniques from efficiency analysis to recover price markups. The second is the production function approach (PFA) which was introduced by Hall (1988) and further developed by De Loecker (2011) and De Loecker and Warzynski (2012). In recent market power studies, both methods are frequently used to estimate output price markups and welfare effects of output market power, to derive policy recommendations and/or to analyze the effect of implemented competition policy measures (e.g., Asker et al. 2014; Edmond et al. 2018; Vancauteren 2013 for the PFA and Lopez et al. 2018; Rudinskaya 2019; Silva et al. 2019 for the SFA). We choose the EU food retailing sector for our analysis since antitrust authorities have recurrently initiated investigations against food retailing companies in several member states, e.g., the Czech Republic, Finland (OECD 2014) or France (European Commission 2019) among others, due to unfair trading practices towards suppliers or excessive food prices compared to neighboring countries (European Competition Network 2012). Further, the sector is characterized by high concentration (McCorriston 2014) and food retailers have been found to resist against competitive forces enabling them to generate persistent profits (Hirsch et al. 2021). Besides, earlier studies also find evidence for anti-competitive behavior of European food retailers (e.g., Gohin and Guyomard 2000; Salhofer et al. 2012; Sckokai et al. 2013).

Therefore, we expect considerable degrees of market power in the food retail sector providing us with a suitable case study for our comparison of markup estimation approaches.

The New Empirical Industrial Organization (NEIO) framework, which relies on the estimation of cost and conduct parameters and conjectural elasticities[58] (Appelbaum 1982; Bresnahan 1982), is widely used to analyze market power. The conjectural elasticity approximates how close a firm's or industry's pricing behavior is to becoming a monopoly. The NEIO methodology has been applied empirically to a large number of European and U.S. industries and retail sectors (e.g., Mérel 2009; Morrison Paul 2001; Perekhozhuk et al. 2013). However, the NEIO approach has been criticized frequently due to its underlying assumptions regarding 1) ex-ante choice of functional forms (Mei and Sun 2008; Perekhozhuk et al. 2017; Sexton 2000), 2) the unrealistic assumption of perfect competition in up- and downstream markets (Sexton 2000), and 3) the game theoretical assumptions defining the interactions of firms in the market under investigation (Corts 1999; Sheldon 2017).

The approaches to deal with the above mentioned issues can be categorized in two different methodological areas. The first relies on estimation of demand systems to make inference on markups without estimating cost parameters (Berry et al. 1995; Nevo 2001). However, the necessary data on demand and product prices are seldom available. The other area uses insights from production theory to estimate production or cost functions, and does not take any stand on demand side conditions (De Loecker and Warzynski 2012; Hall 1988; Kumbhakar et al. 2012). The SFA and the PFA belong to this category since they avoid estimation of the conduct parameter and demand functions (De Loecker and Warzynski 2012; Kumbhakar et al. 2012; Sexton and Xia 2018). However, the SFA and PFA have different underlying assumptions, which also translate into different identification techniques for the market power parameter. As pointed out by Perekhozhuk et al. (2017), different estimation methods can have grave consequences for the results of the analysis of market power. Up till now, no study has been conducted to compare the two methods with respect to their economic and econometric assumptions and the effect on the resulting markup estimates. We aim to fill this gap by explicitly reviewing the two procedures and applying them to EU food retailing. While the inclusion of demand-side approaches in this study would be valuable, necessary data are not available such that we are restricted to supply-side models.

[58] The conjectural elasticity measures the expected change of the industry's overall output due to a change in the firm's output.

Our objective is a comparison of the SFA and the PFA to identify their similarities and differences from a theoretical and empirical perspective. First, we illustrate the theoretical economic derivations underlying both approaches. Thereafter, we lay out the econometric techniques to recover markups of output price over marginal cost for the SFA and the PFA. Last, we apply both approaches to EU food retailing on the firm-level using a rich panel data set from five countries over the period 2010-2018. We discuss the results of the two methods with respect to the estimated technological parameters (returns to scale), markups, approximated welfare losses due to retailers' output market power, and the relationship between markups and market concentration in EU food retailing.

The majority of food retailers in our sample operates close to the efficient scale (i.e., when returns to scale are equal to one). We find that the PFA leads to much larger average markups than the SFA despite the fact that PFA markups can become negative while the SFA specifies that markups must be larger than zero. Depending on the country, approximated excess consumer expenditures are 58.14 to 313.33 percent larger using PFA markups compared to using SFA markups, suggesting that both methods can lead to controversial conclusions with respect to the state of competition in a market. In addition, both methods rank firms differently in terms of market power which is indicated by low correlation coefficients between markups obtained by the two methods. While the sales-weighted industry-level markups show a significant correlation with industry concentration for the PFA, this is not the case for the SFA. Therefore, further regressions of markups on industry and/or firm characteristics to identify drivers of market power on the firm-level lead to ambiguous results.

The rest of the paper is structured as follows: We first describe the theoretical economic considerations underlying the two approaches to compute markups. This is followed by an explanation of the econometric strategies for parameter identification on which both methods are based. We then apply the SFA and the PFA to EU food retailing as a case study and discuss the results and their implications for future market power studies. Finally, we present our conclusions.

5.2 Theoretical Foundations

In this section, we describe the theoretical foundations of the SFA and the PFA and the calculation of markup estimates for each method. However, we omit some minor steps and refer the reader to the original papers for the complete derivations (Kumbhakar et al. 2012 for the SFA and De Loecker and Warzynski 2012 for the PFA).

The intuition of the SFA is that a cost minimizing firm charges an output price (P) which is different from marginal cost (MC) in the absence of perfect competition resulting in the inequality $P \neq MC$. Multiplying both sides of the inequality with the quotient of output (Y) and total cost (C) yields (Kumbhakar et al. 2012):

$$P\frac{Y}{C} \neq MC\frac{Y}{C} = \frac{\partial C}{\partial Y}\frac{Y}{C} = \frac{\partial lnC}{\partial lnY} \quad . \tag{1}$$

We add a markup-component (u) to the right-hand side of (1) to capture the difference between the ratio of revenue over total cost (PY/C) and the cost elasticity ($\partial lnC/\partial lnY$) and turn the inequality into an equality:

$$\frac{PY}{C} = \frac{\partial lnC}{\partial lnY} + u \quad . \tag{2}$$

We now wish to derive an expression for the percentage markup (θ) by which P differs from MC (i.e., $(P - MC)/MC$). For this purpose, we multiply the right-hand side of (2) with average cost (C/Y), subtract MC, and lastly, divide both sides by MC (Kumbhakar et al. 2012):

$$\theta_{SFA} = \frac{P-MC}{MC} = u\frac{C}{Y}\frac{1}{MC} = u\frac{C}{Y}\frac{\partial Y}{\partial C} = u\frac{1}{\frac{\partial lnC}{\partial lnY}} = \frac{u}{\frac{\partial \ln C}{\partial \ln Y}} \quad . \tag{3}$$

Hence, θ_{SFA} is calculated as the markup component u over the estimated cost elasticity (Kumbhakar et al. 2012). Note that we have not taken any stand on the distribution of u at this point such that markups might become negative.

Instead of estimating a cost function, we can use the duality between the cost and the transformation function to derive an input distance function (IDF) expression of the cost elasticity (Diewert 1971; Färe and Primont 1995; Kumbhakar et al. 2012) which is frequently used in the absence of input price data. The IDF is generally defined as (Coelli et al. 2005):

$$D(X_1, \ldots, X_J, Y) = max[d: (X_1/d, \ldots, X_J/d) \in L(Y)]d \geq 1 \quad , \tag{4}$$

where D is the distance function, X is the quantity of an input j, and d is a scalar by which we can contract all J inputs while maintaining the same level of output (Y). $L(Y)$ is the set of all possible input combinations that suffice to produce Y. Based on the Envelope theorem, it follows that the first order condition of the Lagrangian for cost minimization is:

$$\frac{\partial lnC}{\partial lnY} = -\frac{\partial \ln h(\cdot)}{\partial \ln Y} \div \sum_j \frac{\partial \ln h(\cdot)}{\partial \ln X_j} \quad , \tag{5}$$

where h is the transformation function. The classical IDF representation of the technology is achieved by imposing homogeneity of degree one in inputs on the transformation function which leads to (see Kumbhakar 2011 for further details):[59]

$$\frac{\partial lnC}{\partial lnY} = \frac{\partial \ln h(\cdot)}{\partial \ln Y} = \frac{\partial \ln \frac{D}{X_j}}{\partial \ln Y} \quad . \tag{6}$$

Note that homogeneity of degree one is not a characteristic of the technology, but results from the definition of the distance function, which implies that doubling all input quantities will double the distance (Coelli et al. 2005). Hence, even though we replace input prices by input quantities, the IDF formulation yields the same value for the cost elasticity as the cost function approach and therefore leads to identical markup estimates. Combining (3) and (6), the SFA markups (θ_{SFA}) are then:

$$\theta_{SFA} = \frac{u}{\frac{\partial \ln \frac{D}{X_j}}{\partial \ln Y}} \quad . \tag{7}$$

Note that it does not matter which of the j inputs is used to normalize the IDF. We will always obtain the same estimate of the cost elasticity and therefore the same markup (Kumbhakar et al. 2012).

The PFA starts from the first order condition of the Lagrangian for cost minimization with respect to a variable input j (De Loecker and Warzynski 2012):

$$\frac{\partial L}{\partial X_j} = W_j - \lambda \frac{\partial Y}{\partial X_j} = 0 \quad , \tag{8}$$

where W is the price of input j and λ is marginal cost for a given output level since the first derivative of the Lagrangian with respect to output equals λ (De Loecker and Warzynski 2012). After rearrangement and multiplying both sides by the quantity of input j over output Y, we arrive at the output elasticity with respect to input j:

$$\frac{\partial Y}{\partial X_j} \cdot \frac{X_j}{Y} = \frac{\partial \ln Y}{\partial \ln X_j} = \lambda^{-1} \cdot \frac{W_j X_j}{Y} \quad . \tag{9}$$

We multiply both sides of (9) with P/P and solve for $(P - \lambda)/\lambda$ which is equal to $(P - MC)/MC$ since $\lambda = MC$:

[59] Homogeneity of degree one in inputs is equivalent to $\sum_j \frac{\partial \ln h(\cdot)}{\partial \ln X_j} = -1$.

$$\theta_{PFA} = \frac{\partial \ln Y}{\partial \ln X_j} \frac{PY}{W_j X_j} \text{-1} \quad . \tag{10}$$

It does not matter which variable input we use for markup estimation in the PFA, even though the estimated output elasticities vary across inputs. Due to the division by an input's expenditure share in total revenue, the estimated markups will be the same at the cost minimizing input deployment. Note that, from a theoretical point of view, the SFA and PFA should provide the same values for markups, i.e., $\theta_{SFA} = \theta_{PFA} = \theta$. Equating the markup formulation from the IDF of the SFA $(u/(\partial Xj/\partial lnY))$ derived above and that of the PFA (10) yields:

$$\theta_{SFA} = \frac{u}{\frac{\partial \ln \frac{D}{X_j}}{\partial \ln Y}} = u \frac{\partial \ln Y}{\partial \ln \frac{D}{X_j}} = \theta PFA = \frac{\partial \ln Y}{\partial \ln X_j} \frac{PY}{W_j X_j} - 1 \quad . \tag{11}$$

Besides the equality of markups between the two approaches, they should also deliver the same characteristics with respect to the estimated parameters of the technology. While we cannot directly compare the estimates of the cost/input distance function with those of the production function, we can use duality theory to compare the returns to scale (RTS) of the technologies. To obtain the returns to scale from the SFA, we can take the inverse of the cost elasticity derived from the IDF estimation (Chambers 1988; Kumbhakar et al. 2012):

$$RTS_{SFA} = \frac{1}{\frac{\partial \ln \frac{D}{X_j}}{\partial \ln Y}} \quad . \tag{12}$$

Further, we can calculate the RTS of the production function by summing the output elasticities of all single inputs (Kim 1992; Ray 1999):

$$RTS_{PFA} = \sum_{j=1}^{J} \frac{\partial \ln Y}{\partial \ln X_j} \quad . \tag{13}$$

Hence, both methods should result in the same RTS. A divergence of the RTS between the SFA and the PFA would also lend an explanation for (potentially) diverging markups since the technological parameter estimates play an important role in the calculation of markups as indicated in (11). Possible reasons for distinct RTS values may lie in the different identification strategies employed by the SFA and the PFA which we present below.

5.3 Identification Strategy

After the theoretical considerations, we turn to the econometric strategy to estimate markups with the IDF (SFA) and the production function (PFA). Note that we stick to the original papers regarding the estimation strategies and discuss potential implications and possible departures at the end of this section. We choose a translog form for both since it is the most flexible functional form (Christensen et al. 1973; Perekhozhuk et al. 2017). The SFA's IDF is defined as:

$$ln(D) = \alpha_0 + \sum_{j=1}^{J} \alpha_j \, lnX_j + 0.5 \sum_{j=1}^{J} \sum_{k=1}^{K} \alpha_{jk} \, lnX_j lnX_k + \alpha_y lnY + 0.5\alpha_{YY}(lnY)^2 + \sum_{j=1}^{J} \alpha_{jY} \, lnX_j lnY + \alpha_{TT} + 0.5\alpha_{TT}T^2 + \sum_{j=1}^{J} \alpha_{jT} \, lnX_j T + \alpha_{YT} T lnY \quad , \tag{14}$$

where T represents a technology term capturing non-neutral technical change and α are the parameters to be estimated. We impose homogeneity of degree one in inputs (Kumbhakar 2011) by normalizing the IDF by X_1:

$$ln(D/X_1) = \alpha_0 + \sum_{j=2}^{J} \alpha_j \, ln(X_j/X_1) + 0.5 \sum_{j=2}^{J} \sum_{k=2}^{K} \alpha_{jk} \, ln(X_j/X_1) ln(X_k/X_1) + \alpha_y lnY + 0.5\alpha_{YY}(lnY)^2 + \sum_{j=2}^{J} \alpha_{jY} \, ln(X_j/X_1) lnY + \alpha_{TT} + 0.5\alpha_{TT}T^2 + \sum_{j=2}^{J} \alpha_{jT} \, ln(X_j/X_1) T + \alpha_{YT} T lnY \quad . \tag{15}$$

The IDF is non-decreasing and concave in inputs and non-increasing in output (Coelli et al. 2005). We take the first derivative with respect to log output:

$$\frac{\partial \, ln\frac{D}{X_1}}{\partial \, ln\, Y} = \alpha_Y \; + \; \alpha_{YY} lnY \; + \; \sum_{j=2}^{J} \alpha_{jY} \, ln(X_j/X_1) \; + \; \alpha_{YT} T \quad , \tag{16}$$

and add two error terms to (16) to make the model operational (Kumbhakar et al. 2012) resulting in the following equality (Renner et al. 2014):

$$\frac{PY}{C} \; = \; \frac{\partial \, ln\frac{D}{X_1}}{\partial \, ln\, Y} \; + \; u \; + \; v \quad . \tag{17}$$

u captures the markup component from (2) and is assumed to follow a half-normal distribution truncated at zero from below ($u \sim N^+(0, \sigma_u^2)$). v contains all stochastic noise due to, e.g., unobserved variables affecting the revenue-cost ratio and optimization error (Kumbhakar et al. 2012). We assume that v follows a normal distribution ($v \sim N(0, \sigma_v^2)$). Hence, our specification is equal to a stochastic frontier where u measures markup and not cost inefficiency as shown in (2). Lastly, we add subscripts for firm (i) and year (t) and obtain the estimable equation (Kumbhakar et al. 2012):

$$\frac{P_{it}Y_{it}}{C_{it}} = \left(\frac{\partial \, ln\frac{D}{X_1}}{\partial \, ln\, Y}\right)_{it} + u_{it} + v_{it} = \alpha_Y + \alpha_{YY} lnY_{it} + \sum_{j=2}^{J} \alpha_{jY} \ln\left(\frac{X_{jit}}{X_{1it}}\right) + \alpha_{YT} T + u_{it} + v_{it} \, . \tag{18}$$

The coefficients are identified using simulated maximum likelihood (ML) estimation. We compute markups according to (7) using the estimates from (18). Since we do not estimate the

IDF itself but the marginal impact of Y on the IDF, the only property we can test is whether the IDF is non-increasing in output. This is the case if the predicted values in (11) exceed, or are equal to, zero because we specify u as positive deviations from the frontier. The one-sided error term u is estimated according to the procedure proposed by Jondrow et al. (1982):

$$E[u_{it}|\varepsilon_{it}] = \frac{\sigma\delta}{1+\delta^2}\left(\frac{\phi(a_{it})}{1-\Phi(a_{it})} - a_{it}\right) \quad , \tag{19}$$

where $\varepsilon_{it} = u_{it} + v_{it}$, $\sigma = (\sigma_u^2 + \sigma_v^2)^{0.5}$, $\delta = \sigma_u/\sigma_v$, $a_{it} = \varepsilon_{it} \cdot \delta/\sigma$ and $\phi(a_{it})$ and $\Phi(a_{it})$ denote the standard normal density and cumulative distribution function evaluated at a_{it}, respectively (Greene 2005). We rely on the consistent fixed effects stochastic frontier model proposed by Chen et al. (2014) for parameter identification.

For the production function of the PFA we use a second order polynomial functional form (De Loecker and Warzynski 2012) and add a productivity term (ω), which leads to (Ackerberg et al. 2015; Levinsohn and Petrin 2003):

$$lnY = \sum_{j=1}^{J} \beta_j \, lnX_j + \sum_{j=1}^{J} \beta_{jj} \left(lnX_j\right)^2 + \sum_{j=1}^{J} \sum_{k=1}^{K} \beta_{jk} \; ln(X_j) ln(X_k) + \omega + \varepsilon, \, j \neq k \;, \tag{20}$$

where β are the parameters to be estimated, and ε are unanticipated shocks to output with an expected value of zero that the firm neither observed nor expected when deciding on its input deployment. The production function is monotonically increasing and concave in inputs. The procedures for testing monotonicity and concavity are explained in the appendix. Productivity (ω) is known to the firm, but not to the researcher, and represents expected shocks to output, for instance caused by managerial ability or planned maintenance of machinery (Ackerberg et al. 2015; Levinsohn and Petrin 2003). Hence, we must estimate ω along with the β. In accordance with Ackerberg et al. (2015) and De Loecker and Warzynski (2012), we rely on a two-step procedure to identify the production function parameters. That is, we account for unobserved shocks in productivity which might be correlated with input choices causing simultaneity (De Loecker and Warzynski 2012). Based on Ackerberg et al. (2015) and Levinsohn and Petrin (2003), we choose material demand to proxy for productivity. Material demand is used rather than investment as proposed by Olley and Pakes (1996) due to the frequent occurrence of zero values for investment in many data sets (see Levinsohn and Petrin 2003 for a discussion). We define material demand function (q) as (Ackerberg et al. 2015; Levinsohn and Petrin 2003):

$$M_{it} = q_t(X_{it}, Z_{it}, \omega_{it}) \quad , \tag{21}$$

where M is material demand, X are the inputs and Z captures other variables that might affect optimal input demand. Equation (21) imposes the scalar unobservable assumption which means that productivity is the only unobservable in the production function (Ackerberg et al. 2015). Moreover, productivity is assumed to be monotonically increasing in material costs. Inverting productivity out of the material demand equation results in:

$$\omega_{it} = g_t(M_{it}, X_{it}, Z_{it}) \quad , \tag{22}$$

where g is a non-parametric function of material demand, the inputs and the vector Z. In contrast to Levinsohn and Petrin (2003), we do not identify any parameter of the production function in the first stage, but run a non-parametric regression (Ackerberg et al. 2015):

$$\begin{aligned} lnY_{it} = \textstyle\sum_{j=1}^{J} \beta_j \, lnX_{jit} + \sum_{j=1}^{J} \beta_{jj} \left(lnX_{jit}\right)^2 + \sum_{j=1}^{J} \sum_{k=1}^{K} \beta_{jk} \, ln\left(X_{jit}\right) ln(X_{kit}) + \\ g_t(M_{it}, X_{it}, Z_{it}) + \varepsilon_{it} = \psi_t(X_{jit}, M_{it}, Z_{it}) + \varepsilon_{it} \quad . \end{aligned} \tag{23}$$

We obtain estimates of expected output ($\hat{\psi}_{it}$) and the first stage residuals ($\hat{\varepsilon}_{it}$). Since we treat g_t non-parametrically, we do not identify any parameter of the production function in this first stage. The corresponding moment condition is:

$$E[\varepsilon_{it}|I_{it}] = E\left[lnY_{it} - \psi_t\left(X_{jit}, M_{it}, Z_{it}\right)\middle|I_{it}\right] = 0 \quad , \tag{24}$$

where I is the information set of the company. In the second stage, we rely on the law of motion of productivity to identify the production function parameters (Ackerberg et al. 2015) so that:

$$\omega_{it} \ = \ f_t(\omega_{it-1}) \ + \ \xi_{it} \ = \ \rho \, \omega_{it-1} + \ \xi_{it} \quad , \tag{25}$$

where ξ is the innovation to productivity and has an expected value of zero given $I_{it} - 1$. ρ is a parameter to be estimated. That is, we assume productivity follows an autoregressive process of order one (Ackerberg et al. 2015). For the second stage, we form the conditional moment:

$$\begin{aligned} E[\xi_{it} + \varepsilon_{it}|I_{it-1}] = E[lnY_{it} - \textstyle\sum_{j=1}^{J} \beta_j \, lnX_{jit} + \sum_{j=1}^{J} \beta_{jj} \left(lnX_{jit}\right)^2 + \\ \textstyle\sum_{j=1}^{J} \sum_{k=1}^{K} \beta_{jk} \, ln\left(X_{jit}\right) ln(X_{kit}) - f(\psi_{t-1}\left(X_{jit-1}, M_{it-1}, Z_{it-1}\right) - \sum_{j=1}^{J} \beta_j \, lnX_{jit-1} + \\ \textstyle\sum_{j=1}^{J} \beta_{jj} \left(lnX_{jit-1}\right)^2 + \sum_{j=1}^{J} \sum_{k=1}^{K} \beta_{jk} \, ln\left(X_{jit-1}\right) ln(X_{kit-1}) | I_{it-1}) = 0 \quad , \end{aligned} \tag{26}$$

where we plug in the first stage estimates for ψ_{t-1}. The unconditional moments depend on the assumptions regarding the timing of decisions on a firm's input choices (I). We use a generalized method of moments (GMM) procedure to identify the production function parameters and can calculate markups according to (10). However, we do not observe the correct input expenditure shares due to the ε_{it} but have to correct output for the unanticipated shocks (De Loecker and Warzynski 2012):

$$\hat{\theta}_{PFAit} = \left(\widehat{\frac{\partial lnY}{\partial lnX_J}}\right)_{it} \left(\frac{P_{it}(Y_{it} - e^{\widehat{\varepsilon_{it}}})}{W_{jit}X_{jit}}\right) - 1 \quad , \tag{27}$$

where e is Euler's number. We exponentiate ε since we estimate a translog production function.

We now compare the two methods with respect to their assumptions and identification strategies which are summarized in Table 5.1. Both rely on cost minimizing behavior of the firm. While one may use the full profit maximization problem of the firm to calculate markups, cost minimization being part of the profit maximization problem suffices to uncover markups and avoids additional assumptions to be imposed by profit maximization (see e.g., Basu 2019; De Loecker and Warzynski 2012; Nicholson and Snyder 2008). Specifically, the cost minimization framework does not necessitate to take a stand on the kind of the competition between firms nor on the form of consumer demand (Basu 2019; De Loecker and Warzynski 2012). In contrast, the full profit maximization may become very complex, e.g., depending on the type of competition or consumer demand (Basu 2019).

With respect to parameter identification, the PFA uses the generalized method of moments (GMM) estimation and the SFA uses maximum likelihood estimation (MLE). Theoretically, it is also possible to estimate the production function with MLE (see e.g., Greene 1980; Zellner et al. 1966). However, depending on the econometric specification of the production function, i.e., the complexity of the likelihood function, the estimation can become computationally difficult (Tauchen 1986; Tsionas 2012). Besides, when accounting for the presence of endogenous input choices the standard errors produced by MLE are biased (for two-step approaches) or the computation becomes very complex (for one-step approaches) such that GMM procedures are superior (Tran and Tsionas 2013). Further, MLE requires the researcher to impose distributional assumptions on all parameters of the model which may lead to severely biased estimates given that the distributional assumptions are wrong (Fuhrer et al. 1995; Tauchen 1986). Nevertheless, given that the above mentioned issues are solved or negligible, MLE would outperform GMM regarding efficiency in the estimation which is particularly the case for small samples (Fuhrer et al. 1995). However, the consideration of endogeneity caused by simultaneity of input choices and unobserved productivity has received a lot of attention in the literature on estimating production functions, and the most popular ways to alleviate the issue base on GMM estimators (e.g., Ackerberg et al. 2015; Gandhi et al. 2020; Levinsohn and

Petrin 2003) yielding a possible explanation for the widespread application of GMM in the estimation of production functions.

In turn, it is impossible to estimate the cost/input-distance function of the SFA using a GMM specification without losing the stochastic nature of the frontier since the imposition of the distributions on the error terms (u and v) is basically what makes them stochastic. While it is possible to fully estimate a production frontier using GMM, this model will be deterministic and equivalent to corrected ordinary least squares (Aigner and Chu 1968; Richmond 1974). That is, decomposing the joint error ($u + v$) into its pieces is not possible in this case such that u and v would both be attributed to markup (Aigner et al. 1977; Hjalmarsson et al. 1996). Accordingly, one would not end up with a stochastic frontier anymore but instead obtain a deterministic frontier.

Concerning the beforehand mentioned simultaneity bias, the PFA explicitly accounts for unobserved factors that might be correlated with input decisions via the control function which, however, comes at the cost of the scalar unobservable and monotonicity assumptions. In the case of the SFA, the input ratios (X_j/X_1) are exogenous, and thus, such a correction is not required (e.g., Kumbhakar et al. 2013; Renner et al. 2014).

The markups' range using the SFA will only yield positive values as the markup component u is truncated at zero from below and the cost elasticity cannot be negative. Kumbhakar et al. (2012) argue in favor of ruling out negative markups as "*[A]lthough firms might be minimizing cost given output and input prices, they may fail to do so exactly*" (p. 113). Hence, negative markups are not a result of market power (or a lack thereof) but driven by failure to succeed in minimizing cost. This optimization error, i.e., when v_{it} in (18) is smaller than zero, should be omitted from markup calculation (Kumbhakar et al. 2012). On the other hand, the PFA will yield estimates that are positive (negative), if the expenditure share of input j in revenue is smaller (larger) than the output elasticity associated with that input. As Caselli et al. (2018) point out in their study on French manufacturing from 1990-2007, there is a significant number of firms which show negative markups, i.e., firms selling at prices below marginal cost. This applies particularly in the case of companies facing high sunk costs for investments which are expected to generate profits in the future. Alternatively, it can be a strategically beneficial tactic to incur negative markups to outcompete rivals in the market and win market shares for the periods ahead (Caselli et al. 2018). Therefore, there may be good reasons for the occurrence of negative markups that are not due to optimization error but anticipated by firms although the traditional view on oligopoly/monopoly power rules out such cases (Lerner 1934). In fact, companies charging negative markups to enhance their market penetration may be of high interest to competition authorities given that they gain significant market shares and abuse their superior position in later years to increase markups substantially. Besides, Kumbhakar et al. (2012) specify that the error term v is two-sided. Hence, besides excluding "optimization error" from markup (when v_{it} is negative), this will also discard a certain share of positive markups, i.e., when v_{it} is positive, since these cases cannot be caused by failure in minimizing cost.

Consequently, the PFA seems to be more attractive since it imposes no restrictions with respect to markups' range. However, if we assume that sunk costs only play a minor role in an industry or that market structures are rigid, firms will not undercut their marginal costs in output pricing decisions. Moreover, it might be forbidden to set prices below cost, as in France (Colla and Lapoule 2008). In this case, the SFA would be the better approach to proxy the underlying competitive conditions of the industry analyzed since markups will be positive by construction.

Table 5.1 Assumptions, Data Requirements and Identification of the Stochastic Frontier Approach and the Production Function Approach

Aspect	Stochastic frontier approach	Production function approach
Underlying behavior of the firm	Cost minimization	Cost minimization
Identification of the technology's parameters	Cost function/ input distance function	Production function
Method for parameter identification	Maximum likelihood estimation	Generalized method of moments
Treatment of endogenous inputs	Solved by normalization of input prices/quantities	Corrected for by control function
Range of markups	[0:∞]	[-1:∞]
Required data	- Output quantity - Output price - Input prices (cost function) or - Input quantities (input distance function) - Total cost	- Output quantity - Output price - Input prices (at least for one flexible input) - Input quantities

Source: De Loecker and Warzynski (2012) and Kumbhakar et al. (2012)

5.4 An Application to European Food Retailing

Now, we turn to a comparison of the SFA and the PFA when these approaches are applied to EU food retailing. Since food retailers do not actually produce goods but services, we rely on a structural value-added (SVA) production function whereby intermediate inputs do not enter the production process. This means that output is Leontief in intermediate inputs because the products sold do not undergo any physical transformation. We obtain our output measure (Y) by dividing revenues by the harmonized index of consumer prices (Eurostat 2020b). The inputs comprise labor (X_1) which is given by the number of employees and capital (X_2) which we proxy by the amount of fixed assets. We use a set of year dummies for T (Kumbhakar et al. 2012) in the SFA. The costs of materials deflated by the producer price index of the food processing industry serve as a proxy for material demand (Eurostat 2020c) in the PFA. Moreover, to make the PFA estimable, we must specify the information set (I) at $t-1$ to obtain the unconditional moments of (26). We follow Ackerberg et al. (2015) so that:

$$E[\xi_{it} + \varepsilon_{it} | I_{it-1}] =$$
$$E\left[\xi_{it} + \varepsilon_{it} \middle| X_{1it-1}, X_{2it}, X_{1it-1}^2, X_{2it}^2, X_{1it-1}X_{2it}, \psi_{t-1}(X_{jit-1}, M_{it-1}, Z_{it-1})\right] = 0 \quad . \quad (28)$$

Hence, it is assumed that capital (X_2) is chosen one period ahead of production so that the firm already knows its capital deployment for t in $t-1$, i.e., it is dynamic. Labor (X_1) is determined in the period of production, i.e., it is variable. Since Gandhi et al. (2020) show that material demand might not fully reflect productivity, we add another variable to the vector Z to proxy productivity. We use a dummy variable which is equal to one if a company has a market share of at least four percent in terms of revenue and zero if not. The intuition is that, compared to fringe firms, the large retail chains which dominate a market have distribution networks, centrally coordinated procurement and benefit from advertising advantages that go beyond usual economies of scale and enhance productivity (Ellickson 2007, 2013). The threshold of four percent is adopted since most of the countries included in our analysis exhibit a sharp drop between the last firm above the four percent market share mark and the first below it (Hirsch and Koppenberg 2020).

Since we use an SVA production function, we have to adjust markups for the fact that intermediate inputs do not enter the production function. For the SFA, this implies that we must reformulate the estimable equation. The production function is Leontief in intermediate inputs which implies that marginal costs increase linearly with the price of the intermediate input

(W_M), i.e., an increase in output by one unit entails an increase in total cost of W_M. Therefore, the cost elasticity changes to:

$$\frac{P_{it}Y_{it}}{C_{it}} = \alpha_Y + \alpha_{YY} lnY_{it} + \sum_{j=2}^{J} \alpha_{jY}\, ln(X_{jit}/X_{1it}) + \alpha_{YT}T + \frac{W_{Mit}Y_{it}}{C_{it}} + u_{it} + v_{it} \quad , \tag{29}$$

where M is not an element of J. We subtract $W_{Mit}Y_{it}/C_{it}$ on both sides to obtain the equation that we estimate:

$$\frac{P_{it}Y_{it} - W_{Mit}Y_{it}}{C_{it}} = \alpha_Y + \alpha_{YY} lnY_{it} + \sum_{j=2}^{J} \alpha_{jY}\, ln(X_{jit}/X_{1it}) + \alpha_{YT}T + u_{it} + v_{it} \quad . \tag{30}$$

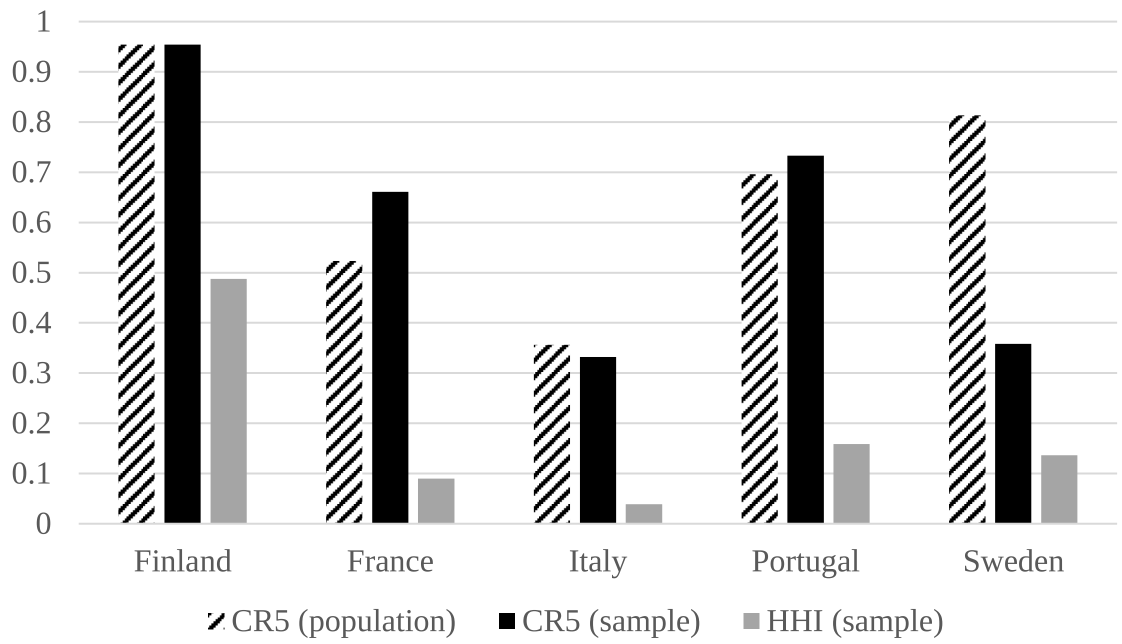
This is identical to subtracting the cost of materials from revenue on the left-hand side as the output quantity equals the quantity of intermediate input (X_M). To obtain the correct markup estimate ($\hat{\theta}_{SFA}$), we simply have to add the share of material costs in total cost to the cost elasticity again:

$$\hat{\theta}_{SFAit} = \frac{\hat{u}_{it}}{\frac{\partial\, \widehat{ln \frac{D}{X_J}}}{\partial\, ln\, Y}_{it} + \frac{W_{Mit}Y_{it}}{C_{it}}} = \frac{\hat{u}_{it}}{\frac{\partial\, \widehat{ln \frac{D}{X_J}}}{\partial\, ln\, Y}_{it} + \frac{W_{Mit}Y_{it}}{C_{it}}} \quad . \tag{31}$$

In the case of the PFA, we can omit intermediate inputs from the production function but have to correct markups calculated according to (27) for materials (De Loecker and Scott 2016):

$$\hat{\theta}_{PFAit} = \frac{1}{\left(\frac{\widehat{\partial lnY}}{\partial lnX_J}\right)_{it}^{-1} \frac{W_{jit}X_{jit}}{P_{it}(Y_{it} - e^{\widehat{\varepsilon_{it}}})} + \frac{W_{Mit}X_{Mit}}{P_{it}(Y_{it} - e^{\widehat{\varepsilon_{it}}})}} - 1 \quad . \tag{32}$$

We retrieve our data from AMADEUS, which is a database providing financial information on firms in all European countries and economic sectors. Our sample consists of five countries: Finland, France, Italy, Portugal and Sweden. These countries were chosen based on data availability and the fact that their retail sectors exhibit different degrees of concentration, which is one of the factors typically mentioned when determinants of market power abuse are analyzed (e.g., Cotterill 1999; Stålhammar 1991). For instance, analyzing the U.S. food processing industry on the sectoral level Lopez et al. (2002) as well as Lopez et al. (2018) find that more concentrated sectors exhibit significantly larger industry-level markups. In a study on the French food retail sector, Hirsch and Koppenberg (2020) estimate that markups of firms belonging to the Top-six national food retail chains are 9.1 percentage points larger than those of fringe firms. The larger the market share of these big retail chains, i.e., the higher the concentration, the larger will be the industry-wide markup. However, concentration and markups might also be negatively related, e.g., when more efficient firms offer products at lower prices than their competitors, thereby gaining market shares leading to an increment in industry concentration while markups decrease (Demsetz 1973). Alternatively, in industries with a large number of smaller firms and low concentration, these firms could still have considerable monopoly price setting power, if the residual demand curve was very inelastic (Syverson 2019).



Source: CR5 of the population are based on USDA 2017a, USDA 2017b, USDA 2017c, USDA 2019, USDA 2020 while values for the sample are arithmetic means over the sample period (2010-2018).

Figure 5.1 Comparison of Concentration in the Population and the Sample (2010-2018)

Despite the (ex-ante) unclear link between concentration and markups, i.e., whether it is positive, negative or nonexistent, we suppose that the various degrees of concentration provide us with a heterogeneous sample of food retail sectors to test the robustness of our results in diverse settings. With respect to our sample, the Finish and Swedish retailing sectors exhibit the highest degree of concentration in the EU with the largest five retailers (CR5) holding a market share of over 80 percent (USDA 2017a, 2017b). France and Portugal have a medium CR5 of between 50 percent and 70 percent (USDA 2019, 2020) while the Italian retail sector is the least concentrated with a CR5 of approximately 36 percent (USDA 2017c). Further, France and Italy are among the three largest retail sectors in the EU (Eurostat 2020a).[60]

We contrast the concentration in the overall industry with the concentration in our sample by country in Figure 5.1. In addition to the CR5, we use the Herfindahl-Index (HHI) for our sample since it better reflects the distribution of market shares compared to the concentration ratio and includes all firms of an industry (e.g., Rhoades 1995).[61] Since the HHI is the standard measure for competition authorities to use when evaluating industry competition (e.g., Kvålseth 2018; Rhoades 1995), we will also use the HHI when relating concentration to markup in our empirical analysis. Note that in contrast to the United States where the Census Bureau publishes industry-level HHI values every five years,[62] information regarding the HHI are unavailable for entire industries in official statistics of the European Union. Figure 5.1 shows that the ranking of the countries in terms of concentration in the population corresponds to that in our sample except for Sweden. This is likely due to the fact that the largest food retailer in Sweden (ICA Sverige AB) is missing in our sample.

Our accounting data set yields information on EU food retailers from 2010-2018 identified by their operation in NACE code 47.11 and 47.2.[63] We use the bacon algorithm to identify multivariate outliers (Billor et al. 2000; Weber 2010) and thus avoid potential biases in accounting data caused by, e.g., profit-smoothing, cross-subsidization or different depreciation methods (e.g., Barlev and Levy 1979; Fisher and McGowan 1983; Hirsch et al. 2020; Long and Ravenscraft 1984). The bacon algorithm is based on Mahalanobis distances, i.e., it examines relationships between the variables, and identifies observations where these relationships are unusual compared to the other firms. Table 5.A1 shows the steps and results of the data preparation process. The original sample contains 3,070, 28,434, 50,464, 26,028 and 11,164 observations for Finland, France, Italy, Portugal and Sweden, respectively. After performing the data processing described above, we are left with a sample of 2,831, 27,377, 47,710, 23,545 and 10,568 observations covering 707, 6,361, 8,914, 4,843 and 1,920 firms in France, Finland,

[60] We also considered including Germany which is the largest EU food retailing sector but the data availability was insufficient.

[61] The Herfindahl-Index (HHI) is defined as the sum of the squared market shares of all companies in a market. The HHI can take on values between 0 (minimum concentration) and 1 (maximum concentration).

[62] See e.g., data.census.gov/cedsci/table?q=concentration&tid=ECNSIZE2017.EC1700SIZECONCEN for the latest values from 2017.

[63] The NACE is the official statistical classification of economic activities in the European Community where group 47.11 defines “Retail sale in non-specialised stores with food, beverages or tobacco predominating” and 47.2 “Retail sale of food, beverages and tobacco in specialised stores” (Eurostat 2008).

Italy, Portugal and Sweden, respectively. Table 5.A2 contains the descriptive statistics of the variables used in the SFA and PFA estimations.

5.5 Results and Discussion

The estimation results for the SFA and PFA are shown in the Appendix (Tables 5.A3 and 5.A4). With respect to functional properties, we identify 707, 18,339, 16,042, 3,146 and 4,192 observations for Finland, France, Italy, Portugal and Sweden which violate concavity and/or monotonicity in inputs for the PFA and/or monotonicity in output for the IDF (cf. Table 5.A5). Several authors have called attention to the importance of consistency of estimated technology parameters with economic theory when seeking to draw reliable inferences. Therefore, we have excluded all observations which do not adhere to the theoretical properties outlined in section 5.3 (e.g., Salvanes and Tjøtta 1998).

Table 5.2 shows the descriptive statistics of markups per country for the SFA and the PFA. When means and medians as locational measures (see Table 5.2) are compared together with kernel density functions of the estimated markups (Figure 5.2), we find that all markup distributions exhibit a right skew highlighting that there is a small share of firms generating very large markups. Therefore, we consider the median to be more appropriate for further comparisons. We observe the highest median for the SFA markups in Sweden (0.095) and the lowest median markup in France (0.039). This indicates that according to the SFA, the median Swedish retailer charges an output price exceeding marginal cost by 9.5 percent, i.e., the price under perfect competition. The highest median PFA markup prevails in Finland (0.221) and the lowest in Portugal (0.162). We find that median markups for the SFA models are well below the PFA markups in each of the countries investigated. This result might seem surprising, as we observe a considerable number of negative markups for the PFA. However, the upper percentiles of the markups generated with the PFA are also located above those from the SFA, thus outweighing the negative values (Table 5.2). This is most pronounced in Italy where we find a 99th percentile of 1.516. The density functions of markups indicate that the distributions of the SFA markups are much denser than those of the PFA in all countries (Figure 5.2). In addition, the PFA distribution is clearly located to the right of the SFA distribution for Finland and France whereas this shift is weaker for the distributions of Italy and Sweden. In the Portuguese case, we only observe a small divergence of the two distributions.

To illustrate the magnitude of the differences in markups, we proxy excess consumer expenditures due to market power for both methods, i.e., compared to the situation where $P =$

MC. For each firm and year, we divide the amount of revenue generated by one plus the markup to obtain the revenue that each firm would have generated under perfect competition. We then determine the differences between the hypothetical revenues under perfect competition and actual revenues and add them up across all firms and years. We are aware that this procedure implicitly assumes completely inelastic demand as, under normal circumstances, different prices would lead to different demand so that revenue changes could not be estimated as easily as our calculation suggests. For this reason, we call our measure excess consumer expenditures and not consumer welfare loss. We would have to estimate a Hicksian demand curve (Lavergne et al. 2001) to obtain a precise welfare loss estimation. However, the purpose of our calculation is to illustrate the discrepancy between estimates based on SFA and PFA markups and not to provide exact welfare loss estimates.

The markup estimates from the SFA (PFA) indicate approximately €670.26 (€1,746.41), €529.71 (€2,189.43), €2,335.76 (€4,262.60), €899.49 (€1,422.44) and €983.51 (€1,920.20) million of excess consumer expenditures for Finland, France, Italy, Portugal and Sweden cumulated over the nine years analyzed, respectively (Table 5.2). We see that the use of the PFA markups yields values which are much larger than for the use of SFA markups in all countries. In relative terms, the difference in approximated excess consumer expenditures obtained by using the PFA instead of the SFA markups ranges from +58.14 percent (Portugal) to +313.33 percent (France) (Table 5.2). Even though our measure is just a proxy, this general tendency will be consistent when using an estimated Hicksian demand curve. Hence, the two methods differ in the estimated overall state of competition within the sectors as well as implied excess consumer expenditures. Consequently, they will most probably lead to different recommendations regarding competition policies or influence the assessment of the state of competition in an industry.

It is also interesting to note the low correlation between markups obtained by the two different methods (Table 5.1). The Bravais-Pearson correlation between SFA and PFA markups ranges from 0.056 (Sweden) to 0.138 (Italy). The Spearman rank correlation coefficients are even smaller, starting at -0.051 (Italy) with the highest at 0.173 (France). Hence, we cannot assume that changing the method simply leads to a shift of markups common to all firms and has no influence on the relative ordering of firms with respect to markups. It also involves a different ascription of a firm's market power compared to its peers. In particular, the Spearman rank correlation indicates that the ranking of firms' markups also differs between the two methods. These results are robust when we exclude negative observations for the PFA, or use the composed error term ($u + v$) of the SFA in the numerator of (30). This is particularly important for studies aiming to identify industry or firm characteristics that are related to markups such as concentration or firm size. As our results suggest, relating markups to other variables could lead to completely different results depending on the method used for markup estimation.

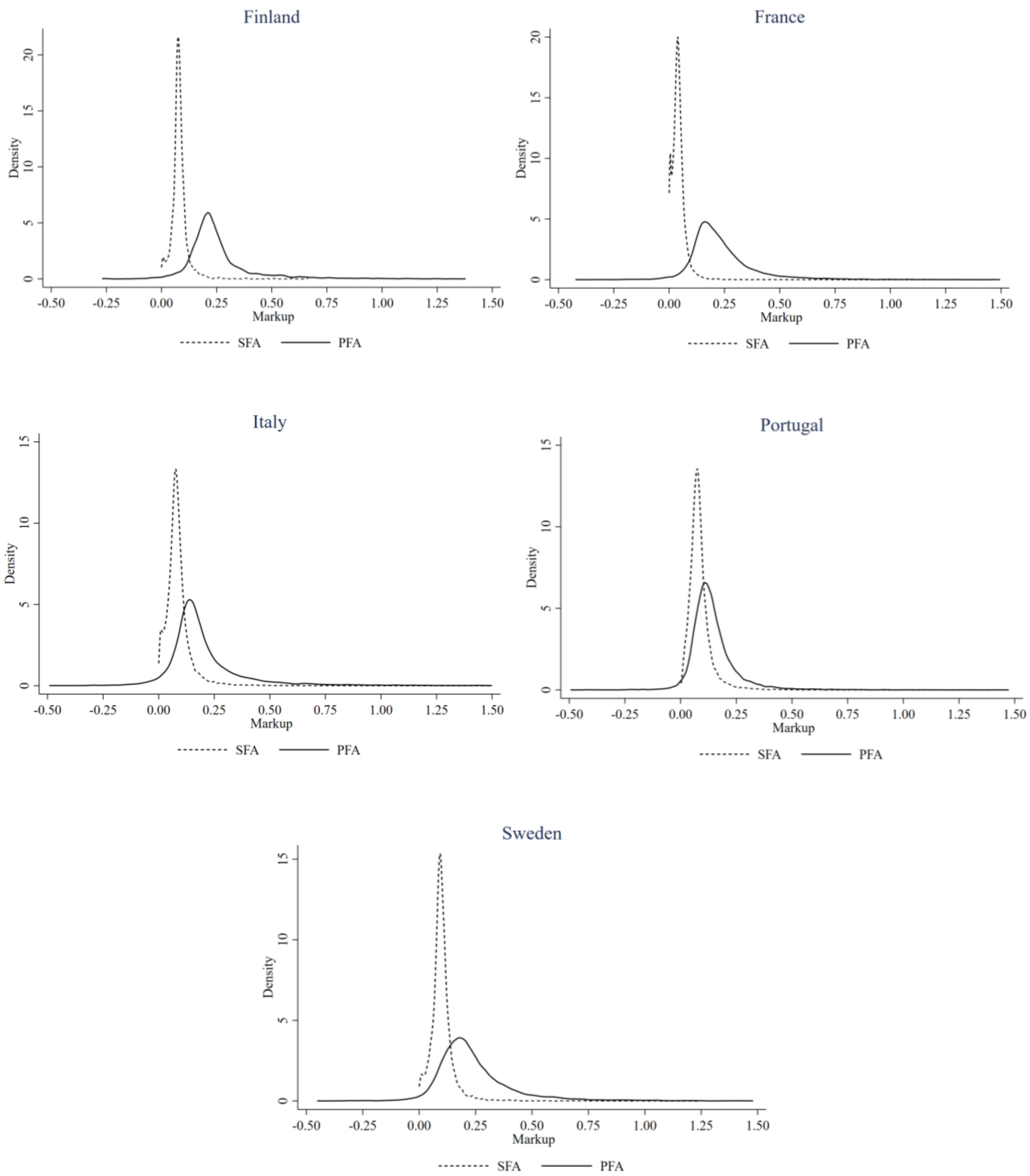
This is supported when relating markups with industry concentration. The Pearson correlation coefficient between the HHI in our sample and sales-weighted industry-level PFA markups amounts to 0.458 which is significantly different from zero ($p<0.01$). Oppositely, the same value for the SFA markups is close to zero (-0.03) and not significant ($p=0.84$). This result is robust when we use the Spearman rank correlation coefficient yielding values of 0.347 ($p=0.02$) for PFA markups and 0.055 ($p=0.72$) for SFA markups, respectively. Since our sample lacks ICA Sverige AB, the largest food retailer in Sweden, we have re-estimated the correlation coefficients for the sample excluding Sweden to avoid potential distortions caused by the deviation of Sweden's HHI in our sample and the population. Still, the Pearson correlation coefficient is larger for PFA markups (0.540; $p<0.01$) than for the SFA markups (0.268; $p=0.11$) while the changes in the rank correlations are negligible. That is, the findings of the PFA are in line with the traditional structure-conduct-performance paradigm (Bain 1954; Mason 1939), in that they suggest that competition is lower in more concentrated food retail sectors. Hence, based on our findings of the PFA further merger and acquisition activities should be seen critical as they may decrease consumer welfare by increasing markups of food retail companies.

Table 5.2 Descriptive Statistics of SFA and PFA Markups

	Finland		**France**		**Italy**		**Portugal**		**Sweden**	
	SFA	PFA	SFA	PFA	SFA	PFA	SFA	PFA	SFA	PFA
Observations	2,124		9,038		31,668		20,399		6,376	
Mean	0.081	0.261	0.043	0.238	0.089	0.295	0.087	0.147	0.102	0.257
Median	0.078	0.221	0.039	0.203	0.079	0.162	0.077	0.126	0.095	0.206
1st percentile	0.005	-0.006	8.96e-4	-0.021	0.004	-0.123	0.012	-0.042	0.006	-0.051
99th percentile	0.212	0.978	0.157	0.851	0.367	1.516	0.307	0.583	0.316	1.203
Correlation coefficients										
Pearson-Bravais	0.109***		0.124***		0.138***		0.084***		0.056***	
Spearman rank	-0.046**		0.018*		-0.051***		0.011		0.020	
Approximated excess consumer expenditures										
Value [€ million]	670.26	1,746.41	529.71	2,189.43	2,335.76	4,262.60	899.49	1,422.44	983.51	1,920.20
Absolute difference [€ million]	1,076.15		1,659.72		1,926.84		522.95		936.69	
Relative difference from SFA [%]	+160.56		+313.33		+82.49		+58.14		+95.24	

Note: *** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations based on AMADEUS



Note: To ensure readability, we omit markups larger than 1.5 and smaller than -0.5.

Source: Own calculations based on AMADEUS

Figure 5.2 Kernel Density Functions of SFA and PFA Markups

With respect to technology parameters, the estimates for the RTS based on the production function and the IDF are summarized in Table 5.3. In addition, Figure 5.A1 displays the density function of the differences between the two RTS estimates by country. The SFA predicts that more than the half of the firms in each of the five countries operates under increasing RTS as is indicated by median RTS measures exceeding one (cf. Table 5.3). The same accounts for the PFA in Finland, France and Sweden. For Italy and Portugal however, we find that the majority of firms faces decreasing RTS (< 1) according to the PFA (Table 5.3). Yet in all cases, the RTS suggest that food retailers are operating close to the efficient scale, i.e., when $RTS = 1$ (Kumbhakar et al. 2012). With respect to differences in the estimates of RTS between the production function and the IDF, we see that the modal divergence is close to zero in Finland, France and Sweden as indicated in Figure 5.A1. Further, the distributions in Finland and France are leptokurtic while the dispersion in Sweden is slightly stronger (cf. Figure 5.A1). Nevertheless, the PFA suggests much smaller RTS in Italy and Portugal compared with the SFA (cf. Table 5.3 and Figure 5.A1). Taking the HHI into consideration (cf. Figure 5.1), the results of the production function seem more plausible than the RTS delivered by the IDF in these two countries: The majority firms already operates below the efficient scale ($RTS < 1$) such that further growth would be infeasible. Therefore, this might explain why the HHI values in Italy and Portugal are relatively low compared to Finland, for instance.

Concerning technological change, the estimated parameters of the year dummies are positive and significantly different from zero in Italy (2012-2018) and Sweden (2011-2018) (cf. Table 5.A3). In addition, they increase steadily during the sample period which indicates that technological change decreases RTS over time since RTS and the cost elasticity are inversely related (see (12)) (Kumbhakar et al. 2012). For Finland, we cannot identify a meaningful pattern of the coefficients' sign and observe only one significant estimate (cf. Table 5.A3). In the remaining two cases, the estimates are negative in the beginning of the period until 2013 (France) and 2014 (Portugal) before they change signs (cf. Table 5.A3). Thus, technological change has increased RTS at the start of our sample period, and has decreased RTS in the end of the period.

Our results are consistent with the development of concentration in the countries analyzed. The largest growth in concentration in the food retail market in Western Europe occurred during the 1990s and the early 2000s and these figures have changed little since then (Bukeviciute et al. 2009; Sexton and Xia 2018). The CR5 in France, for instance, was slightly below 0.55 in 2007 (Bukeviciute et al. 2009) and approximately 0.53 in 2018 (USDA 2019). Likewise, the CR5 in Italy and Portugal remained on an almost constant level (Bukeviciute et al. 2009; USDA 2017c, 2020). Only in Finland and Sweden, the CR5 rose approximately ten and five percentage points from 2007 to 2017, respectively (Bukeviciute et al. 2009; USDA 2017a, 2017b). Hence, sectoral concentration figures confirm that the firms' scale of operation is close to the efficient scale providing low incentives to foster further growth as suggested by our RTS measures in terms of cost savings (cf. Table 5.3).

Table 5.3 Descriptive Statistics of RTS Based on the IDF (SFA) and the Production Function (PFA)

	Finland		France		Italy		Portugal		Sweden	
	SFA	**PFA**	**SFA**	**PFA**	**SFA**	**PFA**	**SFA**	**PFA**	**SFA**	**PFA**
Observations	2,124		9,038		31,668		20,399		6,376	
Mean	1.064	1.049	1.035	1.050	1.089	0.971	1.101	0.970	1.082	1.140
Median	1.063	1.052	1.023	1.062	1.072	0.973	1.077	0.969	1.082	1.111
1st percentile	0.899	0.849	0.860	0.916	0.871	0.642	0.924	0.777	0.888	0.829
99th percentile	1.220	1.229	1.376	1.113	1.630	1.313	1.600	1.244	1.304	1.532

Source: Own calculations based on AMADEUS

When evaluating what method is preferable to recover markups, this issue depends on the context. Suppose that a very large share of firms in an industry charges a certain markup while only a few do not. Due to the fact that the SFA imposes the assumption of mean zero on the distribution of the markup component u by construction, the SFA will overestimate the cost elasticity and thereby underestimate markup. As statistical software nowadays allows to incorporate covariates to parameterize the mean of the markup component's distribution, the aforementioned problem can be alleviated given that there are meaningful variables shaping the markup distribution. An example is Lopez et al. (2018) who use the industry concentration and demand elasticities as scale parameters of the one-sided error term u. However, this is also a question of data availability. In case such data are not available, the PFA would be preferable. An example for an industry where industry-wide time-persistent markups prevail might be the global agro-chemical industry. The sector is dominated by very few very large companies that can all be expected to charge a certain markup. Further, the assumption of non-negativity for markups of the SFA might not hold in industries with high sunk costs, e.g., for market entry. Moreover, companies could decide to undercut the prices of their competitors to gain market shares and outcompete their rivals. Hence, they might incur negative markups, thereby sacrificing current for increased future profits. Again, the agro-chemical industry might be an example of an industry where this could be the case such that the PFA would be advantageous.

On the other hand, the PFA does not provide a direct estimate of the cost elasticity/marginal cost like the SFA[64], but requires further regressions to decompose markup into cost and demand

[64] We can calculate marginal cost by multiplying the predicted value of the cost elasticity with the ratio of cost over output.

side components (see De Loecker and Warzynski 2012; De Loecker et al. 2020; Hirsch and Koppenberg 2020 for examples). Besides, we might be interested in obtaining markups per product category in multi-output settings. The PFA only allows to use a composite output variable while the cost/distance function of the SFA allows to include as many outputs as needed. Therefore, the SFA would be favorable in this instance. Last, there are cases where below-cost-selling is forbidden as outlined in section 5.3 such that the underlying competitive conditions of the sector under investigation will be better captured using the SFA by ruling out negative markups.

In our case study, the PFA delivers results that we perceive as more reasonable as they are much closer to previous studies than the SFA estimates (Gohin and Guyomard 2000; Hirsch and Koppenberg 2020; Sckokai et al. 2013). In addition, the PFA markups show a positive and significant connection with industry concentration while the SFA markups are hardly yielding any relationship with concentration. While the estimated RTS of both methods are quite similar (cf. Table 5.3), markups, and finally, consumer welfare implications, diverge substantially. This applies to industry-wide averages but also to the firm-level given the low correlations between markups delivered by the PFA and SFA. Therefore, the truncation of markups at zero imposed by the SFA seems to be ill-advised in our context. This may be prevented using covariates shaping the distribution of the one-sided error term but such information is unavailable in our data.[65] One may argue that food retailers' profit-to-sales ratios are found to be thin (<10 percent), e.g., in France (2 percent) and the United Kingdom (6.12 percent) (Burt and Sparks 1997) or the United States (1.35 percent) (Evans and Mathur 2014; Just and Gabrielyan 2018) such that the PFA markups are unreasonably high.[66] Our data confirm this as over 90 percent of the firms have profit-to-sales ratios of under 7 percent. However, markups are also used to cover fixed costs such that profit-to-sales ratios and markups are only comparable to a limited extend (see De Loecker et al. 2020 for an in-depth discussion).

5.6 Conclusion

In this paper, we compare two markup identification methods which have been applied frequently in recent market power investigations in (applied) economics. We examine their assumptions and estimation techniques and apply them to the food retailing sectors of Finland, France, Italy, Portugal and Sweden for the period of 2010 to 2018. The first approach (SFA) is

[65] Note that using the concentration measures in the parametrization of the one-sided error term would not have helped since they are not firm specific and only fluctuate marginally over time within each country.
[66] Note that the figure for the U.S. is this small since Evans and Mathur (2014) use after-tax profits.

based on efficiency analysis using the stochastic frontier technique and treats markups as systematic positive deviations from marginal cost pricing. The second method (PFA) is based on the estimation of a production function, but does not impose any restrictions on the range of markups.

Our application to EU food retailing indicates that the two methods lead to significantly different average markups. The estimates from the SFA suggest that there is little departure from perfect competition. The PFA yields much higher values than the SFA and shows a larger dispersion in the distribution of markups. Moreover, the PFA results in much higher estimated excess consumer expenditures due to market power than the SFA. This can, ceteris paribus, potentially be reflected in differing assessments of the state of competition in the sector analyzed. Therefore, researchers should be careful when submitting policy recommendations based on consumer welfare loss calculations stemming from markup estimates and should consider/discuss the underlying assumptions in depth when deriving implications.

For our case study, the estimated technological parameters represented by the returns to scale (RTS) are similar for the two approaches and suggest that the vast majority of food retailers in our sample operate close to the efficient scale, i.e., when RTS are equal to one. Since the RTS pose a key component in the calculation of markups, the divergence in markups between the SFA and the PFA mostly stems from the truncation of SFA markups at zero. The inclusion of covariates shaping the distribution of the half-sided error term of the SFA may solve this issue. However, this necessitates the availability of candidate variables which is a question of data availability. In cases where such information is absent, the PFA is preferable compared to the SFA.

Last, we find that firms are ranked differently in terms of markup in the two approaches. This could entail contradictory results, when markups are further related to industry and firm characteristics to identify drivers and consequences of market power. This is supported by our analysis of the relationship between markups and sectoral concentration. Sales-weighted industry-wide markups yield a significant positive relationship with concentration for the PFA while we do not detect a relationship with SFA markups. Based on the results of the PFA, further concentration will most likely decrease competition in the analyzed countries and will entail adverse effects on consumer surplus. Hence, merger and acquisition activities of major retail chains should be seen critically. According to our analysis, potential justification of mergers or acquisitions based on cost savings due to economies of scale, which ultimately benefit consumers through lower food prices, are untenable given that our RTS estimates do not suggest significant cost decrements due to upscaling.

We would like to encourage other researchers examining market power to discuss the assumptions put forward in greater depth in future since our analysis shows that SFA and PFA markups can lead to different conclusions. Ex-ante assumptions on the markup distribution must be considered with utmost care to avoid biased estimates of the welfare effects of market power leading to errors in the policy recommendations derived. These include the availability of covariates shaping the markup distribution, the presence of industry-wide minimum markups that would distort the estimation of the SFA, the presence of sunk costs as well as the regulatory conditions influencing the competition in the industry under investigation.

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5.7 Appendix

We check for montonicity of the production function in the inputs by calculating partial production elasticities for each of them, i.e., $\eta_{jit} = \left(\frac{\partial lnY}{\partial lnX_j}\right)_{it}$. If the production function increases monotonically in inputs, the partial production elasticities will be over or equal to zero. If we observe negative elasticities, we use a one-sided t test to determine whether they are signficantly negative. The test statistic is given by $t = \hat{\eta}/\hat{\sigma}_{\hat{\eta}}$ for each observation. To obtain an estimate of the elasticity's standard error in the two input cases, we take the square root of:

$$\hat{\sigma}^2_{\hat{\eta}_{jit}} = \hat{\sigma}^2_{\hat{\beta}_j} + \left(2lnX_{jit}\right)2\,\hat{\sigma}^2_{\hat{\beta}_{jj}} + (lnX_{kit})2\,\hat{\sigma}^2_{\hat{\beta}_{jk}} + 4lnX_{jit}\,cov\left(\hat{\beta}_j, \hat{\beta}_{jj}\right) + 2lnX_{kit}\,cov\left(\hat{\beta}_j, \hat{\beta}_{jk}\right) + 4lnX_{jit}lnX_{kit}\,cov(\hat{\beta}_{jj}, \hat{\beta}_{jk}) \quad (33)$$

where cov denotes the covariance. The Hessian must be negative semi-definite for concavity to be fulfilled. In the two input cases, this translates into the following condition (Nicholson and Snyder 2008):

$$\frac{\partial^2 Y}{\partial X_j^2}\frac{\partial^2 Y}{\partial X_k^2} - \left(\frac{\partial^2 Y}{\partial X_j \partial X_k}\right)^2 > 0 \quad (34)$$

The first derivative of Y with respect to any input j in the two input case is:

$$\frac{\partial Y}{\partial X_j} = \frac{\partial\, ln\,Y}{\partial\, ln\,X_j}\frac{Y}{X_j} = \frac{Y}{X_j}(\beta_j + 2\beta_{jj}lnX_j + \beta_{jk}lnX_k) \quad (35)$$

The corresponding own second-order partial derivative yields:

$$\frac{\partial^2 Y}{\partial X_j^2} = \frac{Y}{X_j^2}(2\beta_{jj}(1 - lnX_j) - \beta_j - \beta_{jk}lnX_k) \quad (36)$$

The cross partial derivative is:

$$\frac{\partial^2 Y}{\partial X_j \partial X_k} = \beta_{jk}\frac{Y}{X_j X_k} \quad (37)$$

We use a t-test again to determine whether concavity is violated. The delta method (Greene 2003; Papke and Wooldridge 2005) is applied to obtain an observation-specific estimate of the standard error. All observations which significantly violate the assumptions of montonocity and concavity on a level of significance of ten percent are excluded from our further analysis by means of a one-sided t-test.

Table 5.A1 Steps and Results of Data Preparation Process

Country	Finland	France	Italy	Portugal	Sweden
Original number of observations	3,070	28,427	50,461	26,028	11,164
Number of outliers identified by the bacon algorithm	239	1,050	2,751	2,483	596
Final number of observations	2,831	27,377	47,710	23,545	10,568
Share of final observations in original number of observations (%)	92.21	96.31	94.55	90.46	94.66
Final number of firms	707	6,608	8,914	4,843	1,920

Source: Own calculations based on AMADEUS

Table 5.A2 Descriptive Statistics of the Input and Output Measures

	Mean (standard deviation)				
Country	**Finland**	**France**	**Italy**	**Portugal**	**Sweden**
Number of employees	13.30 (13.42)	30.79 (41.00)	10.64 (12.69)	5.17 (5.50)	6.39 (6.32)
Fixed assets (€1,000)	458.14 (703.55)	1,422.88 (2,545.05)	329.48 (706.19)	79.74 (138.27)	128.98 (205.97)
Output (deflated revenue (€1,000))	5,577.82 (7,365.06)	10,224.50 (13,899.26)	2,369.90 (3,104.39)	569.54 (728.74)	1,786.98 (2,379.64)
Material (deflated material costs (€1,000))	4,062.69 (5,517.27)	7,994.61 (10,924.96)	1,805.72 (2,404.45)	443.28 (593.10)	1,253.49 (1,786.91)
Revenue-cost ratio	1.02 (0.076)	1.01 (0.058)	1.01 (0.07)	1.00 (0.09)	1.02 (0.08)
Observations	2,831	27,377	47,710	23,545	10,568

Source: Own calculations based on AMADEUS

Table 5.A3 Consistent Fixed Effects Stochastic Frontier Estimation Results

	Finland	France	Italy	Portugal	Sweden
Frontier					
lnOutput	-0.012***	0.014***	0.002*	0.025***	-0.003
	(0.003)	(0.001)	(8.21e-4)	(0.001)	(0.003)
ln(X₂/X₁)	-0.004**	-0.001***	0.001**	-2.34e-4	-2.87e-4
	(0.002)	(3.49e-4)	(4.37e-4)	(6.05e-5)	(8.84e-4)
2011	0.001	-0.001**	-0.001	2.31e-5	0.008*
	(0.005)	(6.60e-4)	(0.002)	(0.002)	(0.003)
2012	3.87e-4	-0.004***	0.005***	-0.008***	0.017***
	(0.005)	(7.11e-4)	(0.002)	(0.002)	(0.003)
2013	0.003	-9.44e-4	0.007***	-0.017***	0.023***
	(0.005)	(6.84e-4)	(0.002)	(0.002)	(0.003)
2014	0.008*	0.001*	0.010***	-0.010***	0.030***
	(0.005)	(6.78e-4)	(0.002)	(0.002)	(0.003)
2015	0.008	0.003***	0.014***	0.007***	0.031***

		(0.005)	(7.27e-4)	(0.002)	(0.002)	(0.003)
	2016	3.95e-4	0.007***	0.020***	0.014***	0.033***
		(0.005)	(7.19e-4)	(0.002)	(0.002)	(0.003)
	2017	-0.004	0.005***	0.020***	0.013***	0.035***
		(0.005)	(7.73e-4)	(0.002)	(0.002)	(0.003)
	2018	-0.008	0.002*	0.022***	0.020***	0.033***
		(0.005)	(9.26e-4)	(0.002)	(0.002)	(0.003)
Sigma2	*Constant*	0.009***	0.002***	0.010***	0.012***	0.014***
		(4.90e-4)	(3.96e-5)	(1.28e-4)	(2.20e-4)	(3.25e-4)
Lambda	*Constant*	5.294***	5.900***	3.963***	2.684***	4.386***
		(0.766)	(0.413)	(0.126)	(0.097)	(0.240)
	Observations	2,831	27,377	47,710	23,545	10,568
	Likelihood	1640.52	30,035.25	27,466.46	10,353.57	4,833.37

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations based on AMADEUS

Table 5.A4 Estimation Results for the PFA

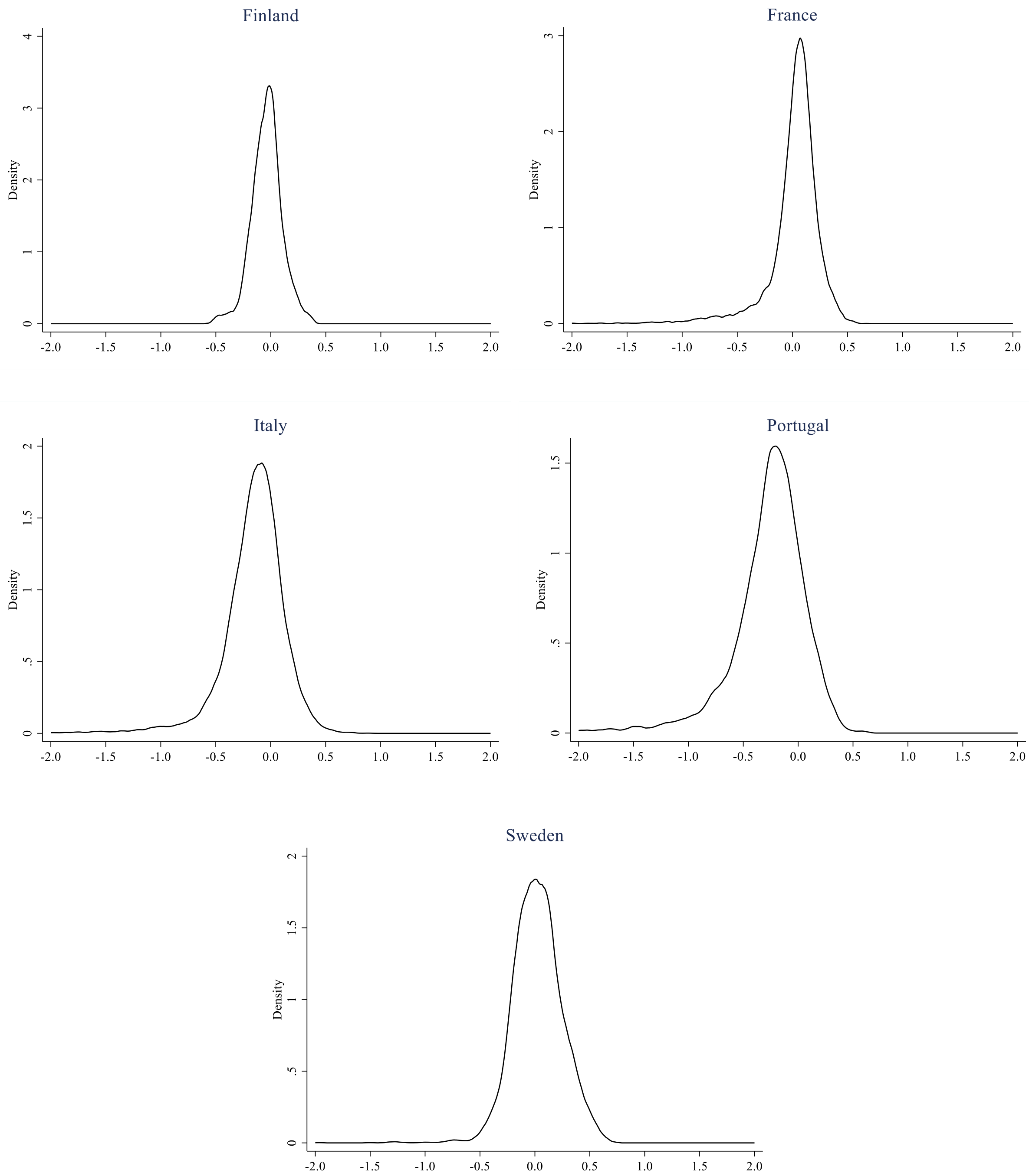
	Finland	France	Italy	Portugal	Sweden
lnX_1	0.863***	1.064***	0.796***	0.742***	0.776***
	(0.007)	(8.36e-4)	(1.71e-4)	(6.97e-5)	(1.86e-4)
lnX_2	0.125***	0.035***	0.161***	0.039***	0.056***
	(0.002)	(1.86e-4)	(2.77e-4)	(3.01e-4)	(2.46e-4)
$(lnX_1)^2$	0.040***	0.065***	0.103***	0.052***	0.086***
	(0.004)	(0.001)	(1.97e-4)	(5.24e-4)	(4.61e-4)
lnX_1lnX_2	0.025***	-0.042***	-0.038***	0.027***	0.029***
	(0.005)	(2.63e-5)	(1.37e-4)	(4.85e-5)	(4.38e-5)
$(lnX_2)^2$	-0.032***	0.004***	-0.010***	-0.012***	-0.015***
	(0.006)	(6.69e-4)	(7.75e-4)	(0.001)	(0.001)
Observations	2,831	27,377	47,710	23,545	10,568

Source: Own calculations based on AMADEUS

Table 5.A5 Results of Regularity Tests of the Stochastic Frontier and the Production Function Estimation

	Finland	France	Italy	Portugal	Sweden
Observations not increasing in output (SFA)	0	0	0	0	0
Observations not increasing in labor (PFA)	0	0	0	0	0
Observations not increasing in capital (PFA)	707	14,554	16,042	3,146	4,192
Observations which are not concave (PFA)	122	18,339	12,471	1,005	1,755
Remaining number of observations	2,124	9,038	31,668	20,399	6,376
Share of observations fulfilling regularity conditions (%)	75.03	33.01	66.38	86.64	60.33

Source: Own calculations based on AMADEUS



Note: To ensure readability, we omit values smaller than minus two.

Source: Own calculations based on AMADEUS

Figure 5.A1 Kernel Density Functions of the Differences Between Estimates of Returns To Scale (RTS) Based on the PFA and the Inverse of the Cost Elasticity of the SFA

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6 Conclusions

6.1 Summary and Conclusions

The thesis pursues three objectives: First, it aims to estimate firm-level output market power in the EU food sector by using new, advanced methods that require less restrictive assumptions than studies under the framework of the New Empirical Industrial Organization. Second, it aims to identify the relationship between markups as a measure of output market power and characteristics of firms in order to derive recommendations for targeted measures on competition policy, as well as to derive recommendations for firms' strategic behavior. Third, this thesis aims to evaluate and compare the advanced methods in order to offer guidance in the methodological choice of future studies on market power.

In order to achieve these objectives, three first-authored articles (Chapter 3, 4 and 5) and two supplementary co-authored articles (Chapter S1 and S2) on farming, food processing and the food retail sectors in several EU countries are presented and embedded into a theoretical and methodological context.

The first article (Chapter 3) investigates market power in European dairy farming for the period of 2004 to 2017. With data from the EU's Farm Accountancy Data Network, a sample of almost 40,000 farms comprising more than 200,000 observations is used to estimate a translog cost function to obtain farms' marginal cost and, subsequently, markups. Organic agriculture serves as a case study to assess whether farmers can generate markup premia in niche markets to sustain a livable income. Overall, the highest markups can be found in Western Europe and Scandinavia whereas the smallest markups are generated in Eastern Europe. Regarding differences in markups between organic and conventional farms, the results of the regressions indicate a markup premium for organic dairy farmers ranging from 58.60 to 134.90 percentage points (0.59 to 1.35 in levels) when accounting for or eliminating extreme markup values. That is, the conversion from conventional to organic dairy farming entails substantial increments in markups. Interestingly, variation in the market share of organic milk in the overall milk market does not entail any significant changes. One may expect that transaction costs decrease with increasing market shares of organic milk which leads to price decreases as the niche market becomes larger, and markups would shrink correspondingly. However, it seems that increasing demand outweighs any increases in supply and the corresponding decreases in transaction costs.

In addition, there is a robust positive link between markups and farm size measured by quantity of milk produced. However, an alternative regression specification controlling for differences in marginal cost between farms yields much smaller coefficient estimates for farm size. Thus, the major part of the markup gains with increasing output stem from cost savings due to economies of scale. Nevertheless, farm growth appears as the superior strategy to boost markups and increase income for European dairy farmers. Accordingly, farm structural change is likely to continue leading to fewer and larger farms. Policy makers may consider supporting farmers in changing their production in a way that allows them to enter new niche markets such as marketing their products as locally produced or increasing transparency via webcams in meat production stables. In addition, the significant negative relationship of farmers' markups and the market share of large retailers points to adverse effects of retailer concentration on competition in primary food procurement sectors. Thus, while the potential consequences on horizontal competition, i.e., within the retailing sector, are the prime consideration in merger admission processes, competition authorities should also pay attention to the effects on upstream sectors. By contrast, the connection between farm-level markups and concentration in dairy processing does not reveal an abuse of market power in procurement by large dairy processors. Instead, medium-sized processors try to push prices down whereas large processors seem to sustain long-term milk supply by paying competitive milk prices.

The second first-authored study (Chapter 4) has investigated markups in the French, Italian and Spanish dairy processing industries for 421, 1,095, and 686 firms, respectively, from 2008 to 2017 using a stochastic frontier approach. The estimated markups show that competition is highest in France where lowest mean markups are observed equaling 0.07, i.e., French dairy processors charge output prices exceeding marginal cost by 7.3 percent on average, followed by Italy (0.13) and Spain (0.20). Relating markups to firm characteristics shows a strong negative and robust link between firm size and markups which is also significantly different from zero across all regression models. This is surprising given that mostly large companies are accused of abusing market power. However, our analysis reveals that the large companies are closest to being perfectly competitive. Consequently, smaller firms have higher bargaining power in the output market compared to multi-/national corporations. Small firms mostly operate in niche markets since, in contrast to large firms, they do not possess cost advantages in the production of mass products due to scale economies. Therefore, product differentiation appears to be the best strategy for small firms to obtain a strong bargaining position on the output side in the EU dairy processing sector. Policy makers should consider supporting small businesses striving to develop of innovative and/or niche products as suggested above for the farming sector.

We find evidence of a strong positive link between markups and profitability such that markups indicate welfare decreasing market power. Combining this with the previous result indicates that small, differentiated firms have a high likelihood of survival in the EU dairy processing sector. Nonetheless, we identify an inverse link between markups and revenue growth in France and Italy. That is, if small but high markup firms wished to grow faster, they would have to accept decreases in markups. While one may be concerned with consumer welfare losses due to the market power of small firms, it is important to remember that large enterprises generate the vast majority of revenue in the industry. This implies that the potential welfare losses are small and may be tolerated to foster a more even distribution of profits among firms. In addition, the negative relationship between markups and revenue growth implies that firms with smaller markups gain market shares and reduce industry-wide revenue-weighted average markups and lower welfare losses.

Similarly, supplementary article one (chapter S1 of the dissertation) focuses on the relationship between firm-level export behavior and markups in the French food processing industry where markups are estimated based on a production function approach. On average, output prices exceed marginal costs by 29 percent (markup = 0.29) across firms while markup distributions are right-skewed in all subsectors, so that the majority of firms incurs low markups and few powerful firms enjoy high markups. The study yields a higher likelihood of exporting for firms with higher markups as well as a positive association between markups and export intensity measured as the share of export revenue in total firm revenue. For a rise in markups by one percent, our models predict an increase in export intensity of up to 4.60 percentage points. Further, firms entering export markets realize an immediate increment in markups once they start exporting. They also gain additional markup increases with rising export experience, i.e., when they remain in export markets for at least two consecutive years which yields 2.1 percentage points (0.02 in levels). Finally, exporters' self-selection into export markets allows them to charge even higher markups compared to non-exporters where the difference in markups between exporters and non-exporters is approximately equal to two percentage points. These outcomes are robust even when we control for differences in marginal cost proxied by firm productivity even though the size of the identified effects decreases. Hence, factors such as product quality and demand-side conditions are also relevant in explaining the link between markup and export behavior in addition to marginal cost differences between firms.

Regarding the implications from a policy making perspective, domestic policy measures common to all firms may lead to adverse effects on domestic prices. This includes policy measures on competition as well as export promotion. Given that a country imposes quality standards, marginal cost will rise for most firms such that firms with low markups - a group to which the majority of companies belongs – will, ceteris paribus, exit the market first. This will lead to an upward shift of the supply curve implying higher prices on domestic markets. Policies pushing prices on domestic markets downwards will incentivize firms to engage in exporting. This will reduce domestic supply and, consequently, increase prices. A similar mechanism applies to export promotion measures. Firms with growing export experience will charge higher markups and, therefore, also higher prices on domestic markets as indicated by the positive link between markups and export continuation. The aforementioned effects should be considered carefully in the design of any political interventions in markets.

Combining the results of Chapter 4 and S1, a strategy of product differentiation with high product quality and a strong export orientation may pay off very well for small companies in the EU food processing sector seeking to sustain their profitability. Thereby, firms can alleviate the dependence on a single market and circumvent competitive pressure in their domestic market. Export promotion measures targeting small firms may be promising in fostering their competitiveness. At the same time, adverse impacts on domestic consumer welfare are minimized and profits are more evenly distributed in the EU food processing industry.

Article three (Chapter 5) compares the production function approach and the stochastic frontier approach to estimate markups with respect to their economic and econometric assumptions. The EU food retailing sector serves as a case study to identify the differences in estimates resulting from the two contemporary methods in an empirical setting in five countries (2010-2018). The most striking difference in the theoretical foundations of the two methods is the assumed distribution of markups. The stochastic frontier approach restricts markups to be larger than zero whereas the production function approach does not impose any boundaries in this regard. The estimation of markups for the diverse set of food retail sectors (Finland, France, Italy, Portugal and Sweden) demonstrates that the distributional assumption is crucial. The country-level Bravais-Pearson correlation coefficients of the firm-level markups delivered by the two approaches ranges from 0.06 to 0.14, which is considered low, although the results are significantly different from zero in all cases. The interpretation changes when using the Spearman rank correlation which is even negative and significantly different from zero for Finland (-0.05) and Italy (-0.05). In the remaining three countries, the rank correlation coefficients are very close to zero (approximately 0.02). Even though the stochastic frontier approach assumes strictly positive markups, mean and median markups are consistently larger for the production function approach in all five countries. This is also reflected in the approximated excess consumer expenditures due to markups charged by retailers. When calculated based on markups from the production function approach, excess consumer expenditures exceed the excess expenditures of the stochastic frontier approach by 58.14 (Portugal) to 313.33 (France) percent. Yet, both methods predict that the deviations from perfect competition are not severe as median markups range from 3.9 percent (stochastic frontier approach; France) to 22.1 percent (production function approach; France).

A possible explanation for the divergence in the results of both approaches are the estimated parameters of the technology. These parameters build the foundation in the computation of markups. The median estimates of returns to scale lie between 0.97 in Portugal (production function approach) and 1.11 Sweden (production function approach). That is, retailers' output and, subsequently, costs increase almost proportionally with input use. While the modal difference in the estimated returns to scale for the production function approach and the stochastic frontier approach is almost zero in Finland, France and Sweden, the production function approach, on average, yields smaller values for Italy and Portugal compared to the stochastic frontier approach. Nevertheless, the differences in the technology do not fully explain the tremendous deviations in the estimated markups. Instead, the distributional assumption imposed by the stochastic frontier approach drives the major share of the deviations in markups between the production function approach and the stochastic frontier approach.

The low correlation of the markups obtained by the two methods may raise concerns that they will lead to different conclusions regarding the state of competition, and ultimately, recommendations for anti-trust policies as well as the relationship of firm and/or industry characteristics to markups. When calculating the correlation coefficient between the Herfindahl-Hirschman-Index and industry-wide revenue-weighted markups, the production function approach shows a significant positive relationship. By contrast, the stochastic frontier approach does not yield any significant relationship between the markups and the Herfindahl-Hirschman-Index. Therefore, future studies should examine carefully the assumptions of the method on which the markup estimation is based. For instance, there are countries, e.g., France, where below-cost selling is forbidden (Colla and Lapoule 2008) such that truncating markups at zero from below is justifiable. However, in many other cases firms will incur negative markups (Caselli et al. 2018). Examples may be firms that face decreasing demand or experience negative demand shocks. Firms could also decide to undercut prices of competitors to gain market shares, thereby potentially incurring negative markups. The stochastic frontier approach would then be too restrictive.

Despite the estimated markups being rather small, the analysis suggests the following implication for competition authorities. Since the majority of firms operates close to the efficient scale, i.e., where returns to scale are equal to one, further mergers and acquisitions within the food retailing sector can hardly be justified by cost savings. Thus, the continuous growth of single food retail chains probably leads to gains in market power in input and/or output markets. The first article (Chapter 3) and the second supplementary article (Chapter S2) support this argument. The negative relationship between the market share of large retailers and farm-level markups (cf. Chapter 3) points to an abuse of market power by large retailers in procurement. The estimation of markups in the French food retail sector (Chapter S2) confirms that retailing is a rather competitive sector as indicated by average markups around 18.2 percent (0.18). However, the investigation of markup differences between top retail chains and fringe retailers shows that dominant retailers charge markups that are 9.1 percentage points (i.e., 0.09) higher than those of fringe firms. Therefore, further increases in market shares of the large retailers is undesirable from the perspective of maximizing welfare.

To sum it up, research within the framework of this dissertation shows: Farmers as well as food processors can benefit from product specialization in terms of markups. In food processing, this is particularly true for small firms which can also generate markup premia by entering and staying in export markets. In contrast to the public perception, increasing market shares of large dairy processors, i.e., rising concentration in the industry, entails positive effects for farmers' markups which may be caused by long-run incentives of processors to ensure milk supply from farmers. For food retailing, however, increments in concentration lead to markup decreases for farmers. Combined with the facts that retailers operate close to the efficient scale and top retailers exhibit significantly larger markups compared with fringe firms, competition authorities should prevent further concentration in the EU food retailing sector to avoid welfare losses for farmers as well as consumers. Besides, the studies show that markups, even though they are also strongly related to fixed cost, enable the firms to gain higher profits implying the presence of welfare decreasing market power. Finally, future research should carefully consider their choice of the method to estimate markups. This thesis has demonstrated that two different methods, both widely accepted in the literature, can yield significantly deviating results although both are based on similar assumptions and use similar data. Thus, when applying these methods the underlying assumptions should be discussed in-depth and the final choice should be thoroughly justified.

6.2 Limitations and Future Research

This thesis has taken a step beyond earlier studies and contributed to a richer understanding of competition in EU food supply chains. While it suggests new directions for future research, it does not cover the following important aspects.

First, the studies only looked at market power in output markets at three stages of the food supply chain. Market power in procurement is also of importance as shown in previous research (Gohin and Guyomard 2000; Perekhozhuk et al. 2015; Perekhozhuk et al. 2013). Therefore, future research should also examine the extent and the determinants of market power in procurement, particularly in food processing and retailing. For this purpose, plant-level data should preferably be available because competition in procurement depends on the presence of competitors in rather narrow geographical regions (Graubner et al. 2011a; Graubner et al. 2011b) as agricultural commodities are bulky, and thus costly to transport, as well as highly perishable (Rogers and Sexton 1994). Unfortunately, since the data sets available for this thesis only contain information on firm-wide results, such an investigation of input market power of processors and retailers has not been feasible.

Moreover, research within the framework of this thesis does not cover the market of agricultural inputs such as fertilizer and plant protection products. However, few global corporations dominate the market, e.g., BASF, Bayer, Corteva or Syngenta, which have engaged intensively in mergers and acquisitions during the past decades (Bonanno et al. 2017). The high concentration within the industry may allow the dominant players to charge significant markups since times until admission of new products are long, and patents create artificial monopolies. The fact that only few firms operate in this market makes it more difficult to estimate market power as there are too few observations for the estimation of a cost or production function.

A model of the entire food supply chain integrating market power would be a useful tool for anti-trust and policy analysis. Such a model could simulate changes in food prices and welfare effects caused by the abuse of market power. However, this exercise requires modelling all markets in all relevant countries as well as their interdependencies due to trade flows. This would allow to make reliable inference regarding the effects of variations of market power in one market on all other markets. The amount of data needed for that purpose is, of course, highly demanding and the complexity of such a model can quickly require tremendous computational effort.

Last but not least, there are also manifestations of market power, e.g., unfair trading practices, which do not necessarily imply markdowns/markups per se. These include systematically delayed payments imposed by the buyer of a product or the enforcement of contracts by one party which are detrimental to the other. While such business practices are of interest to competition authorities, it is unclear whether they also entail welfare losses, i.e., translate into markdowns or markups. Studying the relationship between non-markdown/non-markup measures of market power such as systematically delayed payments and markdowns/markups would expose the importance of these measures in the public debate, and could ultimately lead to the prohibition of further unfair trading practices besides those that are already forbidden (European Commission 2019).

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Supplement

S1 Markups and Export Behavior: Firm-Level Evidence from the French Food Processing Industry

This Chapter is published as

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Authors' Contribution: Yaghoob Jafari had the idea for the research project, developed the research objectives, estimated the regressions for the relationship between markups and export behavior and wrote the manuscript. Maximilian Koppenberg developed the methodology for the markup identification, estimated the markups, wrote the methodology section for markup estimation and provided feedback on the remaining parts of the manuscript. Stefan Hirsch developed the methodology for the regressions relating markups and firm export behavior, estimated the regressions for the relationship between markups and export behavior and provided feedback on the manuscript. Thomas Heckelei provided feedback on the manuscript.

Abstract

The relationship between a firm's markups and its export behavior is highly relevant to individual firms' strategic decisions as well as to governments' policies regarding competition. We investigate the impact of markups on firms' decisions to export and resulting export intensity in the French food processing industry. Moreover, we assess the effect of entry into and remaining in the export market on firms' markups, and evaluate differences in markups between exporters and non-exporters. Our results suggest that higher markups lead to both increased participation in the export market and greater export intensity. In addition, we find that firms obtain higher markups by entering and remaining in the export market. Finally, our results suggest that exporters generate higher markups, on average, than non-exporters. Similar results are found when controlling for differences in firms' productivity. Our findings suggest that trade policies designed to increase firms' participation in export markets such as limits to border restrictions, may counteract domestic competition policies targeted at price-cost margins.

S1.1 Introduction

Food processing industries worldwide enjoy strong protection against competition from foreign trade.[67] However, recent trade reforms have made foreign markets more accessible to (potential) exporters (Curzi et al. 2015; FAO 2019). This fosters firms' export activity that can influence their ratio of price over marginal costs, i.e., markups. At the same time, countries employ various measures to encourage domestic firms to adopt advanced technologies and to produce higher-quality products (FAO 2019). Such measures also involve changes in markups that can in turn affect export participation and intensity. Consequently, the relation between markups and export behavior is of direct interest to policy makers and firms seeking to successfully align their policies and competitive strategies, respectively (e.g., De Loecker et al. 2016; Ponikvar and Tajnikar 2011). This article investigates this simultaneous relationship using the example of the food processing sector in France.

One challenge in identifying the relationship between export decisions and markups is that both result from the interaction of factors that affect production and demand.[68] We disentangle this simultaneity using exogenous characteristics such as firm age and legal form as instruments. First, we analyze the impact of firms' markups on the decision to export and on export intensity. Second, we explore the impact of (i) entering and (ii) remaining in the export market for at least two consecutive years, i.e., the effect of export experience on markups. Finally, we evaluate the differences in markups for exporters and non-exporters.[69]

Theory predicts that firms with relatively low marginal costs and/or higher product quality, i.e., larger markups, enter the export market and adjust their product prices depending on the level of competition they expect to encounter at the export destination (Bernard et al. 2003; Melitz

[67] At the global level the food sector's Most Favored Nation status and applied tariffs weighted by trade shares are 31 percent and 22 percent, respectively (World Bank 2017).

[68] The overall markup-export relationship can be explained by the correlation between individual components of markups and firm export behavior (see Bellone et al. 2016; De Loecker and Warzynski 2012; De Loecker 2013; De Loecker et al. 2016; Kilinç 2019). Firm markups are linked with factors that affect production costs, such as productivity, input prices and quality, firms' oligopsonistic (input buyer) power, and variations in those factors that influence product prices, such as product quality, trade costs and demand-side conditions (market size, consumer preferences, income levels) (see e.g., Hottman et al. 2016). These factors can be firm-, product-, or market-specific and their variation is affected by and/or has an impact on a firm's export behavior. This reflects the idea that the relationship between firms' markups and export behavior is the combination of production- and demand-side factors affecting cost and product prices.

[69] There is evidence for the presence of significant firm- and industry-level markups in the food sector (e.g., Curzi et al. 2021; Garrone and Swinnen 2018; Karagiannis et al. 2018; Koppenberg and Hirsch 2022; Lopez et al. 2018; Sexton and Xia 2018; Vancauteren 2013; Wilhelmsson 2006). Firms' ability to charge markups is partly due to their export behavior and can partly explain that behavior (Bellone et al. 2016; De Loecker 2013; Kilinç 2019).

and Ottaviano 2008). Furthermore, markups can change through Learning by Exporting (LBE) for firms remaining in the export market for a number of years (Bernard and Jenson 1995). However, the empirical evidence on the relationship between exporting and markups is limited. De Loecker and Warzynski (2012) (hereafter DLW) were the first to empirically study the relevance of firms' export behavior for markups using the Slovenian manufacturing sector as a case study. DLW estimated firm-specific markups based on an extended version of the production function approach in Hall (1988).[70] The DLW approach is attractive as it does not require assumptions about how firms compete in output markets. It also has lower data requirements compared to New Empirical Industrial Organization approaches (De Loecker and Scott 2016). Later studies, such as Bellone et al. (2016) and Kilinç (2019), show the relevance of export destination characteristics for markups of companies in France and Luxembourg. However, these results should be understood as a correlation analysis as the authors did not control for the reverse causality between markups and export behavior.

This study adds to the literature in several ways. First, we go beyond the classic DLW methodology, that assumes perfect competition in input markets, when estimating firm-specific markups as a measure of output market power. In this respect, we take into account the potential imperfect competition in the labor input market. Furthermore, to obtain more reliable markup estimates, we improve the estimation of the production function by addressing potential biases in output measurement caused by deflating revenues with industry-wide price deflators. Instead, we use a price index that considers the weighted average of prices in domestic and export markets. Moreover, we account for the firm-specific deviations from the weighted average industry prices in the estimation of the production function. This results in more reliable estimates of production function parameters, which are required for the calculation of markups.

Second, we add to the understanding of the impact of firms' markups on both the probability of participating in an export market and on conditional export intensity. We use a double hurdle control function approach that separates the initial export decision from the conditional intensity, while addressing the simultaneity between markups and export decisions based on suitable instrumental variables (IV) (Garcia 2013). To the best of our knowledge, this impact has not yet been investigated empirically at the firm-level.[71]

[70] Similarly, Zhang and Zhu (2017) investigate the relevance of firms' export behavior to markups in China.

[71] Note that while our study considers the firm markup and export relationship, several other studies have assessed the relationship between the individual components of markups, such as firm productivity and product quality,

Third, we follow DLW and test whether markups are affected by the firm's decision to begin exporting and stay in the export market for at least two consecutive years. Moreover, we follow DLW and estimate differences in markups between exporters and non-exporters. Results of previous studies in this area are inconclusive, especially for developed countries (DLW). To obtain our estimates, we deviate from DLW by accounting for the simultaneity of firms' markups and export behavior using an Extended Regression Model IV approach. Therefore, our results offer more reliable evidence on this issue.

We also control for differences in firms' productivity, which can play an important role in the markup-export behavior relationship (De Loecker and Goldberg 2014; Foster et al. 2008; Greenaway and Kneller 2007). This provides evidence regarding the importance of factors other than productivity that drive the markup-export relationship, such as output quality and demand-side conditions. After controlling for differences in productivity, markups contain information that can be relevant for policy makers in formulating policies affecting domestic competition and for firms in designing strategies for product quality and pricing (De Loecker and Goldberg 2014).

Our analysis uses a sample of 10,927 firms operating in the French food processing sector over the period 2011-2019. With a 20 percent market share, France is the largest contributor to total EU food industry turnover, followed by Germany and Italy. Moreover, the food processing sector constitutes the largest manufacturing subsector in France, contributing 17 percent (€178 billion) of total manufacturing sales in the country (Eurostat 2019c). The food sector in France is characterized by high market saturation, strong competition along the supply chain, and a high degree of retailer concentration, all of which puts food processors under pressure (EY et al. 2014; Wijnands et al. 2007). In addition, the sector is known as one of the most diverse in the world[72] with a variety of globally recognized products that provide firms with promising export opportunities (CNIEL 2015). Accordingly, approximately 24 percent of French agri-food products are exported, with an emphasis on grain products and beverages whose export rates are 49 percent and 30 percent, respectively (FMOAF 2021). Consequently, the French food processing industry presents an interesting opportunity to examine the relationship between markups and firms' export behavior.

with export market participation and export intensity (see e.g., Bellone et al. 2016; Bernard et al. 2007; Curzi and Olper 2012; Eickelpasch and Vogel 2009). See also, Melitz and Redding (2014) for a review.

[72] For example, over 1,500 different dairy products are produced by food processors in France (CNIEL 2015).

The remainder of this article is structured as follows. We first review earlier studies examining the link between firms' export behavior and markups. Next, we describe the empirical strategy used to estimate markups that accounts for potentially imperfect input markets. We then outline regression specifications for analyzing markup-export relationships, present the data, and discuss the results. Finally, we offer some conclusions.

S1.2 Background and Derived Hypotheses

Theoretical and empirical studies on the relationship between trade and markup gained attention following the emergence of trade models of monopolistic competition (see Jacquemin 1982). In parallel, the literature on this relationship gained in popularity with the introduction of intra-industry trade in homogenous goods into the reciprocal dumping models in Brander (1981) and Brander and Krugman (1983) that allow firms to differentiate between domestic and export markets (see Gullstrand et al. 2014).[73] Later, the appearance of rich micro-level datasets in the mid-1990s led to three main insights: First, markups affect firms' export behavior. Second, entering and/or staying in export markets may involve changes in firm markups. Third, this two-way relationship can result in differences in markups between exporters and non-exporters.

S1.2.1 The Impact of a Firm's Markup on Export Participation and Intensity

The influence of markups, i.e., the ratio of output price over marginal cost and its components, on firms' export participation and intensity has received considerable attention in the literature. A firm's physical productivity – which determines its marginal cost – has been identified as one of the key determinants of export participation and intensity. Melitz (2003) uses a monopolistic competition model to illustrate that a firm's decision to serve one or multiple foreign market(s) depends on its productivity. Since a firm has to pay fixed export entry costs to access new markets, its productivity must be strong enough to offset this outlay.[74] Chaney (2008) and Helpman et al. (2008) use Melitz-type models to show that a firm's expected export share is higher when bilateral trade frictions are relatively low.[75] While these models predict

[73] A recognition of the relationship between trade and markups dates back to traditional dumping theory that analyzes monopolistic price discrimination between national markets (i.e., the formal theory of dumping) (see Ethier 1982; Tarr 1979). Schwartzman (1959) was the first to empirically show that market structures (i.e., price over average cost margin) of individual industries differ depending on their level of involvement in trade activities (see Caves 1980 or Caves 1985 for a review).

[74] Using a Ricardian model with geographic barriers, Eaton and Kortum (2002) show that firms' exports increase with productivity due to marginal cost advantages over their competitors. However, the model is based on perfectly competitive markets (i.e., firms do not charge markups).

[75] Chaney (2008) shows that bilateral fixed and variable costs of trade are important factors in determining the role of a firm's productivity in its participation in export markets (extensive margin of trade) and subsequent export

that productivity will have a positive impact on export intensity, defined as the ratio of export sales over total sales, a reverse effect is also possible (Arkolakis 2012). Given that firms with a given level of productivity can reach a certain fraction of consumers in both domestic and export markets, improved productivity enables them to increase the fraction of consumers they reach in both markets. If the positive impact of productivity improvements on domestic sales exceeds the positive impact on export sales, productivity and export intensity will be inversely related.

Output prices are the second component of markup and superior product quality has been identified as a major driver of higher prices (Baldwin and Harrigan 2011; Bellone et al. 2016; Johnson 2012; Kugler and Verhoogen 2012; Manova and Zhang 2012). Products destined for export must offer an output quality premium over what is available in the domestic market. Consequently, exporters realize higher output prices and higher markups than non-exporters even though they use higher-quality, and therefore more costly, inputs (Kugler and Verhoogen 2012), or technologies that result in higher marginal costs (Antoniades 2015; Eaton and Fieler 2019; Hallak and Sivadasan 2013; Johnson 2012).[76] Nonetheless, if export markets have a different appreciation for product quality compared to domestic markets, the impact of the product quality component of markups on exports could be negative (Crinò and Epifani 2012). For example, firms located in countries with high domestic quality standards that produce high quality products are less likely to export to markets with lower quality standards (Crinò and Epifani 2012).

Previous studies have investigated the relationship between the individual components of markups and the decision to export, but we are not aware of any empirical study that analyzes the causal impact of firm markups on the decision to export and resulting export intensity.

Based on these theoretical concepts, we develop hypothesis H1a: higher markups increase the likelihood of export, and H2a: higher markups lead to higher export intensity, conditional on export participation. We also hypothesize that rising markups after controlling for productivity

quantity (intensive margin of trade): the higher the bilateral fixed and variable costs, the lower the extensive margin of trade; the higher the variable cost the lower the intensive margin. Similarly, Helpman et al. (2008) show that bilateral trade frictions between countries influence firms' exports to different destinations and their export values. These models have been widely used in empirical analyses with gravity models. For example, see the application of Chaney (2008), and Helpman et al. (2008) on the impacts of bilateral frictions on food trade in Chevassus-Lozza and Latouche (2012), and Eum et al. (2021), respectively.

[76] These references are based on the insights in Sutton (2007) and employ different functional forms to link sources of product quality with cost and price components of markups.

differences increase the likelihood of export (H1b) and lead to incremental increases in export intensity (H2b).

S1.2.2 The Impact of Firms' Export Entry and Continuation on Markups

We now turn to the effect of a firm's entering into and remaining in export markets on its pricing and marginal costs, and therefore on its markups. Theoretical models suggest that exporters adjust their prices to the price level in the export destination (e.g., Bernard et al. 2003; Melitz and Ottaviano 2008). Accordingly, an exporter's price depends on rivals' marginal costs in the export market. If exporters' domestic prices are higher (lower) than prices in the export market, their markups will, ceteris paribus, decrease (increase) when they enter the foreign market. Market size in the export destination also affects exporters' markup. Competition is stronger in large, integrated markets, which implies relatively small markups (Melitz and Ottaviano 2008). Therefore, depending on the level of competition in the export market, a firm's markup may increase, decrease, or remain constant upon entering a foreign market. In addition, firms choosing to begin exporting may reduce their markups strategically, to increase market penetration, enabling them to compete while they attempt to gain a certain share of the market (Dean 1976). Firms may also upgrade product quality upon entering an export market,[77] or may benefit from economies of scale (DLW), both of which have a positive impact on markups. In that respect, De Loecker et al. (2016) and McQuoid and Rubini (2019) find that decreased marginal costs as a consequence of trade liberalization are incompletely passed through to prices in India, and Chile, respectively. As noted earlier, the food sector is highly competitive (Wijnands et al. 2007); therefore, we do not expect food processors in France to attempt to gain a significant share in the destination market by strategically undercutting their rivals' prices when they enter an export market. Instead, we conjecture that as the French food sector is rather specialized and has many differentiated products (CNIEL 2015), these products have relatively high prices in export markets. Thus, we formulate the following hypotheses: firm markups increase upon export entry (H3a), and that the effect is robust when we control markups for productivity (H3b).

Furthermore, the literature on exporting and firm performance suggests that firms benefit from learning when they remain in an export market for consecutive periods, i.e., they experience LBE (Baldwin and Gu 2005; Bernard and Jenson 1995; DLW). Potential gains can arise through

[77] Quality upgrading occurs in response to customer demand in foreign markets, product quality of rivals (De Loecker 2007), and to the greater incentive to invest in quality upgrading when supplying a larger market (Hallak and Sivadasan 2013).

different channels, such as increased efficiency due to competitive pressures, or the ability to use new technology thanks to international contacts (Baldwin and Gu 2005; Baldwin and Yan 2015; De Loecker 2013). In addition, firms that continue to export after entering foreign markets shift their product mixes toward their best-performing products, leading to overall productivity improvements (Mayer et al. 2014). Therefore, we can expect lower marginal costs and, ceteris paribus, higher firm markups for firms that remain in an export market for consecutive periods. DLW's examination of the Slovenian manufacturing sector yielded evidence to support this mechanism. Exporters may also learn to recognize consumer preferences in foreign markets and observe foreign rivals to improve product quality (De Loecker 2007, 2013). Therefore, we expect that remaining in an export market for consecutive years has a positive impact on markups (H4a) and that this effect is robust when controlling for productivity (H4b).

S1.2.3 Markup Differences Between Exporters and Non-Exporters

Differences in markups are likely to arise between exporters and non-exporters (DLW) as firms with higher markups may participate in export markets and benefit from learning effects of participation, which in turn influences their markups. Bellone et al. (2016) investigate differences in markups between exporters and non-exporters by introducing product quality into the framework proposed in Melitz and Ottaviano (2008). They assume that productivity can increase product quality, and therefore markups, leading to participation in export markets. In this framework, the difference between markups of exporters and those of non-exporters depends on the quality-enhancing impact of productivity and the price effects of competition on the export market (Bellone et al. 2016). The authors applied their model to the French manufacturing industry and found that exporters' markups exceed those of non-exporters by 0.013 units because the quality-enhancing impact of productivity exceeds the downward price pressure from competition. However, they do not control for simultaneity in markups and export participation; thus, their estimates may be biased.

We therefore derive hypothesis H5a, which states that exporters in the food processing sector have higher markups than non-exporters, and H5b, which states that this holds for markups after controlling for productivity.

S1.3 Measuring Markups

We adopt the DLW approach and augment it to account for input market power (e.g., see De Loecker and Scott 2016; Mertens 2020; Morlacco 2020) to recover markups of price over marginal cost. We present the approach here briefly and refer the reader to the appendix for details. Based on the firm's first-order condition of cost minimization, market power in the output market, i.e., markup (μ), is defined as revenue (PY) over the firm's expenditures for a variable input j ($W_j X_j$) multiplied by the elasticity of output with respect to input j (θ_j) adjusted for market power in j's input market, i.e., markdown of j (ψ_j),

$$\mu = \frac{PY}{W_j X_j} \theta_j / \psi_j \quad . \tag{1}$$

While ψ_j is unique for each input j, μ is not. No matter which one of the j inputs we use, equation (1) will always produce the same markup μ (DLW). Hence, we can equate the right-hand side of equation (1) using different variable inputs so that

$$\frac{\psi_k}{\psi_j} = \frac{W_j X_j}{W_k X_k} \frac{\theta_k}{\theta_j}, j \neq k \quad . \tag{2}$$

Although we have estimated the output elasticities and can observe both input expenditures and revenue, we still have $j + 1$ unknowns, indicating that the system of j equations is under-determined (we must identify ψ for each j, and μ). However, if we are willing to assume that for some variable inputs, such as intermediate inputs, ψ equals one, i.e., there is no market power in input market (the input market is perfectly competitive), we can solve for μ, and for ψ for all variable inputs on which we do not impose perfect competition.

We estimate the following gross output production function to obtain estimates for θ:

$$y = \beta_k k + \beta_l l + \beta_m m + \beta_{kk} k^2 + \beta_{ll} l^2 + \beta_{mm} m^2 + \beta_{kl} kl + \beta_{km} km + \beta_{lm} lm + \omega + \varepsilon. \tag{3}$$

Here y, k, l, and m denote the logs of output, capital, labor, and material, respectively. ω captures firm-specific productivity and ε is a random error component. While data on physical quantities of labor and capital are available, this is not the case for output and materials. Deflated revenues are frequently used as a measure of output, just as input expenditures are used as a measure of physical input quantities. However, this leads to biased estimates of production function parameters (see e.g., Bond et al. 2021; Morlacco 2020).

Our strategy for dealing with the bias caused by the absence of output prices is closely related to our theoretical considerations. We assume that exporters and non-exporters typically charge different prices. Therefore, we deflate the revenues of all non-exporters by the same domestic price index, while exporters' domestic sales are deflated by the domestic price index and their export sales are deflated by an export price index. We then assume that most of the deviations from these price indices are firm-specific and that these firm-specific deviations change little over time. Therefore, we use firm-specific fixed effects (G_i) to account for firm-specific deviations from average industry prices. The use of firm-specific effects also captures variations in input prices (De Loecker et al. 2016) and accounts for product differentiation in the food sector by picking up unobserved price differences related to product differentiation (c.f. Bonnet and Bouamra-Mechemache 2016; Richards et al. 2018).[78] The production function is then specified as

$$y_{it}^{*} = G_i + \beta_k k_{it} + \beta_l l_{it} + \beta_m {m_{it}}^{*} + \beta_{kk} {k_{it}}^{2} + \beta_{ll} {l_{it}}^{2} + \beta_{mm} {m_{it}}^{*2} + \beta_{kl} k_{it} l_{it} + \beta_{km} k_{it} {m_{it}}^{*} + \beta_{lm} l_{it} {m_{it}}^{*} + \omega_{it} + \varepsilon_{it} \quad . \tag{4}$$

The only remaining unobservable is ω, which we proxy using material demand (Levinsohn and Petrin 2003).[79] We define material demand as a function of productivity (ω), capital, the firm's lagged export status as well as firm-fixed effects (G_i). Our parameter identification follows Ackerberg et al. (2015) and De Loecker (2013) who apply a two-step generalized method of moments (GMM) approach (see the appendix for details).

Once the GMM estimates have been identified, we can compute the output elasticity with respect to any of the inputs. Here, we are interested in labor and material, i.e., the variable inputs in the production process. We use the output elasticity and the expenditure share of materials in equation (1) to identify markups by assuming that $\psi_M = 1$. The markup estimates from materials can then be used to identify the divergence from perfect competition in the labor market by plugging μ into equation (1) specified for labor and solving for ψ_L.

S1.4 Regression Specifications and Estimation Techniques

In this section, we first specify regressions to test H1 and H2, i.e., to investigate the impact of markups on export participation and export intensity. Since only a small percentage of firms engage in exporting, the dataset contains a large number of zero trade values. Nevertheless, these zeros must be treated as meaningful observations (Helpman et al. 2008) as they represent the optimal choice for these firms. Therefore, we employ the Cragg hurdle regression (Cragg 1971; Garcia 2013; StataCorp 2017; Wooldridge 2010a).[80] The hurdle model is based on $EI_{it} =$

[78] Note: the authors used fixed effects to capture product differentiation when estimating a demand system.
[79] Here we also refer to Curzi et al. (2015) who use intermediate input as a proxy for unobserved productivity in the food sector.
[80] Note: we use a hurdle model, rather than modern gravity models that consider both the participation and decision to export, as the firm trade data in our study is not destination- specific. The hurdle model is also more flexible

$s_{it} * EI_{it}^{*}$ where EI_{it} denotes export intensity, while s_{it} is a latent variable capturing export participation defined as

$$s_{it} = \begin{cases} 1\ if\ \alpha_0 + \alpha_1 ln\mu_{it} + \boldsymbol{X}_{it}\,\boldsymbol{\gamma} + \epsilon_{it} > 0 \\ 0\ otherwise \end{cases}, \tag{5}$$

where μ_{it} reflects estimated markups.[81] The control variables and their corresponding coefficients are defined by the vectors $\boldsymbol{X}_{it}$ and $\boldsymbol{\gamma}$, respectively. We control for labor, capital and material (all in natural log form) to capture differences in factor intensity and size. We also consider year and industry dummies (at the four-digit NACE level) to account for trend and subsector-specific aggregate effects in the dependent variable, respectively. ϵ_{it} is a standard normally distributed error. EI_{it}^{*} is a continuous latent variable that is observed only if $s_{it} = 1$; it is specified in exponential form as:

$$EI_{it}^{*} = exp(\beta_0 + \beta_1 ln\mu_{it} + \ [\boldsymbol{X}_{it}, LagEI_{it}]\boldsymbol{\gamma} + \nu_{it}) \quad . \tag{6}$$

Hence, the hurdle model allows us to explore a firm's two-stage decision process (export participation and intensity) using the same explanatory variables for each decision stage but adding the lag of export intensity ($LagEI_{it}$) at the second stage to control for possible dynamic impacts of export intensity (e.g., see Damijan and Kostevc 2006).[82] In equations (5) and (6), markups are potentially endogenous to export behavior due to the simultaneity described above. We use a control function approach to deal with the potential correlation between $ln\mu_{it}$ and ν_{it} and consider three instrumental variables for this purpose. We use the lag of capital and the firm's legal form, both of which correlate strongly with revenue productivity, and therefore markups (see e.g., De Loecker 2007).[83] We also add firm age as an instrument as it can explain differences in revenue productivity as an important component of markup (Hsieh and Klenow 2009; Restuccia and Rogerson 2008). Moreover, markups vary systematically with firm age (Peters 2020).

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than a simple Tobit model as export participation and export intensity decisions are determined by different processes, which implies that the impact of the same variable may differ.

[81] We consider the logs of markups since markups have highly skewed distributions.

[82] Note: we are not interested in interpreting the coefficient of the lagged dependent variable and therefore ignore its possible correlation with the error term. Moreover, the Cragg hurdle model assumes that errors for the participation decision (first stage) and the quantity decision (second stage) are uncorrelated. However, the results are not sensitive when this assumption is relaxed (Ricker-Gilbert et al. 2011).

[83] Note: De Loecker (2007) uses these instruments in a matching treatment approach to analyze the relationship between firms' productivity and export status. See also Gaigné et al. (2018) for the importance of ownership structure on firm export behavior.

The LBE-related hypotheses (H3 and H4) are tested by investigating whether there is a significant difference between markups of firms that (i) were never active on an export market or left the export market following a period of export activity, (ii) starters, i.e., firms that enter the export market following a non-exporting period, and (iii) continuers, i.e., firms that are exporting and have been doing so for at least two consecutive years. We estimate the model as:

$$ln\mu_{it} = \lambda_0 + \lambda_1 Entry_{it} + \lambda_2 Continue_{it} + [\boldsymbol{X}_{it}, Lagln\mu_{it}]\boldsymbol{\gamma} + \nu_{it} \quad , \tag{7}$$

where $Entry_{it}$ is a dummy variable equal to one if a firm is an exporter during t but was not an exporter in $t-1$, while $Continue_{it}$ is a dummy variable equal to one when a firm exports during both t and $t-1$.[84] Consistent with earlier literature on the LBE effect, we also include the lagged dependent variable ($Lagln\mu_{it}$) on the right-hand side to capture the difference in markups due to entering and staying in the export market (e.g., see Fernandes and Isgut 2005; van Biesebroeck 2005). The constant term reflects the average markup for firms in the base group that have either never entered an export market or do not export during t. We are interested in the coefficients λ_1 and λ_2 that measure differences in markups between starters and continuing exporters compared to the firms in the base group.

In equation (7), $Entry$ and $Continue$ are potentially endogenous due to their being simultaneously determined with markups, and are therefore correlated with the error term, leading to biased estimates for λ_1 and λ_2. For this reason, we use an Extended Regression Model estimator (Stata Press 2019). This approach uses maximum likelihood estimation to determine the parameters of a joint distribution of an endogenous continuous dependent variable and binary endogenous covariates conditional on exogenous covariates. The likelihood function is defined as the product of the marginal distributions of error terms v_i with variance σ^2, $\phi(v_i, \sigma^2)$, and the cumulative joint distributions of the error terms in the reduced form equations for b endogenous binary covariates with lower limits $\boldsymbol{l}$ and upper limits $\boldsymbol{u}$ for each binary covariate and the adjusted correlation matrix of reduced form errors $\sum_{i,b|1}$, $\Phi_b^*(\boldsymbol{l}_i, \boldsymbol{u}_i, \boldsymbol{\Sigma}_{i,b|1})$ (Bartus and Roodman 2014; Roodman 2011; Stata Press 2019): [85]

[84] In addition to the highly skewed distributions observed for markups, an important advantage of using log markups as a dependent variable is that even if all variable inputs that are considered in computing markups are subject to adjustment costs, results of the regression analysis are unchanged as long as the export status is not related to those costs (DLW).

[85] Consider the correlation of error terms in structural and reduced form models as $\boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\Sigma}_b & \boldsymbol{\sigma}_b \\ \boldsymbol{\sigma}_b' & \sigma^2 \end{bmatrix}$ where $\boldsymbol{\Sigma}_b$ is the correlation of errors in reduced form models, σ^2 is the variance of errors in structural model, and σ is the correlation

$$LnL = \sum_{i=1}^{N} ş_i \, Ln\left\{\phi(v_i, \sigma^2)\, \Phi_b^*(\boldsymbol{l}_i, \boldsymbol{u}_i, \boldsymbol{\Sigma}_{i,b|1})\right\} \quad , \tag{8}$$

where $ş_i$ are weights.

This approach requires instrumental variables for the endogenous covariates that are correlated with $Entry$ and $Continue$ in the reduced form models, but uncorrelated with v_{it} in the structural model. We rely on the same set of instrumental variables (i.e., age, lagged capital and ownership) that we used above for markups, as the same underlying process simultaneously drives the firms' markups and export variables.

H5, "Exporters have higher markups than non-exporters," is tested empirically by relating estimated markups to firms' export status as follows:

$$ln\mu_{it} = \delta_0 + \delta_1 Export_{it} + \left[\boldsymbol{X}_{it}, Lagln\mu_{it}\right]\boldsymbol{\gamma} + v_{it} \quad , \tag{9}$$

where $Export_{it}$ denotes a binary variable equal to one if firm i is an exporter in period t and zero otherwise. Its associated coefficient δ_1 reflects the percentage markup performance premium for exporters. Since export status is likely endogenous to markups, we use the same identification and estimation strategy as in equation (8) with the difference that in equation (9), the cumulative distribution of errors terms is associated with only one endogenous binary covariate, $Export_{it}$, rather than a joint distribution of two endogenous covariates.

In the regressions specified in equations (5)-(7) and (9), we assess whether our results are robust to controlling markups for productivity. This involves regressing markups on productivity estimates so that the resulting residuals measure the part of markups that are unrelated to productivity. These 'productivity-adjusted' markups are then used in equations (5)-(7) and (9) in place of the original markups. Instruments and estimation techniques remain unchanged.

S1.5 Data and Descriptive Statistics

We use firm-level data from the ORBIS database provided by Bureau van Dijk (Bureau van Dijk 2011). ORBIS contains financial data for firms in all European countries and economic sectors. The database also contains information on firms' export participation and total export sales. We selected all French firms involved in manufacturing food or beverages as defined by

of error terms in each reduced form model with the error terms in structural model. The adjusted correlation matrix of reduced form model errors is defined as $\boldsymbol{\Sigma}_{i,b|1} = \boldsymbol{\Sigma}_b - \frac{\sigma_b \sigma_b'}{\sigma^2}$. Accordngly, the cumulative joint distribution of the error terms in the reduced form equations is $\Phi_b^*(\mathbf{l}_i, \mathbf{u}_i, \boldsymbol{\Sigma}_{i,b|1}) = \int_{l_1}^{u_1} \ldots \int_{l_d}^{u_d} \phi(\boldsymbol{\varepsilon}, \boldsymbol{\Sigma}_{,b|1})\, d\varepsilon_1 \ldots\, d\varepsilon_d$. For details on the likelihood function, see also Stata Press (2019).

NACE codes 10 and 11 in the years from 2011 to 2019. While information on other countries is readily available in ORBIS, France is the only country where the number of firms that publish their export revenues is sufficient to support an empirical analysis in line with the objectives of our study. There are a total of 28,618 observations in our sample comprising 11,104 firms, where each observation refers to a legal entity publishing its financial information in a specific year. Table S1.1 compares our sample with the population with respect to size categories. We see that the sample reflects about 18.6 percent of the total number of firms (59,757) in French food processing industry and adequately represents the distribution of the population with respect to size (Table S1.1). Note that small firms are slightly underrepresented due to lower requirements with respect to financial information disclosure for companies with fewer than ten employees (European Commission 2013).

Table S1.1 Comparison of the Sample and Population of Food Processors in France by Firm Size

	Sample	**Population [as of 2015]**
Total number of firms	11,104	59,757
Percentage share of firms per size class		
Small firms	91.30	97.59
Medium firms	6.36	1.87
Large firms	2.34	0.54

Note: Small: <50 employees; medium: 50–249 employees; large: >249 employees.

Source: Shares for the population are calculated based on Eurostat (2019a). Shares for the sample based on ORBIS

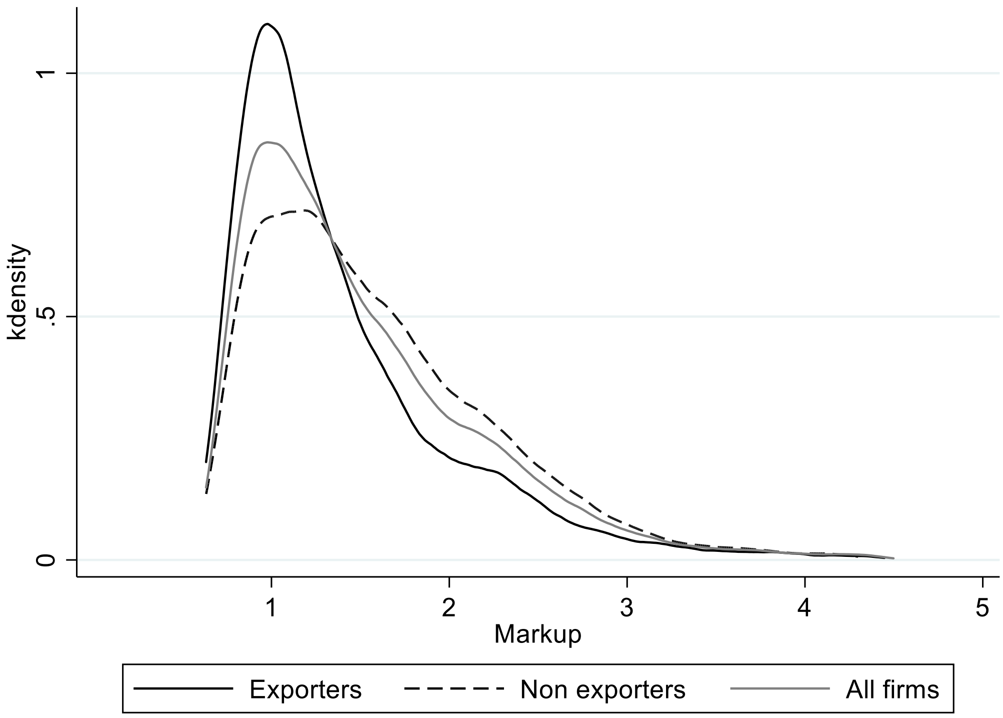
Table S1.A1 of the appendix provides descriptive statistics for the firm-level variables. Labor is defined as the number of employees used to estimate the production function. We use deflated material costs for materials and the value of fixed assets for capital. The production function is estimated by deflating material costs and capital using the respective industrial producer price indices with base year 2015 (Eurostat 2019c). Revenue is deflated to obtain a measure of physical output. While the domestic price index is the harmonized index of consumer prices (Eurostat 2019b), we construct an industry-specific price index for exports using data on country-level export quantities and prices from PRODCOM (Eurostat 2020). The overall sample shows considerable variations in firm revenues, input variables, export intensity (only applicable to exporters) and firm characteristics, such as age and ownership (cf. Table S1.A1 of the appendix). These variables also tend to differ between exporters and non-exporters, with exporters having higher average revenues and input use. Moreover, exporters tend to be older firms compared to non-exporters.

Several studies show that estimates of production function coefficients and regression coefficients may be affected by outliers or faulty observations in firms' reported data (see for example, Cainelli et al. 2015; De Loecker et al. 2016; Demirer 2020; Hirsch et al. 2021; Hirsch et al. 2020). Therefore, we apply the BACON algorithm that identifies multivariate outliers using Mahalanobis distances (Billor et al. 2000; Weber 2010). This reduces the number of firms (firm-year specific observations) to 10,203 (24,594). Accordingly, we use two sets of observations for our analysis. We use "all observations" including outliers as our baseline data, then repeat the estimations using the "observations excluding outliers" as a robustness check.

S1.6 Results and Discussion

We present the mean of the estimated markups for all observations and compare the 10th, 50th, and 90th percentiles in Table S1.A3 of the appendix.[86] Our estimates show that ten percent of firms charge markups of less than 1.03 (i.e., a price that is no more than three percent above marginal cost), 50 percent charge markups below/above 1.84 (i.e., a price that is less/more than 84 percent above marginal cost) and ten percent charge markups greater than 2.75 (i.e., a price that is 175 percent above marginal cost). These results indicate a positively-skewed distribution (see Figure S1.1) and substantial variation across firms, supporting previous findings of firm-level heterogeneity in markups (e.g., Vancauteren 2013; Karagiannis et al. 2018; Garrone and Swinnen 2018; Curzi, Garrone, and Olper 2020).[87] The arithmetic mean of markups across all firms is 1.97; however, given the heterogeneity in firm size and the skewed distribution of markups, we calculate an average industry markup as the sales-weighted average of markups, and obtain a value of 1.29. This lies within the range of estimated average markups of 1.02 to 1.70 previously reported for the food processing sector (see Garrone and Swinnen 2018; Karagiannis et al. 2018; Lopez et al. 2018; Vancauteren 2013; Wilhelmsson 2006). Our results also show substantial variation in wage markdowns, suggesting the importance of considering firms' market power in the labor market (see Table S1.A3 of the appendix). There is also considerable heterogeneity in markups among firms operating in different subsectors of the food industry, as supported by the Bartlett test that rejects equality of variance, and hence means and medians, between almost all pairs of subsectors. This highlights the need for subsector dummy variables in our regression analysis.

[86] The production function coefficients associated with the markup estimation obtained from all observations is presented in Table S1.A2 of the appendix. The estimated coefficients indicate the importance of labor, capital and material inputs as well as the complementarity of labor and material inputs on firms' gross output.
[87] This resembles findings for the distribution of productivity across firms (e.g., Gabaix 2008).



Source: Own calculations based on ORBIS

Figure S1.1 Firms' Markup Distributions

S1.6.1 The Impact of Markups on Firms' Export Participation and Intensity

The results of the hurdle model in capturing the impact of markups on export participation and intensity as specified in equations (5) and (6) are reported in Table S1.2. The statistical significance of the coefficients on the reduced form residuals in both stages of the structural model shows the endogeneity of markups and ensures the other parameters are estimated consistently in this case.[88] The coefficient for markup in the export participation equation is positive for both datasets ("all observations" and "observations excluding outliers"). Since markups are measured in logarithmic form we derive the marginal effect of markups on levels.[89] The results are reported at the bottom of Table S1.2 and reveal that a one percent increase in markups increases the probability that a firm will participate in export markets by 0.018 (all

[88] The results from the reduced form equations are shown in Table S1.A4, column 1 of the appendix. It can be observed that the instruments significantly impact firm markups, particularly when the outliers are removed, which speaks for the suitability of instruments.

[89] Note: the Average Marginal Effect (AME) of markup on export participation is $AME = \varDelta P/\boldsymbol{\Delta} Ln\mu$ where P is the probability of export participation. We use a linear approximation of $\varDelta P/\mu$ as follows: $\varDelta P = AME * (Ln\mu_2 - Ln\mu_1)$ => $\varDelta P = AME *Ln \left(\frac{\mu_2}{\mu_1}\right)$. Accordingly, a one percent rise in markup results in $\varDelta P = AME *Ln\,(1.01)$. This indicates that a one percent increase in markups raises the probability of export participation by $\varDelta P$ percentage points, on average.

observations) and 0.006 percentage points (observations excluding outliers), on average. Table S1.2 also reveals that controlling for productivity lowers the positive effect of markups on the probability firms will participate in export markets, producing marginal effects of 0.016 and 0.006 for all observations and observations excluding outliers, respectively. This suggests that output quality and demand-side conditions influence firms' export decisions. These findings confirm H1 and H2 and are in line with recent theories of trade (e.g., Melitz and Ottaviano 2008) in terms of providing evidence that firms with higher markups and high-quality products self-select into export markets.

Table S1.2 Impact of Markups on Export Participation and Export Intensity

	All observations		**Excluding outliers**	
Export Status				
LnMarkup	4.070***		4.436***	
	(0.692)		(0.491)	
LnL	-0.957***	-0.711***	-0.938***	-0.940***
	(0.194)	(0.192)	(0.129)	(0.139)
LnM	1.624***	1.018***	1.768***	1.276***
	(0.243)	(0.177)	(0.176)	(0.132)
LnK	-0.293***	-0.230***	-0.345***	-0.341***
	(0.050)	(0.049)	(0.043)	(0.045)
LnMarkup (Adjusted)		2.838***		3.839***
		(0.611)		(0.458)
Residual from reduced	-3.888***	-2.676***	-4.237***	-3.692***
form equation	(0.694)	(0.612)	0.494	0.461
Constant	-12.032***	-5.643***	-12.351***	-5.823***
	(1.618)	(0.685)	(1.120)	(0.473)
Export Intensity				
LagExpInt	5.727***	5.738***	5.831***	5.838***
	(0.128)	(0.127)	(0.182)	(0.182)
LnMarkup	4.598***		2.346**	
	(1.218)		(0.997)	
LnL	-1.238***	-1.227***	-0.734***	-0.789***
	(0.339)	(0.337)	(0.263)	(0.285)
LnM	1.628***	1.188***	1.012***	0.804***
	(0.427)	(0.312)	(0.358)	(0.269)
LnK	-0.266***	-0.259***	-0.147*	-0.161*
	(0.089)	(0.087)	(0.089)	(0.094)
LnMarkup(Adjusted)		4.047***		2.211**
		(1.077)		(0.938)
Residual from reduced	-4.708***	-4.144***	-2.253**	-2.111**
form equation	(1.216)	(1.075)	1.000	0.940

Constant	-14.681***	-8.539***	-10.989***	-7.734***
Observations	14,944	14,944	12,177	12,177
LR Chi2	9449.25***	9434.64***	5347.67***	5333.23***
Log Likelihood	3421.281	3414.076	1432.890	1425.668
Marginal impacts on export participation				
LnMarkup	1.828*** (0.502) {0.018}		0.586** (0.256) {0.006}	
LnMarkup(Adjusted)		1.609*** (0.444) {0.016}		0.553** (0.240) {0.006}
Marginal impact on export intensity				
LnMarkup	1.705*** (0.368) [9.4]		0.677*** (0.161) [3.8]	
LnMarkup(Adjusted)		1.419*** (0.323) [7.8]		0.611*** (0.150) [3.3]

Notes: *LnMarkup(Adjusted)* refers to *LnMarkup* controlled for *LnProductivity*; Standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Numbers in {} refers to the approximated average change in the probability of export participation caused by a marginal increase of 1 percent in markups. Numbers in [] refer to the average percentage change in export intensity caused by a marginal change of 1 percent in markups (see footnotes 23 and 24). Sector and year dummies are included as explanatory variables.

Source: Own calculations based on ORBIS

The estimated coefficients that measure the effect of markups on export intensity are also positive. A one percent increase in markup before controlling for productivity leads to an increase in export intensity of 9.4 percent (all observations) and 3.8 percent (outliers excluded); after controlling for productivity the increases are 7.8 percent and 3.3 percent, respectively.[90] This suggests that export intensity has an elastic reaction to improvements in markups and quality.

S1.6.2 The Impact on Markups of Firms' Export Entry and Continuation

Here we assess the change in markups caused by entering into export markets. The results from the reduced form equations are shown in Table S1.A4 of the appendix and indicate that the ownership variable affects entry, and that both ownership and age influence the decision to continue export activities, in particular when outliers are removed from the data sample. Table S1.3 shows the result of estimating the regression specified in equation (7). The null hypothesis

[90] As in footnote 23, $\Delta\ EI = AME * Ln\,(1.01)$. Accordingly, the percentage change in export intensity is approximated by dividing $\Delta\ EI$ by the average export intensity of firms as reported in Table S1.A1 of the appendix.

of “no endogeneity” is only rejected in the case of the $Continue$ variable and when markups are not controlled for productivity, as indicated by the significant correlation of the error terms of the structural and reduced form equations in these cases. We use instruments for $Entry$ and $Continue$ but subsequently perform a robustness check to compare the results with the case where no instruments are used. The coefficient of the $Entry$ variable measures the markup premium or deduction in the first year of exporting. Although there is no evidence that entry has any effect on markups when all observations are used, the influence becomes clear when outliers are excluded; here, entry is associated with a 2.4 percent increase in markups. Similarly, when controlling for productivity differences, a firm’s first year after starting to export is associated with a 2.5 percent increase in markups. This result is in line with DLW and suggests that when a firm enters an export market, its markup performance improves. This may be due to the firm upgrading the quality of its products to be competitive in the export market, or to a decision to export to markets where the level of competition is lower than in the domestic country. As the difference between the markup premiums when entering the export market before and after controlling for productivity are almost equal, we infer that the markup premium is associated with price or quality variations.[91] Thus, our results support H3, i.e., the presence of an immediate learning effect that leads to improved efficiency and quality, but only when outliers are removed from the data.

The coefficient of the $Continue$ variable obtained with the dataset containing all observations suggests that firms that export for at least two consecutive years charge markups that are 2.1 percent higher than markups charged by firms that either exited the export market or never exported at all. This result is robust when outliers are excluded from the data, resulting in an increase in markups of 1.7 percent. When controlling for productivity differences the estimated coefficients are lower, with markups increasing by 1.5 percent for all observations and 1.3 percent for the sample that excludes outliers. These results indicate that continuing to export is related to marginal costs and price changes induced by learning effects that lead to improvements in productivity and product quality. Thus, our results support H4, i.e., the LBE hypothesis conditional on continuous exporting. The results are also consistent with the finding in DLW that by entering the export market firms can benefit from learning effects if they remain committed to exporting for at least two consecutive years.

[91] As DLW postulate, the small productivity differences shown here could also be related to measurement bias associated with productivity measurement.

Table S1.3 Learning by Exporting

	All observations		Excluding outliers	
Variables	**Markups**	**Markups controlled for productivity**	**Markups**	**Markups controlled for productivity**
LnL	0.067***	0.063***	0.057***	0.052***
	(0.004)	(0.004)	(0.004)	(0.005)
LnK	0.019***	0.018***	0.022***	0.020***
	(0.002)	(0.002)	(0.002)	(0.002)
LnM	-0.090***	-0.063***	-0.089***	-0.057***
	(0.005)	(0.004)	(0.006)	(0.004)
Lag.LnMarkup	0.756***		0.762***	
	(0.012)		(0.013)	
Enter	0.013	0.011	0.024**	0.025**
	(0.009)	(0.010)	(0.011)	(0.011)
Continue	0.021***	0.015**	0.017***	0.013**
	(0.006)	(0.006)	(0.006)	(0.006)
Lag. LnMarkup (Adjusted)		0.796***		0.811***
		(0.011)		(0.012)
Constant	0.495***	0.153***	0.469***	0.106***
	(0.033)	(0.024)	(0.036)	(0.027)
Correlation of error terms of structural and reduced form for Entry	.008	.008	-.0128	-.0117
	(0.014)	(0.015)	(0.019)	(.020)
Correlation of error terms of structural form and reduced form for Continue	-.017**	-.005	-.0203**	-.011
	(0.007)	(0.005)	(0.009)	(0.009)
Observations	14,944	14,944	14,944	14,944
Log Pseudo Likelihood	-1187.222	-1430.699	1838.646	1606.674
Wald Chi2	117834.18***	82410.17***	1082790.2*	79195.46*

Note: *LnMarkup (Adjusted)* refers to *LnMarkup* controlled for *LnProductivity*; Heteroskedasticty robust standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Sector and year dummies are included as explanatory variables.

Source: Own calculations based on ORBIS

In addition, as a robustness check we follow DLW by analyzing the effect of entering the export market and continuing to export without instrumenting these variables (see Table S1.A5 of the appendix). As in DLW, we use OLS but also apply Between Effects (BE) estimation.[92, 93] Moreover, since we reject the null hypotheses that markups and the natural log of markups are normally distributed based on a Shapiro-Wilk test, we use a novel and robust 0.5-quantile regression estimator for panel data that is particularly well-suited to handle the strong skewness and extreme values observed in estimated markups (Baker et al. 2016).[94] This allows us to assess the extent to which the coefficients of entry and continuation are affected by the skewness of markups. Table S1.A5 of the appendix shows that our results are robust to both the use of instruments and the skewed distribution of markups. More precisely, when using OLS and quantile estimation we find that firms' entry is associated with an increase in markups, while remaining in the export market for at least two consecutive years is associated with higher markups across all estimators (Table S1.A5).[95]

S1.6.3 Markup Differences: Exporters vs. Non-Exporters

Finally, in Table S1.4 we present the results from estimating the regression in equation (9) to show the difference in markups between exporters and non-exporters. The null hypothesis of "no endogeneity" with respect to export status is rejected (i.e., there is significant correlation between the correlation of the error terms in the structural and reduced form equations), except for the case where outliers are not excluded and markups are not controlled for productivity differences.[96] The coefficient of the binary export variable suggests a markup premium of 2.0 percent and 2.2 percent for exporters compared to non-exporters, based on datasets that include and exclude outliers, respectively. This result is consistent with DLW's study of firms in Slovenian manufacturing sectors and also with recent theories of international trade, such as those proposed by Bellone et al. (2016), Bernard et al. (2003) and Melitz and Ottaviano (2008), which suggest that exporters on average have higher markups than non-exporters. When we

[92] We refrain from estimating equations (7) and (9) using firm-fixed effects as a large number of firms (> 90 percent of exporters) in the dataset do not change their exporting status over time.

[93] Due to the asymptotic normality of the estimators, inference based on OLS and panel estimators is possible even in the absence of a normally distributed dependent variable (Wooldridge 2010b). A sample of 1,500 observations is large enough to assume that the central limit theorem will hold (Wooldridge 2010b), and our dataset comprises more than 15,000 observations.

[94] See Hirsch et al. (2020) for a recent application of quantile regression to agribusiness firm-level data.

[95] Note: we do not interpret the results from OLS, BE and quantile as causal relationship, as endogeneity is not controlled.

[96] The results from the reduced form equations are shown in Table S1.A4 of the appendix and reveal that both age and ownership structure impact firms' exporting behavior.

control for productivity the estimated coefficients are lower but still result in positive markup premiums of 1.5 percent and 1.7 percent, respectively. These results imply that exporting firms either have superior productivity and higher-quality products and/or that the demand conditions they face allow them to charge higher prices. As a robustness check, we estimate equation (9) using OLS, BE and quantile regression and continue to find that exporters have higher markup performance (see Table S1.A6 of the appendix). Consequently, our results also generally support H5.

Table S1.4 Difference Between Exporters' and Non-Exporters' Markup Performance

	All observations		Observations excluding outliers	
Variables	**Markups**	**Markups controlled for productivity**	**Markups**	**Markups controlled for productivity**
LnL	0.067***	0.063***	0.057***	0.052***
	(0.004)	(0.004)	(0.004)	(0.005)
LnK	0.019***	0.018***	0.022***	0.020***
	(0.002)	(0.002)	(0.002)	(0.002)
LnM	-0.090***	-0.063***	-0.089***	-0.057***
	(0.005)	(0.004)	(0.006)	(0.004)
Lag.LnMarkup	0.756***		0.762***	
	(0.012)		(0.013)	
Export status	0.020***	0.015**	0.022***	0.017***
	(0.005)	(0.005)	(0.006)	(0.006)
Lag. LnMarkup(Adjusted)		0.796***		0.811***
		(0.011)		(0.012)
Correlation of error terms in structural and reduced form	-.003	-.015**	-.0284**	-.0174**
	(.0073)	(0.007)	(0.008)	(0.008)
Constant	0.494***	0.153***	0.471***	0.108***
	(0.033)	(0.024)	(0.036)	(0.027)
Observations	14,944	14,944	12,177	12,177
WaldChi2	117838.90***	82413.92***	108254.57***	79180.83***
Log likelihood	313.194	68.401	2787.680	2555.187

Notes: *LnMarkup (Adjusted)* refers to *LnMarkup* controlled for *LnProductivity*; Heteroskedasticty robust standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Sector and year dummies are included as explanatory variables.

Source: Own calculations based on ORBIS

S1.7 Conclusion

This article investigates the relationship between firms' export behavior and markups for the case of the food processing sector in France, based on a dataset of 11,104 firms over the period from 2011-2019. The analysis of this relationship in the food sector is particularly relevant for firms' strategic orientation in competitive food markets as well as for understanding the impact of trade and domestic policies. Trade barriers in the food sector are higher than in other sectors of an economy, implying that trade policies could have direct implications for firms' markups and consumer welfare. Moreover, policies designed to improve firm efficiency and eradicate welfare losses due to market power could influence firms' export behavior.

We evaluate the relationship between firms' markups and export behavior focusing on (i) the impact of markups on export participation and intensity, (ii) the effect of entering the export market and of continuing to export for at least two years on markups, and (iii) differences in markup performance between exporters and non-exporters. We estimate firm-specific markups using a modification of DLW's production function approach, allowing for the possibility of imperfections in both output and input markets. Subsequently, we apply various regression specifications that address the reverse causality between firms' markups and export variables to evaluate the firm export-markup relationship.

Our results suggest that on average, firms in the French food processing industry charge prices that exceed marginal costs by 29 percent. Average markups differ significantly across and within subsectors. We also find that the distribution of markup values, both for the entire sample and for individual subsectors, exhibit a positive skew.

With respect to the impact of markups on export participation and intensity, our analysis reveals that higher markups increase the likelihood that a firm will engage in exporting and will also exhibit a higher export intensity. Our investigation of the effect of export market entry shows an immediate markup increase upon entry. Moreover, we detect that the markup increases further if export activities continue for at least two consecutive years. Finally, our findings indicate that exporters and non-exporters differ in terms of their ability to exercise market power, as firms with higher markups self-select into export markets. This enables them to charge even higher markups.

We also control for productivity differences to study the relationship between firm markups and export behavior. Theoretically, higher markups could be associated with differences in both marginal cost (i.e., productivity) and price. When we control for cost differences across firms we obtain similar results, albeit of lower magnitude. This suggests that factors other than productivity, such as product quality and demand-side conditions, are also important in explaining markup differences across firms and also affect the markup-export relationship. The observed relationship – even after controlling for productivity differences – highlights the importance of product quality and/or differentiation to a firm's choice of export destination markets when designing an export strategy.

The results have some important implications. The uneven distribution of markup values within the food industry in France – even within subsectors – suggests that domestic policy measures that are common to all firms may have adverse effects on domestic prices. These may be anti-trust policies but could also take the form of quality standards, for example, that increase the cost of production for most firms. In this setting low-markup firms are most likely to exit the market first so that the supply curve shifts upwards, leading to higher prices. Secondly, downward pressure on prices in the domestic market due to domestic policy measures incentivizes firms to participate in export markets, further reducing domestic supply.

The observed relationship between markup and export behavior suggests that firms can rely on internal adaptation to increase markups and participate in export markets. Once firms begin to export, markups may increase further. This implies a consistency in firms' decisions to increase markups by relying on firm-specific resources, and to participate in export markets.

The observed positive relationship also implies that policies intended to promote exports, particularly policies promoting border trade, may induce firms to charge higher prices in domestic markets. This is supported by our findings as firms' markups increase with experience in the export market. Hence, a policy promoting exports may have an adverse impact on domestic consumer welfare. Policymakers should consider these adverse effects carefully when weighing domestic anti-trust and/or export promotion measures.

There are some limitations to the research presented here. Despite our careful strategy to use firm-specific deflators to obtain a measure of firms' physical output, there could still be some unobserved variation in firm prices that affects the estimated markups. Therefore, the estimated markup values should be interpreted with caution. Data limitations meant that we could not attribute price differences to their potential sources, i.e., output or input qualities, and it was likewise not possible to differentiate demand-side conditions by market size, consumer preferences, or income levels. Accordingly, the markups here are the average of the markups in domestic and export markets. However, export pricing strategies, and thus markups, depend heavily on the destination market. Therefore, these results should be viewed with a degree of caution. Progress in this respect would require a richer dataset that includes firm-specific domestic production quantities and sales, as well as export quantities and prices differentiated by destination. A richer dataset would offer considerable scope for future research.

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S1.8 Appendix

S1.8.1 Measuring Markups

We adopt the DLW approach and augment it to account for input market power (see, e.g., De Loecker et al. 2016; Mertens 2020; Morlacco 2020) to recover markups of price (P) over marginal cost (MC), i.e., P/MC, from production data. Consider a firm's first-order condition of the Lagrangian (L) for the variable cost minimization problem:

$$\frac{\partial L}{\partial X_j} = W_j + \frac{\partial W_j}{\partial X_j} X_j - \lambda \frac{\partial Y(\cdot)}{\partial X_j} = 0 \;\Rightarrow\; W_j(1 + \frac{\partial W_j}{\partial X_j}\frac{X_j}{W_j}) = \lambda \frac{\partial Y(\cdot)}{\partial X_j} \quad , \tag{1}$$

where X_j is the quantity of variable input j that firms may adjust at any point in time, and W_j is the price of input j.[97] $\frac{\partial W_j}{\partial X_j}$ reflects the marginal effect on the variable input price W_j of a one unit change in a firm's demand for X_j, λ is marginal cost and $Y(.)$ is the production function that produces output Y. The term $\lambda \frac{\partial Y(\cdot)}{\partial X_j}$ denotes the shadow value of an additional unit of X_j, i.e., the marginal valuation of input X_j. Under perfect competition in input markets, $\frac{\partial W_j}{\partial X_j}$ equals zero because no firm can influence its input prices and therefore the unit price W_j associated with a purchase of input X_j is equal to the marginal value of an additional unit of X_j. In the case of imperfect competition in an input market ($\frac{\partial W_j}{\partial X_j} \neq 0$), the expression $1 + \frac{\partial W_j}{\partial X_j}\frac{X_j}{W_j}$, defined here as ψ_j, denotes the wedge between the unit price of input X_j and its marginal valuation, i.e., a markdown, and is a measure of market power in the input market.

Multiplying both sides of equation (1) by X_j/Y and P/P, where P is the output price yields

$$W_j\, \psi_j\, \frac{X_j}{Y} = \frac{P}{P}\, \lambda \frac{\partial Y(\cdot)}{\partial X_j}\frac{X_j}{Y} \quad , \tag{2}$$

where $\frac{\partial Y(\cdot)}{\partial X_j}\frac{X_j}{Y}$ is the elasticity of output with respect to input j, which we denote as θ_j.

This results in firm markups $\mu = P/\lambda$ as

$$\mu = \frac{PY}{W_j X_j}\theta_j/\psi_j \quad . \tag{3}$$

[97] We suppress subscripts for firms and time periods for notational simplicity.

In the case of perfect competition in both input and output markets, μ equals one, i.e., output price P equals marginal cost λ, and the markdown is equal to one ($\psi_j = 1$), i.e., there is no market power in the input market for X_j. The share of expenditures on input j ($W_j X_j$) in terms of total revenue (PY) will then equal the elasticity of output with respect to input j (θ_j). If $\mu > 1$, the firm has market power in the output market and charges prices above the marginal cost. If $\mu < 1$, the firm charges a price below marginal cost and absorbs losses. This can have various causes, such as sunk costs or a strategy to continue serving a particular market (see, e.g., Caselli et al. 2018). In cases where the markdown exceeds one ($\psi_j > 1$), procuring firms are able to push input prices below the marginal value of the input. If the markdown is less than one ($\psi_j < 1$), the input price exceeds the competitive level; this may occur when the input supplier grants bulk discounts (Morlacco 2020), or when input providers' relative bargaining power outstrips that of input buyers (see Dobbelaere and Mairesse 2013; Morlacco 2020).

While ψ_j is unique to each of the j inputs, μ is not. No matter which of the j inputs we use in equation (3), it will always yield the same markup μ (DLW). Hence, we can equate the right-hand side of equation (3) for different variable inputs so that

$$\frac{\psi_k}{\psi_j} = \frac{W_j X_j}{W_k X_k} \frac{\theta_k}{\theta_j}, j \neq k \quad . \tag{4}$$

Given that we have estimated the output elasticities and can observe both input expenditures and revenue, we still have $j + 1$ unknowns, indicating that the system of j equations is under-determined (we must identify j ψ's and μ). However, if we are willing to assume that for some variable inputs, such as intermediate inputs, ψ equals one, i.e., firm has no market power in the input market (the input market is perfectly competitive), we can solve for μ as well as for ψ for all other variable inputs for which we do not impose perfect competition.

We estimate a gross output production function with three inputs, $Y = Y(L, K, M, \omega; \beta)$, where L is labor, K is capital, and M are materials, to obtain estimates for θ. ω captures firm-specific productivity that is known to the firm but not to the researcher (Ackerberg et al. 2015), and β are the parameters to be estimated. We specify Y as a second-order polynomial translog function so that the production function is:

$$y = \beta_k k + \beta_l l + \beta_m m + \beta_{kk} k^2 + \beta_{ll} l^2 + \beta_{mm} m^2 + \beta_{kl} kl + \beta_{km} km + \beta_{lm} lm + \omega + \varepsilon. \tag{5}$$

Here y, k, l, and m denote the logs of Y, K, L, and M, respectively, and ε is a random error term. While data on physical quantities of labor and capital are available, this is not the case for output and materials. Deflated revenues are frequently used as a measure of output, just as input expenditures are used as a measure of physical input quantities. However, this leads to biased estimates of the production function parameters and therefore produces biased estimates of the market power parameters in cases where a firm's price deviates from average industry prices (see, e.g., Bond et al. 2021; Morlacco 2020).

Our strategy for dealing with the bias caused by the absence of output prices is closely related to our theoretical considerations. We assume that exporters and non-exporters generally charge different prices. Our data allow us to distinguish between revenues generated in domestic versus export markets and to obtain an estimate of output (y^*) by calculating

$$y_{it}^* = \frac{P_{DOMit}Y_{DOMit}}{PI_{DOMt}} + \frac{P_{EXPit}Y_{EXPit}}{PI_{EXPt}} \quad , \tag{6}$$

where the subscripts DOM and EXP denote domestic and export destinations for prices and output quantities. PI_{DOMt} and PI_{EXPt} are the domestic and export price indexes in each industry in year t. That is, revenues for all non-exporters are deflated by the same price index while domestic sales of exporters are deflated by PI_{DOMt} and export sales of exporters are deflated by PI_{EXPit}. Deflating the revenues of exporters leads to a firm-specific price index for exporters that depends on the share of their sales generated in the domestic and export markets. It is debatable whether all firms in the domestic market receive the same price, i.e., $P_{DOMit} - PIDOM_t = 0 \; \forall \; i, t$. The same is true for firms' export prices (P_{EXPit}) and the export price index $(PIEXP_t)$. For instance, firms might serve a specific foreign market based on well-established relationships in that country. If the price in this particular market systematically differs from the average export price in the industry, our measure of output is biased. However, we could assume that all deviations from these price indices are firm-specific and that these firm-specific deviations change little over time. We can then use firm-specific fixed effects to account for the firm-specific deviations from average industry prices.

Similarly, if the firm-specific price for material (W_{Mit}) differs from the industry-average price $(\bar{W}_M)$, we would obtain a biased measure for a firm's material deployment (W_M). Differences in input prices will arise in perfectly competitive markets due to local factors or differences in input quality (see, e.g., De Loecker et al. 2016). Since agricultural outputs that serve as intermediate inputs in the food processing sector are homogeneous and subject to strict quality standards, we assume that local factors are the only cause of variations in W_{Mit}. We follow De Loecker et al. (2016) and use firm-fixed effects (G_i) to proxy for the unobserved variation in input prices. By doing so, we also account for product differentiation in the food sector as firm-fixed effects pick up unobserved price differences related to product differentiation (c.f. Bonnet and Bouamra-Mechemache 2016; Richards et al. 2018).[98] The production function is then specified as

$$y_{it}^* = G_i + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it}^* + \beta_{kk} k_{it}^2 + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^{*2} + \beta_{kl} k_{it} l_{it} + \beta_{km} k_{it} m_{it}^* + \beta_{lm} l_{it} m_{it}^* + \omega_{it} + \varepsilon_{it} \quad . \tag{7}$$

The only remaining unobservable is ω, which we proxy using material demand (Levinsohn and Petrin 2003).[99] The intuition here is that material demand is a function of productivity (ω), the dynamic inputs and other exogenous variables (z), and firm-fixed effects (G_i):

$$m_{it}^* = f_t(\omega_{it}, z_{it}, G_i) \quad , \tag{8}$$

where z is a vector capturing the dynamic inputs[100] and exogenous variables affecting material demand. We can invert (8) so that productivity is given by

$$\omega_{it} = g_t(m_{it}^*, z_{it}, G_i) \quad . \tag{9}$$

The dynamic variable is capital and we use a firm’s lagged export status as an instrument in z. Parameter identification is based on Ackerberg et al. (2015). We apply a two-step generalized method of moments (GMM) approach. In the first stage, we run a non-parametric regression

$$y_{it}^* = \kappa_t(l_{it}, k_{it}, m_{it}^*, z_{it}, G_i) + \varepsilon_{it} \quad , \tag{10}$$

from which we obtain estimates for expected output ($\hat{\kappa}_{it}$) and for $\hat{\varepsilon}_{it}$. We approximate κ_t as a high-order polynomial of its arguments. The parameters are identified in the second stage using the law of motion of productivity and by proxying the productivity process as a first-order autoregressive process of past productivity and the past export status following De Loecker (2013):[101]

$$\omega_{it} = h_t(\omega_{it-1}, e_{it-1}) + \xi_{it} \quad . \tag{11}$$

[98] Note: the authors used fixed effects to capture product differentiation when estimating a demand system.
[99] We also refer to Curzi et al. (2015) who use intermediate input as a proxy for unobserved productivity in the food sector.
[100] Inputs are defined as dynamic if their choice in a given year affects firms’ profits in other years.
[101] When detecting learning by exporting it is important to allow for the endogenous productivity process (i.e., allow firms’ current actions to affect future productivity) in the estimation of the production function (De Loecker 2013).

We calculate estimates for productivity ($\widehat{\omega}_{it}$) after the first stage as $\hat{\kappa}_{it} - (\hat{\beta}_k k + \hat{\beta}_l l + \hat{\beta}_m m^* + \hat{\beta}_{kk} k^2 + \hat{\beta}_{ll} l^2 + \hat{\beta}_{mm} m^{*2} + \hat{\beta}_{kl} kl + \hat{\beta}_{km} km^* + \hat{\beta}_{lm} lm^*)$. In the second stage, we identify the parameters of the production function and regress ω_{it} on its lag and on past export status in $t-1$ non-parametrically, using a third-order polynomial to approximate h_t. We can then form the moments for the GMM procedure to recover the production function coefficients (Ackerberg, Caves and Frazer 2015):

$$E[\xi_{it}|l_{it-1}, m_{it-1}^*, k_{it}, l_{it-1}^2, m_{it-1}^{*2}, k_{it}^2, l_{it-1}m_{it-1}^*, l_{it-1}k_{it}, m_{it-1}^*k_{it}] = 0 \quad , \tag{12}$$

Hence, we assume that the capital deployed in t is chosen in $t-1$. We expect that the current choice of variable inputs, labor, and materials, is correlated with shocks to productivity so that $E[\xi_{it}|l_{it}, m_{it}] \neq 0$. Therefore, we rely on lagged labor and material to identify their corresponding parameters.

Once the GMM estimates have been identified, we can compute the output elasticity with respect to any of the inputs. In our case, we are interested in labor and material, i.e., the variable inputs in the production process. We use the output elasticity and the expenditure share of materials in equation (3) to identify markups. This is achieved by assuming that $\psi_M = 1$. The markup estimates from materials can then be used to identify any divergence from perfect competition in the labor market by plugging μ into equation (3), specified for labor and solving for ψ_L.

Table S1.A1 Descriptive Statistics

	All	Non-Exporters	Exporters
Number of firm-level observations	28,618	21,300	7,318
Mean revenues [€1,000]	18,190	5,087	61,783
	(114,306)	(47,399)	(215,854)
Mean number of employees	42	17	126
	(181)	(88)	(327)
Mean of export status dummy	0.256	-	-
	(0,422)		
Mean fixed assets [€1,000]	4,905	1,528	16,100
	(36,700)	(20,700)	(65,100)
Mean material cost [€1,000]	11,152	2,899	38,612
	(83,279)	(26,816)	(163,212)
Mean firm age [years]	17	14	29
	(17.3)	(14.9)	(19.5)
Mean export intensity			0.18
			(.24)
Legal forms of firms			
Partnerships(%)	5.1	3.8	9.3
Private limited companies(%)	83.7	88.6	67.3
Public limited companies(%)	11.0	7.3	23.4
Sole trader proprietorships(%)	0.24	0.30	0.04
Other legal forms(%)	0.01	0.01	0.01

Source: Own calculations based on ORBIS

Table S1.A2 Production Function Estimation Results

Variable	**Estimate**	**(Standard error)**
LnL	0.191	(0.026)***
LnK	0.052	(0.027)*
LnM	0.573	(0.025)***
$(LnL)^2$	0.031	(0.026)
$(LnK)^2$	0.011	(0.027)
$(LnM)^2$	0.041	(0.027)
(LnM)(LnK)*	0.030	(0.024)
(LnL)(LnM)*	-0.073	(0.028)***
(LnK)(LnM)*	-0.035	(0.025)
Observations	28,618	

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Firm dummies are included as explanatory variables.

Source: Own calculations based on ORBIS

Table S1.A3 Average and Median Markup/Markdown for Food Industry

Industry	NACE codes	Number of firms	Average	10th Percentile	Median	90th Percentile	Weighted average
Aggregate industry markup			1.97	1.03	1.84	2.75	1.29
Processing and preserving of meat	1011	1040	2.51	0.92	0.94	6.92	0.97
Processing and preserving of poultry meat	1012	533	2.06	0.87	1.06	2.13	1.50
Production of meat and poultry meat products	1013	2377	1.50	1.00	1.29	1.80	1.29
Processing and preserving of fish, crustaceans, and mollusks	1020	403	1.34	0.79	1.16	2.00	1.18
Processing and preserving of potatoes	1031	37	1.55	0.97	1.41	2.27	1.35
Other processing and preserving of fruit and vegetables	1039	700	1.71	0.78	1.17	3.29	1.26
Manufacture of oils and fats	1041	238	1.53	0.78	1.25	2.13	0.82
Manufacture of margarine and similar edible fats	1042	1	1.25	1.25	1.25	1.25	1.25
Operation of dairies and cheese making	1051	1294	1.20	0.77	0.98	1.44	1.04
Manufacture of grain mill products	1061	657	1.20	0.88	1.12	1.47	1.16
Manufacture of starches and starch products	1062	8	1.15	0.71	1.20	1.46	1.18
Manufacture of bread; manufacture of fresh pastry goods and cakes	1071	14231	2.22	1.60	2.20	2.80	1.66
Manufacture of rusks and biscuits; manufacture of preserved pastry goods and cakes	1072	377	1.97	1.12	1.76	3.08	1.49
Manufacture of macaroni, noodles, couscous, and similar farinaceous products	1073	128	1.84	1.23	1.77	2.56	1.55
Manufacture of sugar	1081	45	1.51	1.04	1.40	2.10	1.45
Manufacture of cocoa, chocolate, and sugar confectionery	1082	681	2.48	1.32	2.11	3.38	1.74
Processing of tea and coffee	1083	332	1.93	1.05	1.54	2.75	1.77
Manufacture of condiments and seasoning	1084	181	1.45	1.10	1.36	1.88	1.33
Manufacture of prepared meals and dishes	1085	560	1.76	0.78	1.49	2.82	1.46
Manufacture of homogenized food preparations and dietetic food	1086	151	2.19	0.94	1.63	3.98	2.14
Manufacture of other food products n.e.c.	1089	657	1.93	0.85	1.45	3.03	1.08
Manufacture of prepared feeds for farm animals	1091	842	1.09	0.77	0.90	1.58	0.89
Manufacture of prepared pet foods	1092	140	1.24	0.84	1.25	1.59	1.42
Distilling, rectifying, and blending of spirits	1101	680	2.07	0.83	1.48	3.61	1.71

Manufacture of wine from grapes	1102	1770	1.67	0.77	1.09	1.98	1.25
Manufacture of cider and other fruit wines	1103	48	2.26	1.07	1.61	3.66	1.27
Manufacture of other non-distilled fermented beverages	1104	6	2.09	0.96	1.77	3.92	1.82
Manufacture of beer	1105	228	2.57	1.34	2.39	3.59	2.56
Manufacture of malt	1106	21	1.74	0.82	0.97	4.32	1.06
Manufacture of soft drinks; production of mineral waters and other bottled waters	1107	252	2.56	1.03	1.83	3.07	1.75
Aggregate industry markdown			0.42	0.07	0.17	1.08	0.70

Notes: Weights in the last column for the calculation of weighted markups represent the share of each firm’s value added in the sub-industry value added. The weights in calculation of markdowns represent the share of each firm’s employment in total employment of the associated sub-industry.

Source: Own calculations based on ORBIS

Table S1.A4 Reduced Form Equations Estimation Results

	All Observations					Observations excluding outliers				
Variables	***LnMarkup***	***LnMarkup (Adjusted)***	***Export Status***	***Entry***	***Continue***	***LnMarkup***	***LnMarkup (Adjusted)***	***Export Status***	***Entry***	***Continue***
L.logk	0.019***	0.020***	-0.034	-0.074	-0.042	0.023***	0.028***	0.052	-0.032	0.050
	(0.006)	(0.007)	(0.040)	(0.057)	(0.043)	(0.006)	(0.006)	(0.048)	(0.061)	(0.055)
age	0.000*	0.000***	0.002***	-0.001	0.003***	0.001***	0.001***	0.002**	-0.001	0.003***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
legalform2	-0.112*	-0.060	-0.708	3.699	-0.890*	0.081***	0.075***	0.832***	0.182	0.741***
	(0.061)	(0.066)	(0.464)	(270.832)	(0.531)	(0.013)	(0.014)	(0.084)	(0.125)	(0.084)
legalform3	-0.096	-0.060	-0.198	3.735	-0.452	0.138***	0.137***	0.985***	0.194	0.890***
	(0.060)	(0.065)	(0.459)	(270.832)	(0.528)	(0.014)	(0.016)	(0.092)	(0.133)	(0.093)
legalform4	-0.050	-0.007	-0.072	3.712	-0.314	0.162***	0.142**	1.121**	-3.288***	1.391***
	(0.060)	(0.066)	(0.461)	(270.832)	(0.529)	(0.053)	(0.060)	(0.472)	(0.194)	(0.472)
logl	0.275***	0.310***	0.152***	-0.026	0.177***	0.246***	0.287***	0.127***	-0.028	0.194***
	(0.003)	(0.004)	(0.020)	(0.031)	(0.021)	(0.004)	(0.004)	(0.028)	(0.040)	(0.030)
logk	-0.350***	-0.290***	0.018	0.070	0.021	-0.356***	-0.284***	-0.017	0.017	-0.010
	(0.003)	(0.003)	(0.041)	(0.058)	(0.044)	(0.003)	(0.003)	(0.048)	(0.062)	(0.056)
logm	0.051***	0.058***	0.213***	0.012	0.204***	0.061***	0.068***	0.217***	0.070**	0.192***
	(0.006)	(0.007)	(0.016)	(0.024)	(0.016)	(0.006)	(0.006)	(0.021)	(0.034)	(0.023)
Constant	2.406***	1.126***	-2.456***	-5.178	-2.456***	1.905***	0.716***	-3.881***	-2.005***	-4.041***
	(0.069)	(0.075)	(0.501)	(270.832)	(0.557)	(0.033)	(0.048)	(0.299)	(0.422)	(0.313)
Observations	14,944	14,944	14,944	14,944	14,944	12,177	12,177	12,177	12,177	12,177
R-squared	0.712	0.548				0.728	0.571			

Notes: *LnMarkup(Adjusted)* refers to *LnMarkup* controlled for *LnProductivity*; Heteroskedasticity robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Sector and year dummies are included as explanatory variables.

Source: Own calculations based on ORBIS

Table S1.A5 Learning by Exporting Robustness Checks (All Observations Included)

	Markups			Markups controlled for productivity		
Variables	**OLS**	**BE**	**Quantile**	**OLS**	**BE**	**Quantile**
Lag.LnMarkup	0.756***	0.872***	0.935***			
	(0.014)	(0.006)	(0.000)			
LnL	0.067***	0.034***	0.020***	0.063***	0.028***	0.018***
	(0.005)	(0.003)	(0.000)	(0.004)	(0.003)	(0.000)
LnM	-0.089***	-0.048***	-0.026***	-0.063***	-0.030***	-0.018***
	(0.005)	(0.003)	(0.000)	(0.004)	(0.002)	(0.000)
Lnk	0.019***	0.011***	0.005***	0.018***	0.010***	0.004***
	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)
Enter	0.015*	0.013	0.007***	0.014*	0.011	0.006***
	(0.008)	(0.010)	(0.000)	(0.008)	(0.010)	(0.000)
Continue	0.016***	0.016***	0.015***	0.014***	0.014***	0.015***
	(0.005)	(0.005)	(0.000)	(0.005)	(0.005)	(0.000)
Lag.LnMarkp (Adjusted)				0.796***	0.903***	0.947***
				(0.011)	(0.005)	(0.000)
Constant	0.493***	0.253***		0.153***	0.056***	
	(0.035)	(0.021)		(0.025)	(0.018)	
Observations	14,944	14,944	15,408	14,944	14,944	15,408
R-squared	0.888	0.883		0.847	0.842	
Number of firms	6,405	6,405	6,489		6,405	6,489

Notes: *LnMarkup(Adjusted)* refers to *LnMarkup* controlled for *LnProductivity*; Heteroskedasticty robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Sector and year dummies are included as explanatory variables.

Source: Own calculations based on ORBIS

Table S1.A6 Exporters vs. Non-Exporters Robustness Checks (All Observations Included)

	Markups			Markups controlled for productivity		
Variables	**OLS**	**BE**	**Quantile**	**OLS**	**BE**	**Quantile**
Lag.LnMarkup	0.756***	0.872***	0.927***			
	(0.014)	(0.006)	(0.001)			
Lnl	0.067***	0.034***	0.017***	0.063***	0.028***	0.019***
	(0.005)	(0.003)	(0.000)	(0.004)	(0.003)	(0.001)
LnM	-0.089***	-0.048***	-0.021***	-0.063***	-0.030***	-0.019***
	(0.005)	(0.003)	(0.001)	(0.004)	(0.002)	(0.001)
LnK	0.019***	0.011***	0.004***	0.018***	0.010***	0.004***
	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)
Export dummy	0.016***	0.015***	0.041***	0.014***	0.013***	0.014***

	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.001)
Lag.LnMarkup (Adjusted)				0.796***	0.903***	0.946***
				(0.011)	(0.005)	(0.002)
Constant	0.493***	0.253***		0.153***	0.056***	
	(0.035)	(0.021)		(0.025)	(0.018)	
Observations	14,944	14,944	15,408	14,944	14,944	15,408
R-squared	0.888	0.883		0.846	0.842	
Number of firms	6,405	6,405	6,489		6,405	6,489

Notes: *LnMarkup(Adjusted)* refers to *LnMarkup* controlled for *LnProductivity*; Heteroskedasticty robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Sector and year dummies are included as explanatory variables.

Source: Own calculations based on ORBIS

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S2 Power Imbalances in French Food Retailing: Evidence from a Production Function Approach to Estimate Market Power

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Abstract

We analyze whether an association of firms to the dominant oligopoly of food retail groups is related to higher oligopoly market power. We apply a production function approach for the estimation of firm-level markups to a sample of 3,366 French food retailers over the period 2006-2014. The results suggest the presence of power imbalances between firms of the dominant oligopoly and fringe firms. We also detect a positive connection between markups and profitability pointing to a reduction in consumer welfare due to retailers' oligopoly market power.

S2.1 Introduction

EU food retailing is characterized by the presence of dominant oligopolies of large-scale retailing groups that operate alongside a considerable number of smaller fringe retailers (Ellickson 2007, 2013; EY et al. 2014). The associated potential for large retailers to exert market power can lead to power imbalances with adverse effects on the competitiveness of smaller stores, consumer welfare and overall value chain efficiency (e.g., Cotterill 1999; De Loecker et al. 2020; European Competition Network 2012; OECD 2014; Sexton and Xia 2018). This has made potential abuses of market power by dominant retailers a top priority on the policy agenda of EU antitrust authorities (OECD 2014).

In this article, we evaluate whether an association of firms to the dominant oligopoly of the largest six (Top-6) food retailing groups is related to higher oligopoly markups of prices over marginal costs. We thereby focus on French food retailing which comprises the largest EU food retailing sector with a sales volume of $366 billion (Eurostat 2019; USDA 2019). The six largest French food retailers account for approximately 90 percent of the market share such that the sector is characterized by considerable concentration[102] providing a favorable environment for unfair commercial practices (OECD 2014). Accordingly, the sector has been subject to several antitrust monitoring actions focusing on competition of large-scale retailers (European Competition Network 2012). Just in November 2019, the European Commission has initiated an investigation of potential collusion by two French retailers (European Commission 2019).

Several papers report evidence for the presence of oligopoly and oligopsony market power of food sector firms (e.g., Cakir and Balagtas 2012), or food retailers in particular (e.g., Gohin and Guyomard 2000; McCorriston 2014; Salhofer et al. 2012; Sckokai et al. 2013). However, these studies are based on approaches from the New Empirical Industrial Organization (NEIO) which impose restrictive assumptions and data requirements (Corts 1999; Sexton 2000; Sheldon 2017). Therefore, we use a production function approach (PFA) introduced by Hall (1988) and De Loecker and Warzynski (2012) that overcomes these drawbacks. While the PFA has been applied in empirical work on manufacturing (e.g., Caselli et al. 2018), publicly traded (e.g., De Loecker et al. 2020) and food processing firms (e.g., Vancauteren 2013; Wilhelmsson 2006) little attention has been paid to food retailing.

We go beyond previous work and assess markup differences between firms in the dominant oligopoly and fringe retailers. Our results suggest that firms associated to a Top-6 retail group

[102] The six largest food retailers are Auchan, Carrefour, Casino, E.Leclerc, ITM, and System U (OECD 2014).

generate significantly higher markups. We also detect a positive relationship between markups and profitability pointing to diminishing consumer welfare due to retail market power.

In the following we outline the PFA approach for the estimation of firm-level markups. The next section describes the dataset followed by the presentation of our results. The final section concludes.

S2.2 Estimation of Markups

Suppose that firm i in period t produces according to the following production function (De Loecker and Warzynski 2012; Hall 1988):

$$Q_{it} = Q_{it}(X_{it}^1, \dots, X_{it}^n, K_{it}, \omega_{it}) \quad , \tag{1}$$

where Q_{it} is output[103] X_{it}^n are variable and intermediate inputs (labor and material), K_{it} is capital while ω_{it} reflects productivity (Ackerberg et al. 2015; Gandhi et al. 2017). It is further assumed that firms are cost minimizers which leads to the following Lagrangian:

$$L(X_{it}^1, \dots, X_{it}^n, K_{it}, \lambda_{it}) = \sum_{n=1}^{N} p_{it,n} X_{it}^n + r_{it} K_{it} - \lambda_{it}(Q_{it}(\cdot) - Q_{it}) \quad , \tag{2}$$

where $p_{it,n}$ and r_{it} reflect prices for variable inputs and capital. The FOC of (2) w.r.t. variable input n is:[104]

$$\frac{\partial L_{it}}{\partial X_{it}^n} = p_{it,n} - \lambda_{it} \frac{\partial Q_{it}(\cdot)}{\partial X_{it}^n} = 0 \quad , \tag{3}$$

where λ_{it} reflects marginal costs of input n. Rearranging (3) and multiplying with $\frac{X_{it}^n}{Q_{it}}$ and $\frac{p_{it}}{p_{it}}$ leads to:

$$\frac{\partial Q_{it}(\cdot)}{\partial X_{it}^n} \frac{X_{it}^n}{Q_{it}} = \theta_{it}^x = \frac{p_{it}}{\lambda_{it}} \frac{p_{it,n} X_{it}^n}{p_{it} Q_{it}} \quad . \qquad (4).$$

Since markup is defined as $\mu_{it} = \frac{p_{it}}{\lambda_{it}} - 1$, (4) can be rewritten as:

$$\mu_{it} = (\theta_{it}^x / \alpha_{it}^n) - 1 \quad . \qquad (5).$$

Thus, firm-level markup can be calculated as the quotient of output elasticity of input n (θ_{it}^x) and this input's expenditure share in total sales (α_{it}^n) minus one. While α_{it}^n can be directly

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[103] We use harmonized consumer price indices to convert value added to physical measures of output (Eurostat 2020).

[104] Note that the calculation of markups does not depend on the variable input used for deriving the FOC in (3).

calculated from accounting data θ_{it}^{x} relies on the estimation of $Q_{it}(\cdot)$ for which we assume a second-order polynomial translog specification. To account for endogeneity in the estimation of $Q_{it}(\cdot)$, we follow Ackerberg et al. (2015) and use a two-step generalized method of moments (GMM) control function approach with intermediate input material[105] as proxy variable and the Top-6 status of retailers as additional control variable potentially affecting optimal input demand (De Loecker and Warzynski 2012; Gandhi et al. 2020)[106].

Subsequently, we estimate the relationship of markups and association of firms to a Top-6 retailing group using a (robust) 0.5-quantile regression panel estimator (0.5-qregpd). We thereby consider the relevance of different retailing formats as well as firm and industry controls that are related to market power based on IO and strategic management theory. The 0.5-qregpd estimator is particularly suited to capture the high skewness of estimated markups, and allows to address potential endogeneity (Powell 2022).

Markups can arise through a variety of reasons that are not associated with a decline in welfare such as innovations that increase the firm's fixed-cost share forcing it to generate higher markups in order to retain profitability. In this case, markups are not necessarily positively related to profitability and do not have to imply welfare decreasing market power (De Loecker et al. 2020). We therefore relate markups and profitability using a dynamic panel model to assess the presence of welfare reducing market power. This model captures the dependence of profitability over time and can be estimated with the Arellano and Bond GMM approach (e.g., Baltagi 2013).

S2.3 Data

We utilize information from the AMADEUS accounting database on firms operating in French food retailing defined by NACE classes G47.11 and G47.2. Financial reports are available at the legal-entity-level, i.e., for firms that operate one or several retail stores. Firms can either be associated to a retail chain or operate as individual retailers. Note that for those retail chains that are operated as cooperatives or franchisors data is available at the level of independent cooperative members or franchisees. Hence, although our data is not at the store level the

[105] This is based on the assumption that the respective gross output is proportional to material demand (Ackerberg et al. 2015) which appears reasonable for retailing firms.

[106] We assume that the Top-6 status is the best available proxy for the state of competition in food retailing and constitutes the main exogenous factor distinguishing firms optimal input demand through an advantageous bargaining position towards the food industry and well-coordinated sales and distribution channels, that can lead to competitive advantages and less vigorous competition in input markets for Top-6 firms.

average number of outlets a firm in the dataset operates is with 1.6 relatively small (cf. Table S2.A1).

Ownership information, company names and industry reports are used to identify firms that are associated to a "dominant" retailing group. Note that these groups potentially operate several chains with different store formats. We follow Ellickson (2007) and Ellickson (2013) and focus on the Top-6 groups as a clear bound on the sales captured by these retailing groups can be observed (OECD 2014). Moreover, a steep decline in sales from the sixth to lower ranked groups justifies treating non-Top 6 firms as fringe firms (USDA 2018, 2019).[107] We also control for the relevance of the $legal\ form$ (limited-private, limited-public, partnership/ cooperative) and the type of store(s) a firm runs distinguishing between $hypermarkets/supermarkets$, the most popular outlet format in French retailing (USDA 2018, 2019) and $individual/$ $specialized\ supermarkets$ including neighborhood stores. Amongst the Top-6 firms we additionally identify $discounters$ and firms running $convenience\ stores$ a typical store type in French retailing with longer opening hours and a smaller product assortment (Rudawska and Bilinska-Reformat 2018; USDA 2018). Finally, the following control variables that have previously been related to markups and profitability by IO and strategic management literature (e.g., Gschwandtner 2012) are added: $firm-size$, $growth$, age and $gearing$ as well as Herfindahl indices of industry concentration. The final sample comprises 3,366 French food retailing firms during 2006-2014. For variable definitions and descriptive statistics, we refer to Table S2.A1 in the appendix.

S2.4 Empirical Results

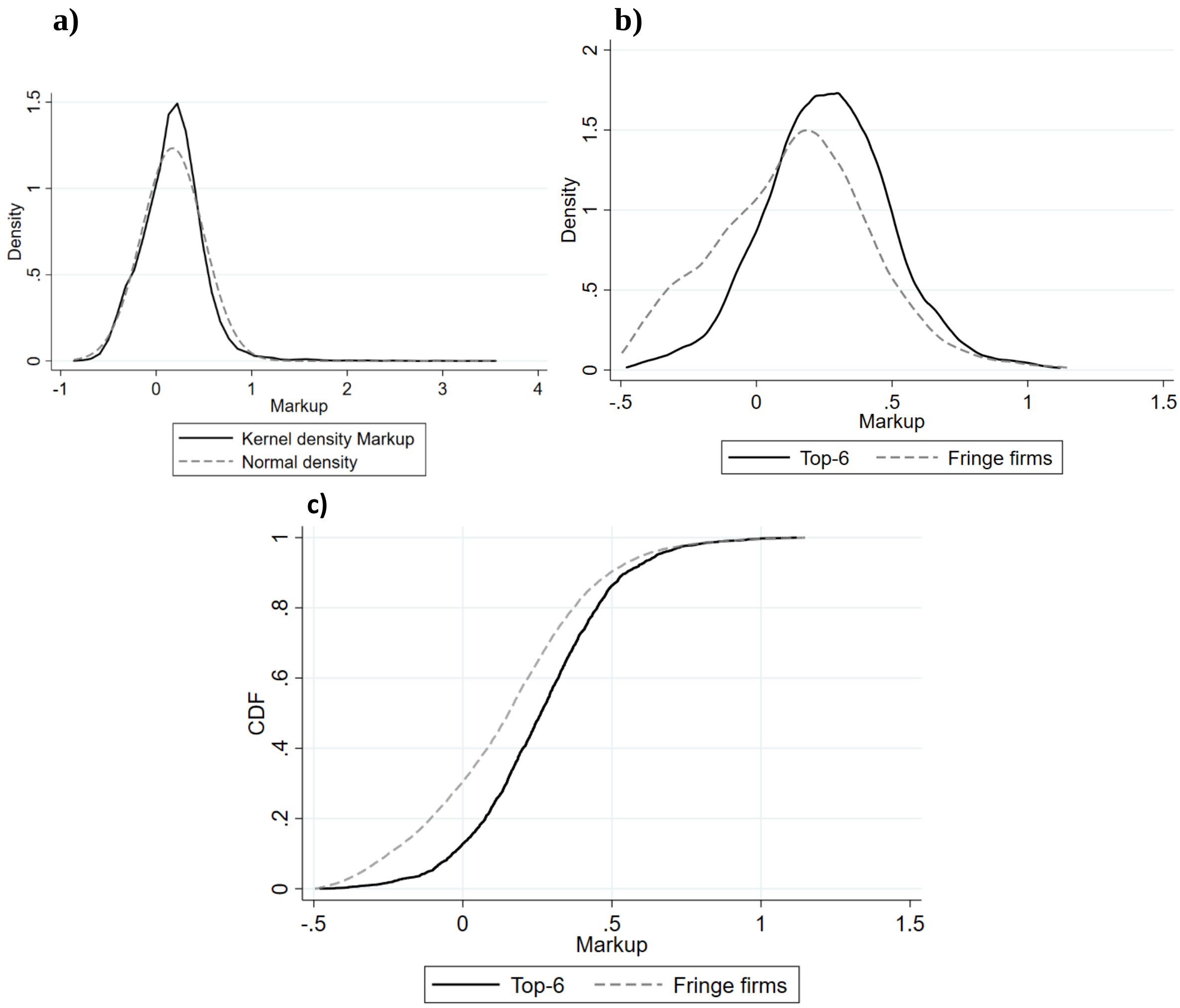
S2.4.1 Descriptive Analysis

The results suggest that firms on average generate oligopoly markups of 18.2 percent. When comparing average markups of firms associated to a Top-6 group and fringe firms, we observe significantly higher values for the former (0.273 vs. 0.161). This is confirmed by the densities and cumulative distribution functions (CDFs) shown in Figure S2.1 (b and c) as well as the Kolmogorov-Smirnov-test for equality of distributions which reveal that markups of Top-6 firms stochastically dominate those of fringe firms.

From Figure S2.2 it can be observed that markups for both Top-6 and fringe firms have decreased over the analyzed timespan reflecting intensified competition among retailers in

[107] The seventh largest retailing group only has a market share of 3 percent (USDA 2018,2019).

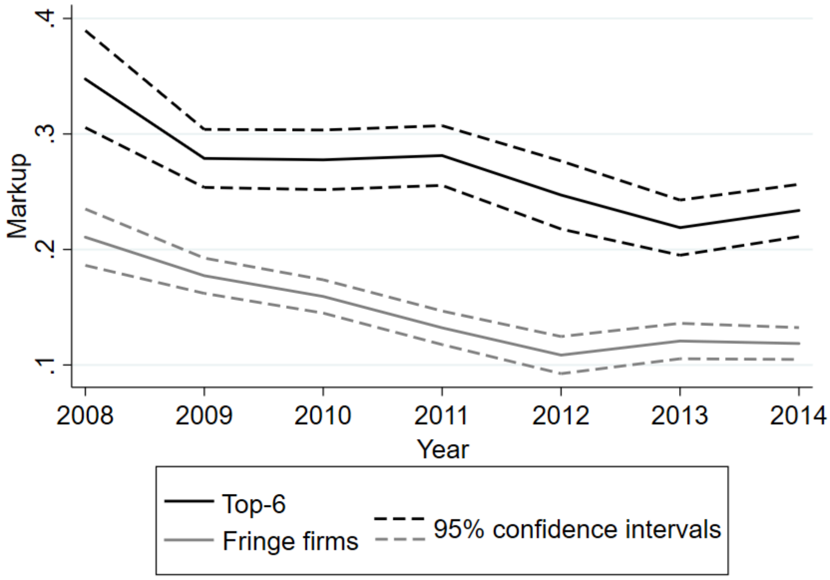
downstream markets (e.g., Corstjens and Steel 2008), as well as the impact of the 2009 economic crisis and its aftermaths. The decline is potentially amplified by repealed legal restrictions for opening new stores with the aim to decrease entry barriers. Moreover, if the retail market is competitive, the exercise of buyer power towards processors can lead to lower purchasing costs in upstream markets that are passed on to consumers leading to decreases in oligopoly markups (Dobson et al. 2001; European Competition Network 2012). In turn, for the case of increasing commodity prices, Assefa et al. (2017) and Richards et al. (2012) find retail prices to be unresponsive.



Notes: a) Kernel density of markups, b) Kernel densities of Top-6 and fringe firms, c) CDFs of Top-6 and fringe firms. For better interpretability b) and c) reflect 99 percent quantiles of markups; Kolmogorov-Smirnov D-test: 0.195 ($p<0.001$); Skewness/Kurtosis-test for normality: 21.336 ($p<0.001$)

Source: Own calculations based on AMADEUS

Figure S2.1 Densities and Cumulative Distributions (CDFs) of Markups for Top-6 and Fringe Firms



Source: Own calculations based on AMADEUS

Figure S2.2 Development of Markups Over Time

S2.4.2 Econometric Analysis

Figure 1a) which depicts the distribution of markups and the Skewness/Kurtosis-test for normality reveal high skewness of markup estimates indicating the necessity of a robust estimator when markups serve as dependent variable. Table S2.1 shows the results of the 0.5-qregpd estimation revealing that markups of Top-6 firms significantly exceed those of fringe retailers by 9.1 percentage points confirming the descriptive evidence. This points towards competitive advantages of dominant firms in form of vertical coordination or well-coordinated distribution channels (Dobson et al. 2001; European Competition Network 2012). We also find that individual/specialized supermarkets generate significantly lower markups compared to hypermarkets/supermarkets. Furthermore, the results suggest that operating discounters is associated with further increases in markups for Top-6 firms. Moreover, we find that partnerships such as buyer groups or retail cooperatives with the aim to pool sales means and increase competitiveness of independent members are related to higher markups (European Competition Network 2012).

Finally, column 2 of Table S2.1 shows the dynamic panel model results revealing a positive connection between markups and profitability measured by $return\ on\ assets$ (ROA). This is evidence for a reduction in consumer welfare due to food retailers' oligopoly market power. In both models presented in Table S2.1 firm-size, growth, gearing and concentration are treated as endogenous and lagged values are used as instruments.

Table S2.1 Regressions Results for Markups and Profitability

Variable	Markup (Qreg)	ROA (dynamic panel)
ROA(t-1)	-	0.435***
		(0.111)
Ln(Markup)	-	0.042**
		(0.017)
Store type variables		
Top-6	0.091***	0.014**
	(0.024)	(0.007)
Discounter	0.134***	0.009
	(0.042)	(0.014)
Individual/	-0.147***	-0.022
specialized	(0.024)	(0.029)
Convenience/	0.122	0.097
neighborhood	(0.099)	(0.029)***
Controls		
Number of stores	4.63e-4	-0.001
	(0.001)	(0.001)
Private-limited	-0.176***	0.014
	(0.040)	(0.011)
Partnership/	0.146***	0.036
Cooperative	(0.056)	(0.024)
Firm-size	0.011***	0.007**
	(0.002)	(0.003)
Firm-size²	-1.66e-4***	-9.35e-5
	(4.87e-5)	(6.46e-5)
Firm-growth	0.030***	0.302***
	(0.011)	(0.083)
Firm-age	-0.015***	0.001
	(0.004)	(0.001)
Firm-age²	1.28e-4***	-1.21e-5
	(3.83e-5)	(9.63e-6)
Gearing-ratio	2.57e-4***	-2.65e-4***
	(5.46e-5)	(1.02e-4)
Herfindahl	4.24e-4**	-5.00e-4*
	(2.06e-4)	(2.80e-4)
Wald χ^2		168.570***
AR(2)		1.350
Hansen χ^2		10.970
Observations	11,119	7,766

Note: Robust standard errors in parentheses; ***, **, * significant at the 1, 5, 10 percent-level.

Source: Own calculations based on AMADEUS

S2.5 Conclusion

In this article we have analyzed power imbalances in the French food retailing sector using a PFA to estimate markups. We find that (oligopoly) markups have decreased over the analyzed time span, supporting earlier findings which suggest that food retailing is a highly competitive sector characterized by intensive price and non-price rivalry in downstream markets resulting in low margins (Corstjens and Steel 2008; Richards et al. 2018). Previous findings also reveal that the effect of oligopsony power on input prices dominates the impact of oligopoly power on consumer prices (e.g., Salhofer et al. 2012). Nevertheless, our results indicate power imbalances between dominant retailers and fringe firms and the presence of welfare decreasing market power towards consumers.

Yet, further work should consider the net effect of oligopoly and oligopsony power of retailers towards upstream sectors such as processors and farmers on the overall efficiency of the supply chain. In this context, strategies such as bundling discounts, slotting allowances, vertical contracts, and the functioning of local competition should be considered (Dertwinkel-Kalt and Wey 2020; European Competition Network 2012; Hamilton and Innes 2017). Local competition plays an important role in French food retailing where in certain shopping areas stores are concentrated on a few retail groups that only face competition from a small number of competing operators (OECD 2014).

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S2.6 Appendix

Table S2.A1 Variable Descriptions and Descriptive Statistics

Variable	**Definition**	**Mean (Stdv.)**
Variables for production function		
Deflated revenue	Revenue in 1000€ deflated with harmonized consumer price index for food	11,179.310 (16,859.800)
Deflated value added	(Taxation + Netincome + Costs of employees + Interest paid) each in 1,000€ and deflated with harmonized consumer price indices for food	1,336.247 (2,303.891)
Capital	Fixed Assets (1,000€)	1,541.684 (3,203.660)
Labor	Number of employees	36.283 (62.580)
Material costs	Total costs for raw inputs/materials (1,000€)	9,001.557 (13,364.640)
Input share (α_{it}^{n})	Total Costs of Employees/Value Added (%)	0.911 (0.267)
Firm variables		
Markup	(Price/Marginal Cost)-1	0.182 (0.501)
Top-6	Firm is affiliated to a Top-6 retailing group regarding sales (0/1)	0.188 (0.390)
Discounter	Firm operates discounter stores (0/1)	0.019 (0.136)
Hypermarket/ supermarket	Firm operates store(s) in NACE class G47.11 (retail sale in non-specialized stores with food, beverages or tobacco predominating) (0/1)	0.730 (0.444)
Individual/ specialized	Firm operates store(s) in NACE group G47.2 (retail sale of food, beverages and tobacco in specialized stores) (0/1)	0.270 (0.444)
Convenience/ neighborhood	Firm operates convenience store(s) with a smaller product assortment and longer opening hours	0.012 (0.110)
Number of stores	Number of retail stores a firm operates	1.645 (4.632)
Private limited	Firms legal form is private limited (0/1)	0.404 (0.491)
Public	Firms legal form is public limited (0/1)	0.585 (0.493)
Partnership/ Cooperative	Firm is member of a horizontal partnership e.g., retail cooperatives (0/1)	0.011 (0.105)
ROA	Return on Assets (%) calculated as Operating Profit(Loss)/Total Assets	0.097 (0.112)
Firm size	Total Assets (1,000€)	3,208.033 (5,903.541)
Firm growth	Yearly growth factor of Total Assets	1.058 (0.271)

Firm age	Years since incorporation	19.697
		(10.313)
Gearing ratio	Debt/Equity (%)	102.130
		(150.297)
Industry-level controls		
HHI NACE	Herfindahl Index: Sum of the squared market shares of firms in 4-digit NACE sector	86.577
		(46.234)
Observations		11,119
Firms		3,366