STOCKHOLM SCHOOL OF ECONOMICS
Department of Economics
5350 Thesis in Economics
Spring 2024

Markups in Sweden: Decomposing the Trends

Agnes Erlandsson (24879) and Erik Leiditz Thorsson (42427)

Abstract: This paper estimates the average markup in Sweden between 1999 and 2021 utilizing a firm-level dataset on the financial history of the entire population of publicly and non-publicly traded firms. Using the production function approach to estimate markups, we find that the average markup decreases from 2.08 in 1999 to 1.47 in 2021 with a large variation in the intermediate years. The results show that the variation in the average markup is driven by the top 10% of firms in the markup distribution. By performing a firm- and sector-level decomposition, we study the dynamics of the average markups over time. The results suggest that the decrease in markups occurs for firms across all sectors. We also find a positive effect on the average markup from reallocation of economic activity from low markup firms to high markup firms. The results suggest that large firms charge high markups in Sweden across all sectors. However, there is limited evidence on the development of market power as large firms grow without charging higher markups.

Keywords: markups, production function approach, market power, competition
JEL: D2, D4, L1

Supervisor:	Andreea Enache
Date submitted:	May 13, 2024
Date examined:	May 24, 2024
Discussant:	Joakim Davidsson
Examiner:	Magnus Johannesson

Acknowledgments

We would like to express our sincere gratitude to our supervisor Andreea Enache, Assistant Professor of Economics at the Stockholm School of Economics, for her invaluable insights and for encouraging us to explore new perspectives. Her encouragement ensured we stayed motivated to find new paths and solutions throughout the process. Furthermore, we want to thank Tove Forsbacka Karlsson, Ph.D. Candidate in Economics at Stockholm School of Economics, for her expertise and guidance in production function estimation. Her comments have helped us understand the strengths and limitations of our thesis and how to approach them in an appropriate way.

Lastly, we extend our gratitude to our colleagues in the M.Sc. Program in Economics at the Stockholm School of Economics for their positive energy and encouragement, which made the writing process joyous.

Table of Contents

1 Introduction

Firms' ability to exert market power is constantly on the agenda. Lately, more evidence points to firms' market power increasing (Autor et al., 2020; De Loecker & Eeckhout, 2018). Market power refers to firms' ability to charge prices above their marginal costs. If a firm holds excessive market power, it could indicate insufficient competition. In the long run, this could hurt the individual consumer since competition from a traditional economic perspective drives innovation and pressures prices downward (Belleflamme & Peitz, 2015). Since the 1980s, there is evidence that firms' markups have increased globally from 1.15 to 1.6 in 2016 (De Loecker & Eeckhout, 2018). A study made on US firms found that the increase in markups is concentrated in the upper percentile of the markup distribution while staying flat for the median, suggesting that there are a few firms enjoying market power, driving up the average markup over time (De Loecker et al., 2020). Corroborating evidence points towards more productive firms, so-called "superstar firms", accounting for the increase in markups (Autor et al., 2020). Due to its significant importance for economists and policymakers, there is a need to delve deeper into the topic.

While market power is increasing globally, some heterogeneity exists among countries. For instance, some evidence points to Sweden being an outlier where the markups have stayed relatively flat since the 2000s (De Loecker & Eeckhout, 2018) or even decreased between 1997 and 2015 (Weche and Wambach, 2021). Apart from these papers, there is a notable research gap concerning the evolution of firms' market power in Sweden, specifically in terms of markups. While there exist sector-specific analyses on markups in Sweden (see e.g., Agrawal et al., 2021; Gullstrand et al., 2014; Wilhelmsson, 2006), there is limited research exploring markups over time combined with the dynamics across sectors.

In this paper, we estimate markups for Swedish firms using an extensive firm-level dataset on the complete population of publicly and non-publicly traded firms from 1998 to 2021. Utilizing these markups, we perform a decomposition analysis at both the firm- and sector-level to understand the dynamics of markups over time. To estimate markups, we follow the production function approach, an increasingly popular procedure that relies on the access to accounting data of firms (see e.g., De Loecker & Eeckhout, 2018; De Loecker et al., 2020; Díez et al., 2021). Using this procedure, we estimate sector-year specific output elasticities of labor to obtain firm-level markups.

We find that the average markup in Sweden decreased from 2.08 to 1.47 between 1999 and 2021, contrasting the global trend of increasing markups (De Loecker & Eeckhout, 2018). During this period, we observe a high variability in the average markup, driven by the top 10% of firms in the markup distribution, while markups remain relatively constant for 90% of firms. The decomposition at the firm-level shows that the decrease in the average markup over time is driven by a general effect of all firms in the economy decreasing their markups, under the assumption that firms' market shares remain constant. Moreover, we find evidence that high markup firms grow in terms of market shares, signaling increases in market power over time. The sector-level decomposition shows that the decrease in markups can be attributed to all sectors, and that there is no significant reallocation of market shares between sectors. We conclude that the change in average markup over time cannot be attributed to any specific sectors but to large firms across all sectors in the economy.

The contributions of this paper to research are twofold. To begin with, this is the first paper that estimates markups for firms in Sweden to investigate the dynamics of the average markup over time, considering both firm- and sector-level dynamics. Next, we are the first paper to estimate the output elasticity of labor using a sector-year specific production function, estimating it only using data from the year in question. Most previous research uses a five-year rolling-window approach, where the production functions are estimated with the inclusion of data from future years (see e.g., De Loecker & Eeckhout, 2018; De Loecker et al., 2020; Díez et al., 2021). By estimating sector-year specific estimates, we have the possibility to provide more realistic results where we do not allow future technological improvements to leak back in time and influence the estimations.

The paper is structured in the following way. In Section 2, we start by reviewing the current body of research regarding market power and markup estimation. In Section 3, we present our data, followed by the methodology in Section 4. Next, we present our findings in Section 5 and robustness checks in Section 6. Lastly, we discuss our findings and end with a concluding comment in Sections 7 and 8, respectively.

2 Literature Review

2.1 The Rise of Market Power?

An increase in market power is constantly on the agenda for economists and decision-makers. Market power refers to the extent to which a firm can charge prices above marginal costs.[1] A traditional measurement to structurally assess market power is the Herfindahl–Hirschman index, a common tool among competition authorities (Affeldt et al., 2021). However, little is known regarding firms' ability to exert market power, set high markups, and how much it hurts consumers. Most studies on market power as measured by markups are concentrated to specific locations, often the US and India, or specific industries (see e.g., Berry et al., 2019; De Loecker et al., 2016; De Loecker & Warzynski, 2012; Vancauteren, 2013). Although the evidence is only suggestive, the results likely indicate a global phenomenon as we live and interact in a global marketplace with few exceptions.

Recent research by De Loecker et al. (2020) on US data finds that markups have increased significantly from 1.21 in the 1980s to 1.61 in 2016. There is a significant increase between 1980 and 2000, after which it stagnates for 10 years around 1.45 before another significant increase between 2011 and 2016. They further find that the increase is driven by firms in the upper percentiles of the markup distribution, while most firms do not experience a rise in markups. Moreover, the increase in markups occurs across all sectors and is primarily due to technological change, mainly through increased fixed costs, and a change in market structure through a decrease in the number of competitors (De Loecker et al., 2020). This suggests that there are firms with much higher productivity than other firms, so-called "superstar firms", leading to increased market concentration and market power (Autor et al., 2020).

Working papers argue that a similar phenomenon of rising market power also occurs outside the US (see De Loecker & Eeckhout, 2018; Díez et al., 2018; Jakubik et al., 2023). De Loecker and Eeckhout (2018) provide the most extensive study on a global scale and find that aggregate markups have been increasing globally since the 1980s, except for South America, where markups have stayed constant. There is a significant increase in the global markup from 1.17 to about 1.45 between 1980 and 2000, after which it stays relatively constant at around 1.45 until 2010, when there is a significant increase from around 1.4 to 1.6. In Europe, we observe a similar pattern, where markups have stayed relatively flat around 1.4 between 2000 and 2010, followed by a notable spike driven primarily by Denmark, Italy, and Switzerland. The same pattern is seen in North

[1] Marginal cost equals the cost of producing an additional unit or serving an additional customer (OECD, 1993).

America. De Loecker and Eeckhout (2018) further show that the increase can mainly be attributed to advanced economies, whereas the result varies for less advanced nations. Although markups have increased on an aggregated level, some heterogeneity exists among countries. It is, however, essential to note that quality firm-level data is relatively scarce, especially in developing nations. For instance, De Loecker and Eeckhout (2018) exploit the financial statements of 67,491 firms in 134 countries between 1980 and 2016, which naturally calls for some concern given the small sample size.[2]

Studies in Europe show mixed results for different nations, sectors, and industries. However, as with studies conducted on a global scale, studies limited to Europe also lack results across industries and sectors over time. Cavalleri et al. (2019) find evidence that markups have stayed relatively stable in the euro area between 2006 and 2016, even marginally decreasing. Weche and Wambach (2021) study Europe during the same period, and find heterogeneous results across countries. Moreover, they find that the average markup marginally increases from 2013 to 2015 and is driven by the top 50% of firms in the markup distribution. Similarily, De Loecker and Eeckhout (2018) observe heterogeneous results across European countries, yet they find an increase in markups since the 1980s on an aggregated level.

Since the European Union introduced merger control in 1990, market power has increased as measured in market share. This is especially true after the policy reform in 2004, when the focus shifted from structural indicators, like barriers to entry and market dynamics, to effective competition (Affeldt et al., 2021). Intuitively, increasing market power could also lead to rising prices and markups, harming the individual consumer. As the economic research community is aware of the importance of estimating market power, there are technical reasons why it is not more widely studied.

2.2 Competition in the Swedish Market

Research on how market power and markups have developed in Sweden over time is scarce. A global study by De Loecker and Eeckhout (2018) shows that markups have risen in Europe but fail to find support for the "superstar firms"-phenomenon, as argued by Autor et al. (2020). Using US-based estimates for output elasticity of variable inputs, they find that the Swedish market has experienced a more moderate increase in markups than observed in the majority of other European countries or on an aggregated level. De Loecker and Eeckhout further find that markups in Sweden increased from 0.94 in 1980 to 1.31 in 2016, whereas the average markups in Europe during the same period increased

[2]To combat this, it is common in the production function estimation literature to use a five-year rolling-window approach (see e.g., De Loecker et al., 2020; Díez et al., 2018). The method relies on estimating all data for the specific year, as well as data two years back in time and two years forward in time, naturally leading to larger sample sizes.

from 1.01 to 1.63. Since the beginning of the 2000s, Sweden's aggregated markup has remained relatively stable at around 1.3, as highlighted by De Loecker and Eeckhout (2018). Weche and Wambach (2021) even find that the average markup in Sweden has decreased by 0.5 between 2007 and 2015, from 2.9 to 2.4.

Apart from the aforementioned studies presented on an aggregated level, there is still little knowledge regarding the development of market power in Sweden. While there exists industry-specific studies using firm-level data, the food industry has been explored in greater detail, where findings suggest that market power is prevalent. Wilhelmsson (2006) study the food and beverage market using data on large Swedish firms between 1990 and 2002 to investigate whether Sweden's accession to the EU resulted in a decrease in market power as measured by markups. Wilhelmsson finds an average markup of 1.09 over the entire period, with some variation between industries, ranging between 0.95 and 1.15. More specifically, the aggregated markups decreased prior to entering the union, followed by a marginal increase. This contrasts the author's view that markups should decrease as market competition increases following the accession to the EU market.

Moreover, Gullstrand et al. (2014) estimate markups for exporting firms in different parts of the supply chain in the Swedish food sector. The authors find that the average markup for the food processing industry from 1997 to 2006 is approximately 1.27, whereas the wholesale industry experience slightly lower markups, around 1.14, estimated for the time period 2003 to 2006. Olofsdotter et al. (2011) report similar results on less aggregated industries within the processing of food products. Estimating markups using data between 1998 and 2007, they find that markups vary across different food processing industries, ranging between 1.21 and 1.4. They find that this signals that the food industry exhibits signs of market power despite the increase in import competition following the Swedish entry to the EU.

In recent years, the Swedish Competition Authority (2018) has contrastingly assessed market power in terms of concentration in the Swedish food processing market. They present evidence that market concentration in this industry has increased over the past 20 years, mainly due to mergers and acquisitions . It comes as a result of strong Swedish brands being acquired by multinational corporations, but also from large Swedish companies acquiring small firms. According to the authors, the three largest companies in this industry make up 75% of the manufacturing in each product category. In contrast, within the subsequent segment of the supply chain, namely grocery wholesale, the top three companies control 85% of the turnover.

2.3 Estimation Approaches

Estimating markups is an increasingly popular way to measure firms' market power and market concentration. As mentioned above, the body of literature on the development of markups over time is relatively limited outside the US. One reason is the difficulty of estimating firm-level markups. To obtain markups, data on prices, quantity, and marginal costs are needed. However, as valuable as marginal costs can be in economics, it is only a theoretical concept that can be used to analyze firms' behavior, and unlike quantities and prices, there is rarely data available on marginal costs. Hence, economists have tried to find ways to estimate markups to research market power.

The most popular tool in industrial organization until recently has been estimating demand systems (De Loecker, 2011). Demand estimation involves estimating own- and cross-price elasticities using data on prices, quantities, product- and consumer characteristics.[3] Additionally, behavioral assumptions must be made on the price-setting firm to estimate markups. As one might guess, this detailed data is often unavailable or limited to specific locations at a given time, making the approach less useful.

2.3.1 Production Function Estimation

As econometric methods develop and comprehensive data becomes more readily available, other tools have been developed that answer the shortfalls of demand estimation. Estimating dynamic demand systems has yet to be optimized, making other approaches increasingly popular. Instead, by estimating the production function, researchers have made advancements and changed the landscape of competition economics. Contrary to estimating demand systems where results generally are not applicable to other settings, estimating the production function can give information regarding market power that can be extended over time, markets, and industries.

The evolution of markup estimation techniques within the framework of production functions has undergone advancements over the years, as evidenced in seminal work such as the paper by Ackerberg et al. (2015). Using the approach developed by Ackerberg et al., De Loecker and Eeckhout (2018), and Díez et al. (2021) utilize firms' accounting data to obtain the output elasticity of the firm's variable input bundle by estimating the production function. Under the assumption of cost-minimizing firms, they can use the firms' first-order condition to find an expression of markups that depends on the output elasticity of the variable input and the ratio of the variable input costs to sales.

However, estimating the production function has historically been challenging due to

[3] Own- and cross-price elasticities refer to the responsiveness (elasticity) of quantity demanded of a good or service relative to a change in its own price or a change in another good- or service's price, respectively (OECD, 1993).

endogeneity issues. First, the firm might have knowledge regarding input choices like labor and capital that could correlate with unobserved productivity. The second problem arises as firms decide to exit the market, leading to selection bias. A firm's decision to exit is probably correlated with a downfall in its unobserved productivity, leading to a selection bias (Ackerberg et al., 2007). Firms deciding to exit the market are likely to do so as they have knowledge of productivity shocks before exiting, leading to a biased sample (Ackerberg et al., 2007). Traditional approaches to addressing these endogeneity issues include using instrumental variables (IV) and fixed effects (FE). However, both are subject to limitations. IV instruments, such as input and output prices, often fail to meet the condition of affecting only the dependent variable through the explanatory variables. At the same time, FE assumptions of constant unobserved productivity over time are often violated by significant changes like trade policy shifts and privatization (Ackerberg et al., 2007).

2.3.2 Methodological Advances in Markup Estimation

Addressing the endogeneity issues in production function estimation has been done using various methodologies. Recovering markups by estimating the production function was first introduced by Hall (1986). Hall obtains markups using the production function under the assumption of a cost-minimizing firm. Contrary to demand estimation, Hall recovers markups by leveraging accounting data and retrieving them by considering the difference between the share of an input's cost to total cost and sales.

Building upon Hall's approach, Olley and Pakes (1996) utilize US data to investigate telecommunication producers following the breakup of AT&T. The divestiture of AT&T in 1984 occurred after years of deregulation in the market, allowing Olley and Pakes to study productivity and entry and exit from the market. In their analysis, they address the endogeneity concerns of inputs when estimating the production function by using investments as a proxy for productivity shocks. By assuming strict monotonicity, firms' investment decision, which depends on capital inputs and productivity, is invertible, allowing them to control for productivity when estimating the production function. The methodology follows a two-stage procedure where the labor coefficient is estimated in the first stage, and the coefficient on capital and the constant are estimated in the second stage.

The work by Olley and Pakes (1996) was later developed by Levinsohn and Petrin (2003), who condition out the serial correlation between inputs and unobserved productivity shocks by instead using intermediate inputs as a proxy.[4] Levinsohn and Petrin question

[4] Intermediate inputs refer to inputs used to produce the good or service rather than for final consumption.

Olley and Pakes' approach as investment levels have to be non-zero, highly restricting the amount of available data due to lumpiness in investments. Using intermediate inputs as a proxy could also be beneficial as it entails lower adjustment costs, as firms can adjust their intermediate inputs more quickly than investments. Thus, productivity should respond more directly to intermediate inputs as a proxy (Levinsohn & Petrin, 2003).

Ackerberg et al. (2015) critique both Olley and Pakes' and Levinsohn and Petrin's approaches, claiming that the coefficient on labor cannot be identified in the first stage of their procedure. Labor and intermediate inputs are both assumed to face no adjustment costs and, as such, are chosen simultaneously. These choices depend on the capital choice, which faces adjustment costs and is decided in the previous period, as well as productivity. Given that, with the assumption that productivity is a function of capital and intermediate inputs, labor is simply a function of the firm's choices of capital and intermediate inputs. Consequently, with no remaining variation in labor, it becomes collinear, and the coefficient on labor cannot be estimated.

To overcome these issues, Ackerberg et al. (2015) refrain from estimating the coefficient on labor in the first stage. They assume that intermediate inputs are chosen after the choice of labor, such that the intermediate inputs are not only a function of capital and productivity but also conditional on labor. The first stage is estimated to net out the error of the production function, but no coefficients are estimated in the first stage of the procedure. Instead, all coefficients are estimated in the second stage of the procedure. The benefits of this approach are that it allows labor to have dynamic effects and can produce consistent estimates even when there are adjustment costs to labor, such as firing and hiring costs.

2.3.3 Output Elasticity Trends in Markup Estimation

In recent years, the methodology introduced by Ackerberg et al. (2015) has been used to estimate the output elasticity of inputs, often to obtain markups across time. However, in the majority of papers on markup estimation, the output elasticities are not reported individually (see e.g., Badinger & Breuss, 2005; De Loecker & Eeckhout, 2018; De Loecker & Warzynski, 2012; Díez et al., 2018; Weche & Wambach, 2021). On the other hand, in papers where output elasticities are reported separately, the authors often find similar results. For example, De Loecker et al. (2020) find an average output elasticity of variable inputs in the range of 0.8 and 0.9 in the US between 1956 and 2016. Díez et al. (2021) find slightly lower estimates, ranging between 0.6 and 0.8. Moreover, Van Vlokhoven (2023) reports ambiguous output elasticities, ranging somewhere between 0.5 and 0.95; however, in terms of how it is reported, it is not clear if this is the true range.

The estimates found in research can be interpreted as decreasing returns to scale in variable inputs. Output elasticities measure the change in output resulting from a change in inputs. Suppose an increase in all inputs results in a proportionally smaller increase in output. In that case, this is known as decreasing returns to scale, with the output elasticity of variable inputs being less than one. In comparison, if input changes lead to a proportional increase in output, it is referred to as increasing returns to scale, with an output elasticity above one (Goolsbee et al., 2016).

2.4 Markup Decomposition: Dynamics and Insights

Besides focusing on estimating the average markup and its economic implications, attention has been directed towards decomposing the average markup. The most commonly used decomposition in the markup literature is the Haltiwanger (1997) decomposition, which measures within, between, covariance, and entry-exit terms. The tool is then used to understand the dynamics and underlying factors for the changes in the average markup. Utilizing this, one can better understand whether pricing behavior, market competition, and market structure change over time, which is of interest to policymakers.

De Loecker et al. (2020) perform both firm-level and sector-level decomposition and find that on a firm level, a significant portion of the increase in the average markup in the US can be attributed to the reallocation of economic activity across firms. Firms setting high markups are gaining more sales, while low markup firms are selling less, a pattern consistent with a model on imperfect competition that firms setting high markups obtain higher market shares. Furthermore, the authors find that the within-firms effect, measuring the degree to which firms increase their markup, keeping their market share constant, has been a driver of the increase in the average markup, implying that firms' pricing power has increased. The paper does not identify any notable entry-exit effect on the increase in average markup since the 1990s.

Contrary to the firm-level analysis, De Loecker et al. (2020) find unexpected results at the sector-level analysis. A significant portion of the average markup increase is attributable to within-sector drivers rather than between sectors or reallocation of economic activity. This points towards all sectors in the economy experiencing increases in markups. In contrast, the authors expect that specific booming sectors, such as tech, would increase more than other sectors.

A recent critique has been raised by Van Vlokhoven (2023), highlighting potential issues with decomposition due to measurement errors, leading to biases in both the between and within terms. The sign of the biases caused by the variation in output elasticity depends on the relationship between firm size and market shares. The issue stems from estimating constant output elasticities across firms, a strong assumption requiring all firms to have identical factor-augmenting technologies.[5] Recent literature shows that it is not the case, but that factor-augmenting technologies vary across firms, leading to biases in the decomposition terms as a result of the heterogeneity in output elasticities across firms (David & Venkateswaran, 2019; Doraszelski & Jaumandreu, 2018; Raval, 2019).

[5]Factor-augmenting technologies refer to the improvement in productivity of different factors in production, such as labor and capital (Carraro & De Cian., 2013).

3 Data

This paper uses data from the Serrano Database, consisting of data on firm-level financial history of the complete population of Swedish firms (Weidenman, n.d.). We set out to estimate markups using the production function approach, which requires accounting data to estimate the output elasticity of labor. From the Serrano Database, we use yearly data on balance sheets, financial statements, and general company data available between 1998 and 2021 for publicly and non-publicly traded limited liability companies. In particular, we use data on sales, variable costs, capital stock, and 2-digit NACE codes to define the sector to which a company belongs. The Serrano Database reports yearly values, adjusted for broken accounting periods and omissions and gaps in companies' financial statements (see all adjustments in Appendix A3).

3.1 Data Cleaning

Due to concerns in the measure of inputs, we include firms in the private sector, excluding the financial sector. Previous concerns have highlighted the difficulties in measuring inputs in service sectors such as finance and insurance, health care, education, and professional and business services (Basu, 2019). In Sweden, the majority of firms in health care and education are run by the public sector, and therefore we choose to exclude them from our sample. We only include firms with five or more employees to achieve comparability to previous research primarily focused on large public firms. Since 42% of businesses in Sweden are run as sole proprietorships, this implies that we drop a substantial amount of available data (Statistics Sweden, 2024). Still, as apparent in Table 4 in Appendix A1, the mean number of employees in the sample is 23, which is substantially different from, for example, De Loecker et al. (2020), where the mean number of employees in their dataset is 8,363. Lastly, we trim the dataset on the sales ratio to intermediate inputs and personnel expenses for the top and bottom 1%, where the percentiles are calculated by year. In this way, we ensure that all firms in the final sample have data on both sales and variable costs, which are essential to our estimations. In order to produce estimates of the output elasticity of labor separately for each sector and year, we also exclude sectors with less than 50 observations in a given year.

3.2 Methodology of Proxy Construction

To measure firms' variable costs, we use personnel expenses, including salaries and social security expenses, and intermediate inputs costs, which consist of raw materials and consumables. For physical capital, we use tangible fixed assets comprised of buildings and land, machinery and equipment, and other tangible fixed assets. While personnel expenses and capital are included in the Serrano Database, raw materials and consumables are not. However, the data on raw materials and consumables are available in the raw data on financial statements from the Swedish Companies Registration Office. This data has not been adjusted in accordance with the Serrano Database. It thus contains values from broken accounting periods and has not been interpolated or imputed for gaps in the financial statements. In order to use this data, it has to be transformed in the same way as the Serrano Database. This data transformation is not within the scope of this paper. Therefore, we construct a proxy for raw materials using observations that report yearly costs of raw materials and consumables. We further demonstrate that this proxy approximately represents the full sample used in this paper.

The proxy we construct consists of firm-level production costs and the sector-year mean of the ratio of raw materials to production costs. In the Serrano Database, most firms report production costs, including raw materials and consumables, goods for resale, and other external costs directly related to production. The reason why not all firms report raw materials is due to the existence of two different accounting methods for income statements in Sweden: function-based and cost-based. In the function-based method, the costs are divided between the functions they are associated with (e.g., sales and administration). In comparison, the cost-based method is divided after the cost type (e.g., raw materials and personnel costs). Companies are free to choose which method to use; however, in accordance with the Swedish Annual Accounts Act (1995), you can only switch methods if you have specific reasons or to improve interpretability.

Moreover, small companies can report using K2, which demands reporting a cost-based income statement (The Swedish Accounting Standards Board, 2023b). There are three requirements to be considered a small company in Sweden: having less than 50 employees, less than 40 million SEK in total assets or less than 80 million SEK in net turnover (The Swedish Accounting Standards Board, 2023a). Companies that fulfill at least two of these can report their financial statements using K2. As such, the cost-based method is the most common, where 95.67% of the firm-year observations in the Swedish Companies Registration Office data use this method. The different methods are used to approximately the same extent by large firms (>250 employees) in their respective samples. Thus, we exclude firms that report function-based financial statements as they do not report variable costs separately. This will not bias the proxy we construct since the full sample we look at only reports in accordance with the cost-based method.

To construct a measure for intermediate input costs, we use the observations from the Swedish Companies Registration Office with yearly data on raw materials and consumables. We match this to our sample from the Serrano Database on the firm-year level and construct a firm-specific ratio of raw materials to production costs for those firms that report both. We create the yearly mean ratio of raw materials to production costs in each

2-digit sector using these ratios

$$Ratio_{st} = \frac{\sum_{i=1}^{n} \frac{RawMaterials_{sft}}{ProductionCosts_{sft}}}{n_{st}}. \tag{1}$$

We then calculate intermediate input costs as

$$v_{ft}M_{ft} = Ratio_{st} * ProductionCosts_{ft} \tag{2}$$

where $v_{ft}M_{ft}$ is the cost of intermediate inputs, $Ratio_{st}$ is the ratio of raw materials to production costs per 2-digit sector s in time period t, and $ProductionCosts_{ft}$ is the production costs for firm f in time period t.

3.3 Tests and Plots on Distributions

For this proxy to be unbiased, we require the sample used for the proxy to come from the same distribution as the true population. In this case, our true population is the final sample of 1,214,172 observations. The sample of firm-year observations that report raw materials and consumables on a yearly basis consists of 312,586 observations. The firms that report raw materials are selected based on whether the firm uses broken accounting periods or reports yearly financial statements. If firms that report yearly differ from firms that report using broken accounting periods, we would face selection bias in our estimations. In accordance with the Swedish Accounting Act (1999), only individuals, partnerships where an individual is to be taxed for all or part of the partnership's income, and legal entities managing a joint property subject to joint ownership taxation are required to report financial statements yearly following the calendar year. However, our analysis is based on limited liability companies, in which these are not included. Limited liability companies may choose freely to apply a fiscal year other than the calendar year, referred to as a broken fiscal year. As a result, nothing in this selection should introduce bias in our estimations.

If these samples come from the same distribution, the proxy can be assumed to be unbiased. Whereas this would mean that the smaller sample would be representative of our final sample, and we could estimate the average markup using these observations, it would lead to a significant decrease in observations. This could become a problem since we estimate sector-year specific production functions, and to ensure there are enough observations per estimation, we use the proxy variable compared to using raw materials and consumables. It would also lead to dropping more sectors due to fewer observations per sector-year, which is undesirable as we conduct a sector analysis. Regardless, we also report the estimations using the sub-sample reporting raw materials in our robustness section.

To test whether our proxy is unbiased, we compare the distributions of the sample reporting raw materials to our full sample. First, we run the combined Kolmogorov-Smirnov test, a nonparametric test for the equality of distributions across groups. As a complement, we also visually inspect the distributions.

Table 1: Combined Kolmogorov-Smirnov Test

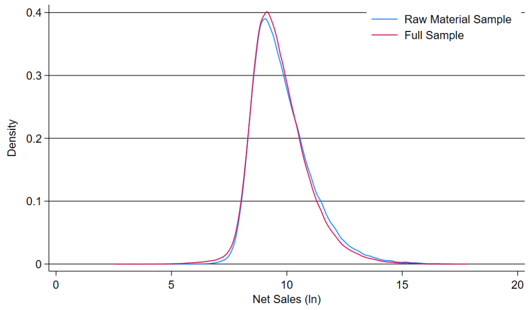
Parameter	Net Sales	Personnel Costs	Capital	Number of Employees
Test Statistic (D)	0.0314	0.0652	0.0668	0.0766
P-Value	0.000	0.000	0.000	0.000

Note: The table presents results from a Kolmogorov-Smirnov combined test conducted to assess the goodness-of-fit of the data to another distribution. The combined test statistic and its associated p-value are reported for each comparison.

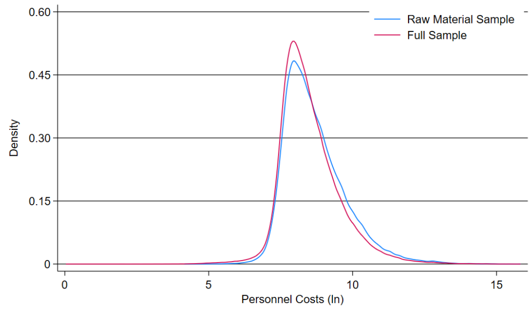
In Table 1, we present the results from the Kolmogorov-Smirnov tests for the variables net sales, personnel costs, capital, and number of employees. All four tests for differences across distributions are significant at a 1% level, suggesting that the samples come from different distributions. This speaks against our hypothesis that these come from similar distributions. However, when running the Kolmogorov-Smirnov test with large sample sizes, even the smallest differences can lead to strong conclusions about the samples coming from different distributions (Chakravarti et al., 1967). Therefore, we visually inspect the kernel densities of the relevant variables to compare the distributions across the two samples in Figure 1.

The kernel density plots of different variables across the two samples in Figure 1 show that the distributions are similar regarding net sales, personnel costs, and capital. This supports our use of the proxy based on the assumption that the samples originate from the same distribution. However, in Figure 1d, it is evident that the firms in the raw material sample are larger in terms of number of employees compared to the firms in our full sample. While there is a difference, the mean number of employees in the raw material sample is 29, and in the full sample, it is 23. The median is 11 and 9, respectively. In a range between 5 and 20,699, we still find the samples similar enough to proceed with the proxy.

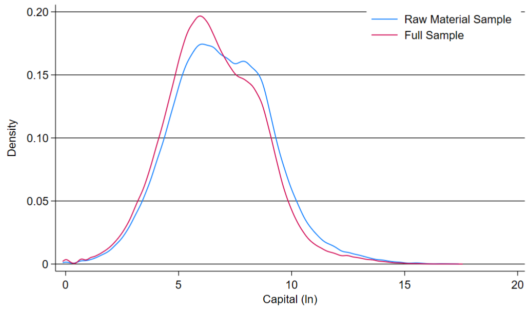
Proceeding with the proxy may introduce bias due to the differences in distributions. There is evidence of a u-shaped relationship where larger firms have smaller output elasticities of variable inputs, but at a certain threshold, output elasticities increase with the size of firms (Dìez et al., 2021). In our samples, we observe that the difference in firm size is most evident towards the lower part of the distribution. As such, the bias introduced could lead to us underestimating output elasticities as we assume firms in the full sample are larger than they are. The effect that this will have on markups is less evident. Lower



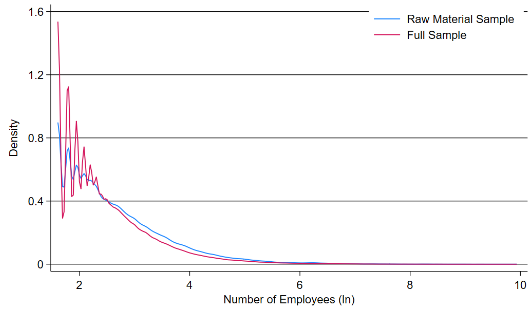
(a) Kernel Density of Net Sales



(b) Kernel Density of Personnel Costs



(c) Kernel Density of Capital



(d) Kernel Density of Number of Employees

Figure 1: Kernel Density of Variables Across Samples

output elasticity of labor has a negative effect on markups in a standard Cobb-Douglas production function. However, as discussed in the methodology, we use a Leontief production function, where a counterforce affects the markup estimation. Keeping the usage of raw materials in production constant, an underestimated output elasticity of labor also leads to a larger markup. In conclusion, the effect on the average markup is ambiguous.

3.4 Final Dataset

We deflate all nominal variables using the Swedish GDP deflator from the Federal Reserve Economic Data, FRED, which collects economic time series data from national and private sources (FRED, 2023). Ideally, the utilization of sector-specific price deflators corresponding to the relevant time period would be preferred, but due to data constraints, it is not feasible. Only firms that report positive capital, intermediate inputs, personnel expenses, and sales are included in the analysis. The final dataset consists of 149,372 unique firms across 53 sectors over the entire time period. The number of unique firms in 1998 is 41,111, while in 2021, there are 54,714 unique firms. In total, this gives 1,214,172 firm-year observations. In Appendix A1 Table 4, we report summary statistics of the final sample. We also report the average sales, personnel expenses, and intermediate input costs over time, as seen in Figure 15.

4 Methodology

We will now present our empirical framework used to obtain firm-specific markups from 1999 to 2021, following the approach of Ackerberg et al. (2015). To derive markups, specific firm-level data on prices, marginal costs, and quantities are needed. Since marginal cost is a theoretical concept that is rarely obtainable in data, we use the production function approach to estimate markups. This approach only requires data on the firm's sales and variable input costs using the firm's cost minimization problem. As a result, we do not need to consider constraints or regulations placed on the level of competition across firms in the market, as well as conditions influencing the demand from consumers.

4.1 Markup Estimation

The production function approach is used to estimate markups, which relies on several assumptions. First, firms are assumed to be cost minimizing. Second, the crucial assumption is that variable inputs in production can be adjusted without frictions. In comparison, capital is subject to adjustment costs and frictions. Since we have access to specific data on variable costs, labor, and intermediate inputs, we must also make assumptions about how intermediate inputs enter the production function. In line with De Loecker et al. (2020), the firm's production function is assumed Leontief in intermediate inputs. As Ackerberg et al. (2015) mention, their procedure should not be used with production functions that are not assumed Leontief in intermediate input. This would require further restrictions on the model. Assuming a Leontief production function, it is implied that intermediate inputs, M_{ft}, such as materials, cannot be substituted for labor, L_{ft}, or capital, K_{ft}. Under these assumptions, we have the following gross output production function

$$Q_{ft} = min\{L_{ft}^{\theta_t^L} K_{ft}^{\theta_t^K} \Omega_{ft}, \theta_t^M M_{ft}\} \tag{3}$$

where Ω_{ft} is firm productivity for firm f in time period t, θ_t^L is the time-variant output elasticity of labor, θ_t^K is the time-variant output elasticity of capital, and θ_t^M is the time-variant output elasticity of intermediate inputs.

To derive an expression for firm-level markups, we use the firm's cost minimization problem. This is given by

$$\min \; w_{ft}L_{ft} + r_{ft}K_{ft} + v_{ft}M_{ft} \tag{4}$$

subject to

$$Q_{ft}(\cdot) < \bar{Q}_{ft} \tag{5}$$

where w_{ft}, r_{ft}, and v_{ft} denote the factor prices of labor, capital, and intermediate inputs, respectively, for firm f in time period t. The gross production output function is represented by $Q_{ft}(\cdot)$, and $\bar{Q}_{ft}$ is an upper limit on the quantity of output that a firm can produce. The constraint represents a threshold at which, regardless of the inputs in $Q_{ft}(\cdot)$, production cannot surpass.

Since we assume firms to be cost minimizing, we can find an expression for markups using the first-order conditions with respect to labor, L_{ft}, and intermediate inputs, M_{ft}, as given by

$$w_{ft} - \lambda_{ft}^L \theta_t^L L^{\theta_t^L - 1} K_{ft}^{\theta_t^K} = 0 \tag{6}$$

$$w_{ft} - \lambda_{ft}^L \theta_t^L \frac{Q_{ft}}{L_{ft}} = 0 \tag{7}$$

$$v_{ft} - \lambda_{ft}^M \theta_t^M = 0 \tag{8}$$

where λ_{ft}^L and λ_{ft}^M are the Lagrangian multipliers of the variable inputs in production. With the Leontief production function, the firm's shadow price of producing one more unit, $\lambda_{ft}^L + \lambda_{ft}^M$, is equal to the firm's marginal cost. Using this, we express markups as

$$\begin{aligned} \mu_{ft} &= \frac{P_{ft}}{\lambda_{ft}^L + \lambda_{ft}^M} && (9) \\ &= \frac{P_{ft} Q_{ft} \theta_t^L}{w_{ft} L_{ft} + v_{ft} \theta_t^L \frac{Q_{ft}}{\theta_t^M}} && (10) \\ &= \theta_t^L \frac{P_{ft} Q_{ft}}{w_{ft} L_{ft} + \theta_t^L v_{ft} M_{ft}} && (11) \end{aligned}$$

where $P_{ft}Q_{ft}$ is net sales, $w_{ft}L_{ft}$ is personnel expenses, and $v_{ft}M_{ft}$ is the cost of intermediate inputs. These three variables are disclosed in firms' financial statements, requiring the estimation of the output elasticity of labor, θ_t^L, to recover firm markups.

4.2 Production Function Estimation

To obtain the output elasticity of labor, we estimate the production function for each 2-digit sector and year, following the approach by Ackerberg et al. (2015). The authors propose using the value added production function compared to the gross production function when it is assumed to be Leontief. The reason is that under this assumption, intermediate inputs do not provide any additional information to the estimation. This is because an increase in intermediate inputs directly corresponds to the same increase in output. This gives us the following Cobb-Douglas production function

$$Y_{ft} = exp(\omega_{ft} + \varepsilon_{ft}) L_{ft}^{\theta_t^L} K_{ft}^{\theta_t^K} \tag{12}$$

where $\omega_{ft} = ln(\Omega_{ft})$ is unobserved productivity and ε_{ft} is the measurement error in output.

In line with De Loecker and Warzynski (2012), for each sector and year, we consider the logged version of equation (12), the value added production function

$$y_{ft} = \theta_t^L l_{ft} + \theta_t^K k_{ft} + \omega_{ft} + \varepsilon_{ft} \tag{13}$$

where $l_{ft} = ln(L_{ft})$, $k_{ft} = ln(K_{ft})$ and $y_{ft} = ln(Y_{ft})$.

The main challenge with estimating the output elasticity of labor using equation (13) is that productivity shocks, ω_{ft}, are unobservable, and there is a simultaneity problem in that shocks in productivity could lead to changes in input choices. This will lead to biased results as firms are likely to know their productivity before making choices regarding labor and capital. However, it is unobservable to the econometrician, violating the exogeneity assumption. Estimating equation (13) by OLS would then lead to biased and inconsistent results. The issue becomes more pronounced when input choices react quickly to shocks (Marschak & Andrews, 1944). We therefore rely on using the control function approach to estimate the production function consistently and, thereby, output elasticity of labor (Ackerberg et al., 2015). The method relies on the fact that the variable inputs, labor, and intermediate inputs respond to shocks in productivity without frictions, while capital is assumed to be quasi-fixed. It faces adjustment costs, such that it does not respond one-to-one to a shock in productivity today. However, it is correlated to the persistent productivity shocks, as choices of capital in a time period depend on how productive the firm expects to be in the following time period.

Another challenge with the estimations is that we only have access to revenue data and not physical units of output and inputs. As a result, the data suffers from omitted price variable bias, as in revenue data, prices are included, making it impossible to infer physical output without specific price data. To control for the differences in input and output prices, we follow De Loecker et al. (2020) and use market shares, as measured by sales shares, of firms at the 2-, 3-, and 4-digit NACE levels.[6] This control is assumed to precisely account for discrepancies in input and output prices when output prices accurately reflect the variation in input prices. In such instances, a shift in input prices directly translates to a change in the output price, assuming the demand function follows a logit form (De Loecker et al., 2020). As noted by De Loecker and Warzynski (2012), treating deflated sales as physical could lead to a downward bias in output elasticities. As discussed previously, the effect on the average markup is ambiguous when using a Leontief production function.

[6] NACE levels are the 'statistical classification of economic activities' in the European Union (European Commission, 2023).

4.2.1 Control Function Approach

As mentioned above, a firm's productivity, which is observable to the firm itself, is seldom observable by the econometrician. To address the concern, we use the control function approach, which is based on a few assumptions. Unobserved productivity is assumed to follow a first-order Markov process, such that $\omega_{ft} = g(\omega_{f,t-1}) + \xi_{ft}$, where $g(\omega_{f,t-1})$ can be considered the predictable part of productivity, and ξ_{ft} as the innovation term, that is not observable to the firm until time period t. Capital in time period t, k_t, is decided in time period $t-1$ and, as such, is uncorrelated to the innovation term in time period t. On the contrary, labor is assumed to be a flexible input, such that a shock in productivity today leads to changes in the labor input, l_t. The intermediate input demand function is given by $m_{ft} = f_t(k_{ft}, l_{ft}, \omega_{ft})$. This function can be inverted under two assumptions. First, it is essential that productivity is the sole unobservable factor in the intermediate input demand function. Second, intermediate inputs must be strictly monotonic in productivity, meaning that, conditional on labor and capital, increasing productivity must always lead to increases in intermediate inputs. We can then write the demand function

$$\omega_{ft} = f_t^{-1}(k_{ft}, l_{ft}, m_{ft}) \tag{14}$$

where productivity can be expressed as a function of labor, capital, and intermediate inputs.

We can then substitute the productivity in the value added production function using the inverted input demand function

$$\begin{aligned} y_{ft} &= \theta_t^L l_{ft} + \theta_t^K k_{ft} + f_t^{-1}(k_{ft}, l_{ft}, m_{ft}) + \varepsilon_{ft} && (15) \\ &= \Phi_t(k_{ft}, l_{ft}, m_{ft}) + \varepsilon_{ft} && (16) \end{aligned}$$

where $\Phi_t(\cdot)$ is some function of capital, labor, and intermediate inputs.

To estimate the output elasticity of labor, θ_t^L, we use a two-stage procedure. The first stage estimates the nonparametric function $\Phi_t(\cdot)$ using OLS. We approximate it with a 3-degree polynomial in k_{ft}, l_{ft}, and m_{ft}. This provides us with an estimate of $\hat{\Phi}_t(k_{ft}, l_{ft}, m_{ft})$ that can be used to find an expression of productivity, that is,

$$\omega_{ft} = \Phi_t(k_{ft}, l_{ft}, m_{ft}) - (\theta_t^L l_{ft} + \theta_t^K k_{ft}). \tag{17}$$

We input equation (17) into (15) using the assumption of productivity following a first-order Markov process. The production function can then be written as

$$y_{ft} = \theta_t^L l_{ft} + \theta_t^K k_{ft} + g(\Phi_{t-1}(\cdot) - (\theta_t^L l_{f,t-1} + \theta_t^K k_{f,t-1})) + \xi_{ft} + \varepsilon_{ft}. \tag{18}$$

The second stage of the procedure uses generalized methods of moments to do a nonlinear search for two second-stage moment conditions to estimate θ_t^L and θ_t^K, which are,

$$E\left[(y_{ft}-\theta_t^L l_{ft}-\theta_t^K k_{ft}-g(\Phi_{t-1}(\cdot)-(\theta_t^L l_{f,t-1}+\theta_t^K k_{f,t-1})))\begin{pmatrix} k_{ft} \\ l_{f,t-1}\end{pmatrix}\right]=0 \tag{19}$$

For equation (19) to hold, we require that the moment conditions are uncorrelated to current shocks in productivity. As a consequence of the timing assumption in capital, that capital in period t is decided in $t-1$, a shock in productivity today will not lead to any changes in capital input today. The assumption relies on there being adjustment costs, such as it takes time to procure, transport, and deploy capital. Instead, labor is assumed to be a variable input that will react to shocks in productivity; therefore, we use labor in $t-1$ as an instrument since it will not be correlated with shocks today.

4.3 Decomposition of the Average Markup

First, we calculate the average markup, μ_{ft}, in the economy over time. It is computed as follows

$$\mu_t = \sum_f m_{ft}\mu_{ft}, \tag{20}$$

where m_{ft} is the weight of the firm, in our case, sales shares, and μ_{ft} is the estimated firm-specific markup.

4.3.1 Firm-Level Decomposition

We decompose average markups to analyze what drives the results on the firm-level. With this, we can differentiate which effect comes from changes in the average markup for all firms in the economy and what comes from the reallocation of economic activity between firms setting different markups. In line with Haltiwanger (1997), we decompose the average markup accordingly

$$\begin{aligned}\Delta\mu_t = &\underbrace{\sum_i m_{i,t-1}\Delta\mu_{i,t}}_{\Delta\text{ within}} + \underbrace{\underbrace{\sum_i \tilde{\mu}_{i,t-1}\Delta m_{i,t}}_{\Delta\text{ market share}} + \underbrace{\sum_i \Delta\mu_{i,t}\Delta m_{i,t}}_{\Delta\text{ cross term}}}_{\text{reallocation}} \\ &+ \underbrace{\sum_{i\in\text{ Entry}} \tilde{\mu}_{i,t}m_{i,t} - \sum_{i\in\text{ Exit}} \tilde{\mu}_{i,t-1}m_{i,t-1}}_{\text{net entry}}\end{aligned} \tag{21}$$

where $\tilde{\mu}_{i,t}=\mu_{i,t}-\mu_{t-1}$, and $\tilde{\mu}_{i,t-1}=\mu_{i,t-1}-\mu_{t-1}$. The within term measures the extent to which the average markup has changed while keeping firms' market shares constant. The reallocation term consists of both the change in market share and a cross term. The market share term measures the changes in the firm's market share, keeping the markup constant. The cross term considers markups and market shares and measures their joint changes. If the cross term is positive, firms growing larger are those that also increase their markups, while shrinking firms are setting lower markups. If it is negative, it implies that growing firms are setting lower markups and vice versa. The change in market share and cross term together create a measure of reallocation of the average markup. A positive reallocation term would indicate that there is reallocation of economic activity to growing firms that might be exercising market power and setting high markups, implying lower levels of competition in the economy. It could also mean that there is technological change, such that the distribution of productivity in the economy changes (De Loecker et al., 2021). Lastly, we have the net entry effect, which measures whether entering firms set different markups than exiting firms. If the effect is positive, entering firms set higher markups than the exiting firms, and vice versa.

4.3.2 Sector-Level Decomposition

Further, we perform a similar decomposition on the average markup within and between sectors. This can help in analyzing whether it is particular sectors that explain changes in the average markup or if all sectors are similar and the result is instead driven by individual firms within each sector. One can then draw conclusions on whether the economy as a whole is experiencing changes in market power or if it is sector-specific.

$$\Delta\mu_t = \underbrace{\sum_s m_{s,t-1}\Delta\mu_{st}}_{\Delta \text{ within}} + \underbrace{\sum_s \mu_{s,t-1}\Delta m_{s,t}}_{\Delta \text{ between}} + \underbrace{\sum_s \Delta\mu_{s,t}\Delta m_{s,t}}_{\Delta \text{ cross term}}. \tag{22}$$

Similar to the firm-level decomposition, we have the within, between, and cross term. Since there is no entry or exit in terms of sectors, this term is now excluded. The within term measures the extent to which the average markup has changed at the sector-level. The between term measures changes in composition across sectors, keeping the markup constant. If this is positive, more firms set high markups. Lastly, the cross term measures the joint change in composition and markups.

5 Results

In this section, we present our baseline results. We begin by presenting average markup and its distribution over time. Next, the average markup is decomposed at the firm- and sector-level to investigate what drives the development of markups in Sweden between 1999 and 2021. Lastly, we present the results from our estimations of the output elasticities of labor as they explain a large part of the variation in the average markup over time.

5.1 Average Markup

The sales-weighted average markup is presented in Figure 2 where we observe a decrease from 2.08 in 1999 to 1.47 in 2021. There is a sharp decrease in the average markup between 1999 and 2004, after which it varies between the range of 1.5 and 1.7. During this period, we notice one sharp decline in 2008. However, in 2010, the markup bounced back up to the 2007 level. Lastly, the markup remains relatively stable until 2018, when there again is a decline in markups. Notably, we see a relatively high variability, where the average markup ranges between 1.47 and 2.08.

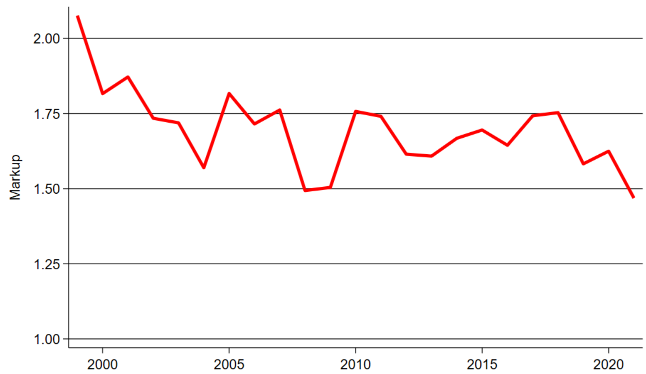


Figure 2: Average Markup

Note: The figure illustrates the average markup, which is sales-weighted by year and trimmed at the 1 percentile level.

Despite significant variations during the intermediate years, it is clear that the average markup is trending downwards from 1999 to 2021. This is more evident when comparing the kernel densities of the average markup in 1999 to 2021. As displayed in Figure 3, more firms had higher markups in 1999 than in 2021. However, it is important to highlight that the estimations in 2021 exhibit less sound results, as evidenced by markups falling below one and, in some cases, even reaching negative values. The spikes observed around -0.5 and around 0.1 suggest that there may be inaccuracies present in the estimations, as it is improbable that firms charge such low markups. This could also lead to us underestimating the average markup at the end of the period.

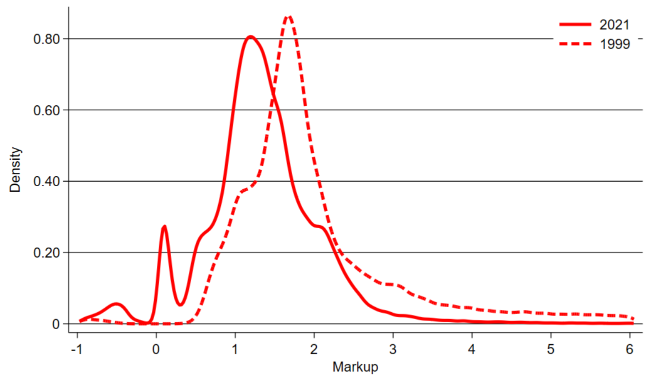


Figure 3: Kernel Density of Average Markup in 1999 and 2021

Note: The figure illustrates the kernel density of the average markup, which is unweighted and trimmed at the 1 percentile level.

In Appendix A4 Figures 16, 17, and 18, we display markups for all 2-digit sectors in our sample and observe a significant variation both in and between the 53 sectors. This is observed in the majority of the sector-specific markups and can be seen as unreliable and potentially weaken our results. Although we observe a downward trend in the average markup, it is important to note the heterogeneity among sectors. The variation is partly due to our choice of focusing on specific sectors, and by consolidating these sectors on a more aggregated level, we could obtain more powerful estimates. This would, however, be at the expense of analyzing individual sectors.

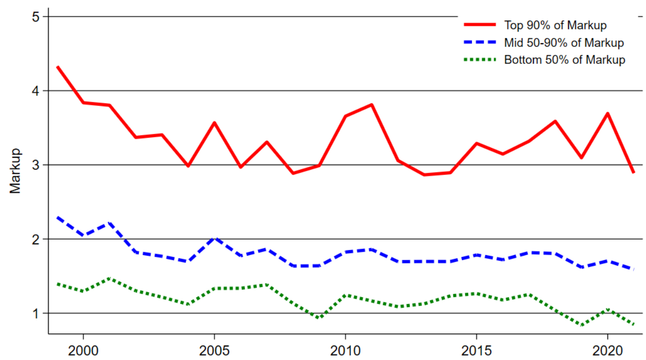


Figure 4: Distribution of Markups

Note: The figure illustrates the distribution of the average markup at different percentile levels. The average markup is sales-weighted by year and trimmed at the 1 percentile level.

In Figure 4, the distribution of the average markup over time is presented. The distribution of firms is calculated yearly, meaning that the top 10% of firms in the markup distribution can be different every year. As displayed in the figure, it is clear that the top 10% of firms drive the large variation in the average markup. For the bottom 50% of the distribution, we observe a slight downward trend in the average markup, suggesting that markups have decreased over time for most firms in the economy. In comparison, the firms in the middle of the distribution see a slight decrease in markups at the beginning of the 2000s, after which it stays relatively constant. Notably, the average markup has decreased at all parts of the distribution during the first five years. Nevertheless, we observe high markups for the top 10% of firms consistently throughout the analyzed period, which could suggest that these firms exert market power.

5.2 Firm-Level Decomposition

In Figure 5, we present the results from the firm-level decomposition of the average markup to analyze what drives the trend over time. The graph presents three counterfactual experiments where we compare the average markup to the evolution of the three terms referred to as within, reallocation, and net entry, keeping the other terms constant. The initial level of the markup is set to the level in 1999, and the evolution of the terms represents their cumulative change over time. Inspecting the different terms, it is clear that the within-effect is the main driver of the changes in the average markup over time. This means that, keeping firms' market shares constant, markups in Sweden have decreased over time for all firms across the economy.

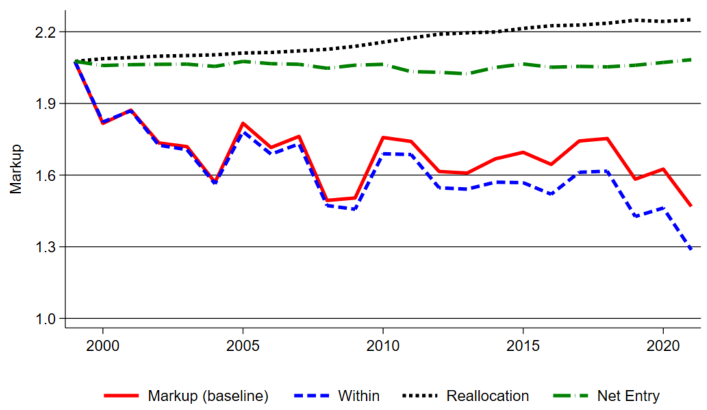


Figure 5: Firm-level Decomposition of the Average Markup

Note: The figure illustrates the decomposition of the average markup at the firm level. The average markup is sales-weighted by year and trimmed at the 1 percentile level.

Furthermore, the net entry effect remains essentially constant over time. This could imply that firms entering and exiting the market are setting similar markups or have similar market shares. Interestingly, the reallocation of the average markup shows a positive trend, indicating reallocation of economic activity to high markup firms. This could partly be attributed to increases in market shares, keeping the markup constant, such that firms that set high markups in the time period before are growing in terms of market shares. It could also be attributed to the joint effect of high markup firms increasing in both markups and market shares, while low markup firms experience a decrease in markups and market shares. The increase seen in the reallocation term acts as a counterforce to the decreasing markups over time and could indicate that firms exert market power on their customers as they grow.

5.3 Sector-Level Decomposition

In this section, we break down the sector-level average markups for the entire time period from 1999 to 2021, as presented in Table 2. We decompose the average markup at the 2-digit sector-level, where the sector-specific average markups are calculated using sales shares as weights.

Table 2: Sectoral Decomposition of the Average Markup

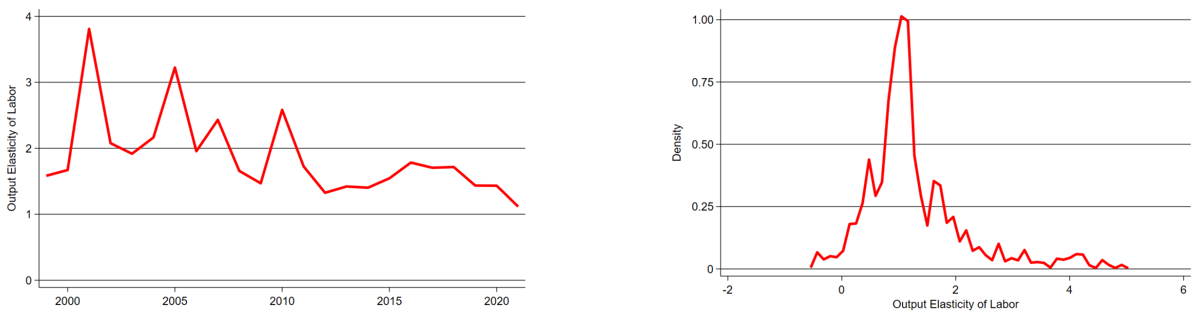
Year	Markup	ΔMarkup	ΔWithin	ΔBetween	ΔCross
2000	1.816	-0.260	-0.264	0.097	-0.093
2001	1.872	0.055	0.036	0.020	-0.001
2002	1.734	-0.137	-0.151	0.004	0.009
2003	1.719	-0.015	0.013	0.010	-0.039
2004	1.570	-0.150	-0.175	0.029	-0.003
2005	1.817	0.247	0.239	-0.014	0.023
2006	1.715	-0.101	-0.117	-0.000	0.016
2007	1.762	0.046	0.059	-0.023	0.010
2008	1.494	-0.268	-0.285	-0.008	0.025
2009	1.504	0.010	-0.002	0.008	0.004
2010	1.757	0.253	0.270	-0.011	-0.005
2011	1.741	-0.016	-0.013	0.022	-0.026
2012	1.615	-0.126	-0.131	0.025	-0.021
2013	1.608	-0.007	-0.038	0.000	0.031
2014	1.668	0.059	0.072	-0.031	0.018
2015	1.695	0.027	0.015	0.035	-0.022
2016	1.645	-0.051	-0.048	0.001	-0.003
2017	1.743	0.098	0.103	0.005	-0.009
2018	1.753	0.010	-0.024	0.014	0.020
2019	1.583	-0.170	-0.162	-0.025	0.016
2020	1.625	0.042	0.069	0.007	-0.033
2021	1.469	-0.156	-0.170	0.024	-0.011

Note: The table shows the yearly decomposition of the average markup at the sector level. The average markup is sales-weighted by sector and year and trimmed at the 1 percentile level.

In the majority of the years presented, the within-sector effect has been driving the change in sector-level markups. This means that most changes in markups occur within sectors, and there is no distinct reallocation of economic activity across sectors. While the between-sector effect is at most times smaller than the within-effect, we observe some years where it has a higher impact on the average markup. This implies that, by keeping the sector-level markup constant, market shares are shifting across sectors. Compared to the firm-level decomposition, we do not see a clear trend in the reallocation term, as measured by the cross-term. It is both negatively and positively affecting the changes in sector-level markups over time. Considering the sector-specific markups presented in Appendix A4 Figures 16, 17 and 18, it might not be surprising that we find no clear trends in the sector-level decomposition. The average markups across sectors are highly volatile over time, and for the majority of sectors, the average markup can be difficult to interpret. This spills over to the sector-level decomposition, where it becomes difficult to draw certain conclusions based on the volatile sector-specific markups.

5.4 Average Output Elasticity of Labor

We present the estimations of the output elasticity of labor over time in Figure 6a. The graph shows a considerable variation in the average output elasticity of labor over time, ranging between 1.1 and 3.8. At the beginning of the time period, we observe a high average output elasticity with greater variability. In 2001, the output elasticity of labor is equal to 3.8, which implies that a 1% increase in labor would result in a 3.8% increase in output.



(a) Average Output Elasticity of Labor

(b) Kernel Density

Figure 6: Average Output Elasticity of Labor

Note: Figure 6a illustrates the average output elasticity of labor, which is sales-weighted by year and trimmed at the 1 percentile level. Figure 6b illustrates the kernel density of the average output elasticity of labor, which is unweighted and trimmed at the 1 percentile level.

To see whether this is true for the entire sample or if it is driven by firms with large sales shares, we also report the kernel density of the output elasticity of labor in Figure 6b. Here, we can see that most firms have an elasticity above 1, which aligns with the theory of increasing returns to scale in labor. In comparison, previous research frequently finds evidence of decreasing returns to scale in labor, contradicting our results. Hence, the markups estimated using these output elasticities of labor should be carefully interpreted. For summary statistics on the estimated output elasticities of labor, see Appendix A2 Table 5, where we present the full range of our estimations.

6 Robustness

In this section, we test the robustness of our results. First, we apply a modified methodology in line with previous research to see whether our estimates are sensitive to our choice of method. In addition, we test different factors influencing the average markup and show that the results are driven by our estimates. We also test for aggregating the sectors at a higher level and find less volatile markups. Lastly, we apply various sampling restrictions and find that the results remain robust.

6.1 Estimation Using a Rolling-Window Approach

For comparability to previous research (see e.g., De Loecker et al., 2020; Díez et al., 2018), we present the average markup estimated using a five-year rolling-window approach. This method relies on using all data for the specific year to be estimated, as well as data two years back in time and two years forward in time. Figure 7 illustrates the average markup calculated using a rolling-window approach where the negative trend is similar to our baseline results. However, the average markup is lower than in our baseline results, with less variation, ranging from roughly 1.35 to 1.55. We can attribute this entirely to the changes in the estimated output elasticity of labor, as no other changes are made to the dataset.

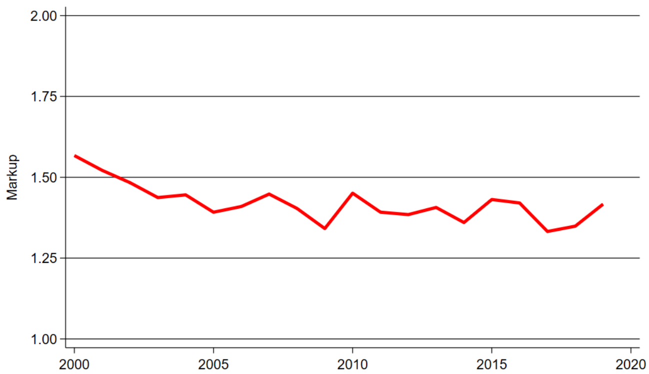


Figure 7: Average Markup

Note: The figure illustrates the average markup, estimated using a five-year rolling-window approach. It is sales-weighted by year and trimmed at the 1 percentile level.

The results presented in Figure 8 suggest that the output elasticity of labor has decreased over time, with significant increases around 2010 and 2018. These results are, as expected, not fluctuating to the same extent as in our baseline results. The estimated elasticities are significantly lower and more aligned with previous research and the theory of decreasing returns to scale than our baseline results (ranging between 0.7 and 1.1 instead of 1.1 and 3.8). Less variation in the elasticities should come naturally, as there is significant data leakage using this methodology. Future technological changes will influence current output elasticities of labor, leading to smoother results when using this methodology. The lower estimated elasticities may be attributed to the five times increase in the sample size for each sector-year production function, leading to more smooth estimates.

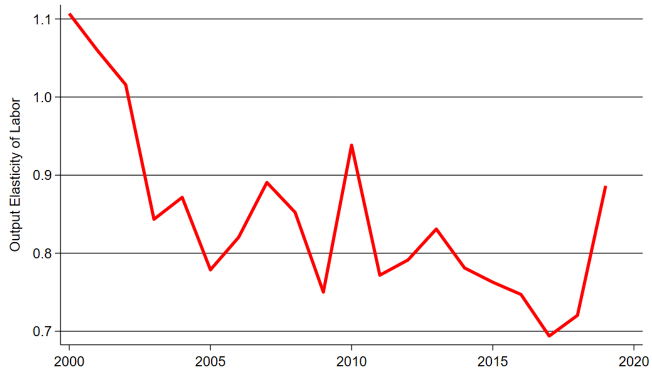


Figure 8: Average Output Elasticity of Labor

Note: The figure illustrates the average output elasticity of labor, estimated using a five-year rolling-window approach. It is sales-weighted by year and trimmed at the 1 percentile level.

Given that the estimated output elasticities of labor are more in line with previous research and the theory of decreasing returns to scale when using a rolling-window approach, we additionally present the firm-level decomposition using the average markup calculated using these estimations. As evident in Figure 9, while the average markup is overall lower, the conclusions that can be made from the impact of the different effects on our baseline results are robust to the choice of methodology.

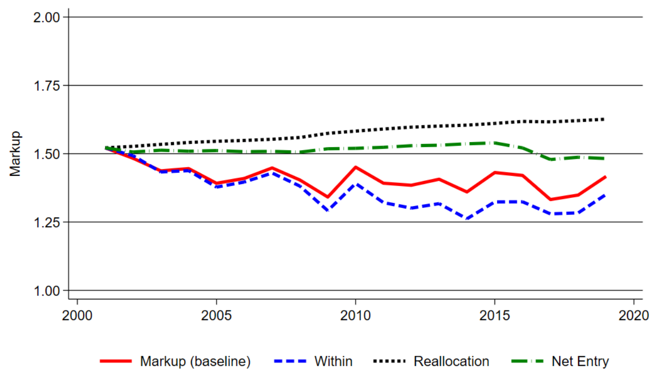


Figure 9: Firm-level Decomposition of the Average Markup

Note: The figure illustrates the decomposition of the average markup at the firm level, estimated using a five-year rolling-window approach. It is sales-weighted by year and trimmed at the 1 percentile level.

6.2 Exploring Assumptions and Sampling Restrictions

Three factors can influence the average markup presented in the results section: the estimated output elasticities of labor, the choice of weights in calculating the average markup, and the actual ratio of inputs costs to sales. Thus, in this section, we present the average markup using input weights compared to sales weights when calculating the average markup. We also consider markups using a fixed economy-wide output elasticity of labor. Furthermore, we consolidate sectors to the highest level of aggregation feasible since this can provide more powerful estimations of the output elasticity. Moreover, the estimated output elasticity of labor can be influenced by the assumptions made when constructing the proxy used for raw materials. As such, we show the average markup after reconstructing the proxy for raw materials by using a fixed economy-wide proportion of raw materials in production. We also contrast our results by using only the observations that report raw materials yearly and show that these results differ from our average markup as calculated using a proxy for raw materials. This robustness check tests both the use of our proxy in the estimation of the output elasticity of labor, as well as using the real intermediate input in the ratio of input costs to sales instead of the proxy. Lastly, we show that our results are not driven by the sampling choices, such as trimming and the number of observations per year and sector.

First, we compare our results to running an OLS with sector-year fixed effects, where a constant output elasticity of labor of 0.967 is applied, as seen in Table 3. If we compare this to our baseline results, we can see that the fixed effects model shows that markups have been relatively constant since the early 2000s, at an average markup between 1.5 and 1.6. These results are different from our baseline results and show that our results are sensitive to changes in the estimated output elasticity of labor, as seen in Figure 10.

Table 3: Cobb-Douglas Estimation

	Sales (ln)
Capital (ln)	0.0703***
	(0.000262)
Labor (ln)	0.967***
	(0.000515)
Constant	0.991***
	(0.00390)
N	1,214,172
Year*Sector Fixed Effects	Yes
Adjusted R-Squared	0.842

Standard errors in parentheses.

* $p < .10$, ** $p < .05$, *** $p < 0.01$

In addition, instead of aggregating to an economy-wide output elasticity, we also aggregate sectors to their respective sections. This results in 15 sections, compared to the 53 ana-

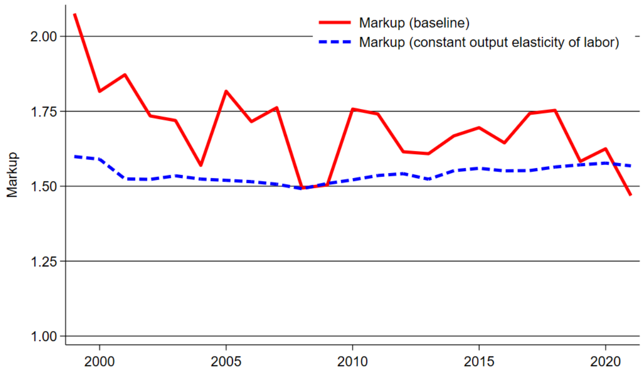
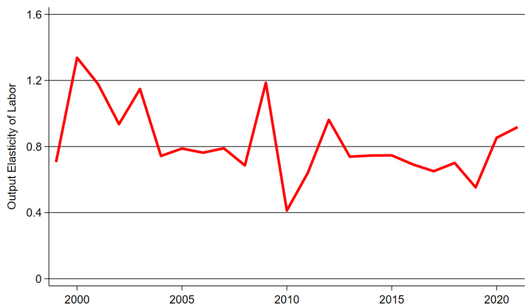


Figure 10: Comparison to Constant Output Elasticity of Labor

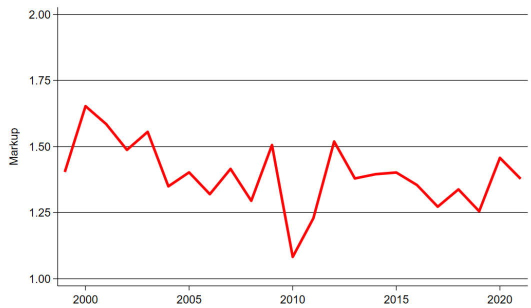
Note: The figure illustrates the average markup using the estimated output elasticities compared to using a constant output elasticity, as seen in Table 3. It is sales-weighted by year and trimmed at the 1 percentile level.

lyzed sectors in the baseline results. This is the main reason for not using this aggregation

in the main results, as it would decrease the number of sectors that can be analyzed in the sector-analysis.



(a) Average Output Elasticity of Labor



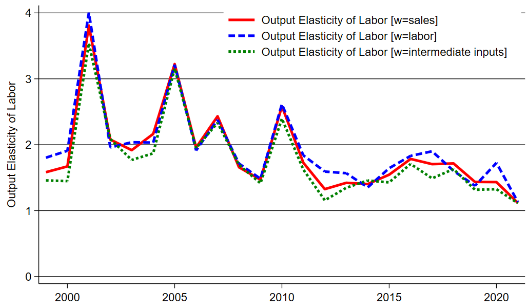
(b) Average Markup

Figure 11: Estimation with Highest Level of Sector Aggregation

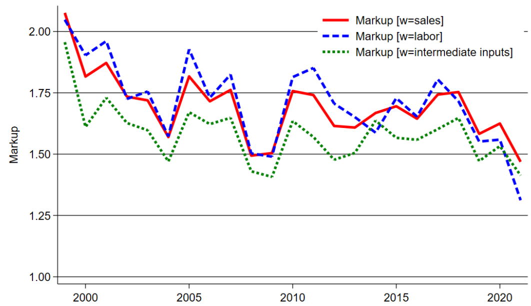
Note: The figures display the average output elasticity of labor and average markup, estimated using the highest level of sector aggregation. It is sales-weighted by year and trimmed at the 1 percentile level.

We present the results from this robustness test in Figure 11, we find that the average output elasticity of labor is substantially lower but still has significant variation over time. For example, in 2010, we notice a substantial decrease from 1.2 to 0.4, which can be considered unlikely to happen in one year. Disregarding the drop in 2010, the average markup is slightly more constant and, on average, lower than the baseline results. Similar to when using an economy-wide output elasticity of labor, our baseline results are sensitive to changes in the output elasticity of labor and choices regarding aggregation across the economy. In comparison, it is still evident that the within-sector effect drives the changes in the average markup when conducting a sector-level decomposition of the average markup, as presented in Appendix A6 Table 7. In Appendix A5 Table 6, we also present the sector decomposition using the 3- and 4-digit NACE codes and show that the results are robust to the more specific sector classifications.

Next, we plot the average markup using different weights. In our baseline results, we weigh the average markup using sales shares. To ensure that the sales weights do not drive the results, we test the robustness using both labor and intermediate inputs as weights. Reviewing both Figure 12a and Figure 12b, we observe that the choice of weight does not significantly impact the average output elasticity of labor. However, the average markup is slightly lower when using intermediate inputs as weight, although the trend is similar. As such, it is plausible that the estimated output elasticity of labor drives our results, not the chosen weights.



(a) Average Output Elasticity



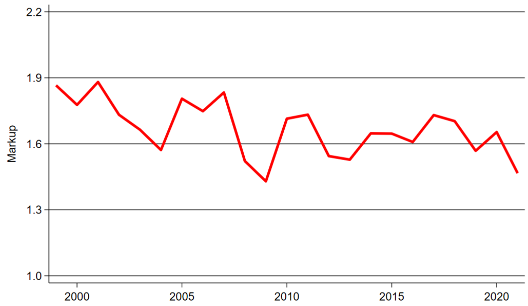
(b) Average Markup

Figure 12: Different Input Weights

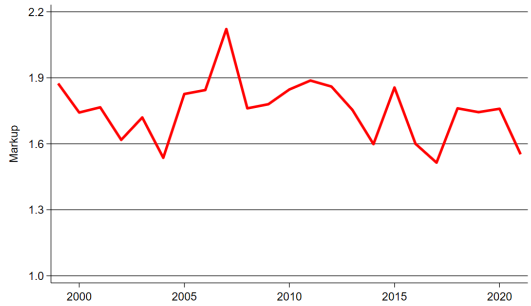
Note: The figures display the average output elasticity of labor and average markup, using different input weights trimmed at the 1 percentile level.

The proxy for raw materials is constructed using sector-year specific ratios for raw materials to production costs. We thus assume that the raw materials used in production differ across industries and time. This assumption could affect the estimated output elasticities of labor. Hence, we provide an alternative definition of the proxy. In Figure 13a, we apply a fixed economy-wide ratio of raw materials used in production equal to 60%. This is the mean of the ratio of raw materials to production costs in the entire sample. Whereas this leads to a more volatile average markup in the intermediate years and a less pronounced decrease at the beginning of the 2000s, the trend is still similar to the baseline results.

Furthermore, we plot the average markup using only observations that report raw materials on a yearly basis. The results differ from our baseline, where we observe a clear downward trend. Instead, when only using the sample the proxy is built on, we observe a volatile development with no clear trend, yet the range is similar, as shown in Figure 13b. One explanation for the significant difference in the estimated markup is the drop in observations. Instead of a total of 1,214,172 observations, the sample is decreased to 286,936, naturally making the estimations more sensitive. It is thus important to note



(a) Fixed Ratio

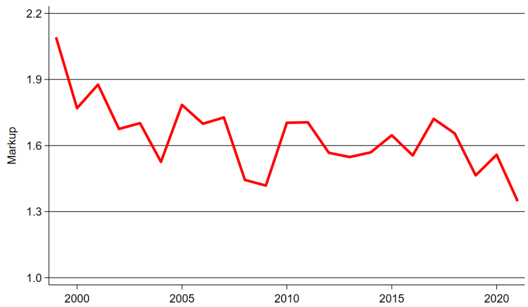


(b) Raw Materials

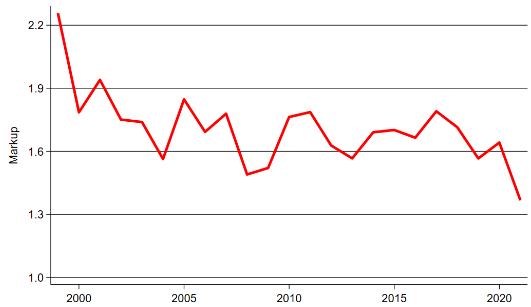
Figure 13: Average Markup under Alternative Intermediate Inputs

Note: Figure 13a displays the average markup using an economy-wide fixed ratio. Figure 13b displays the average markup, estimated using the sample reporting raw materials. They are sales-weighted by year and trimmed at the 1 percentile level.

that the average markup estimated in our baseline is sensitive to the created proxy. Consequently, it is difficult to conclude whether the average markup calculated using the proxy versus those observations that report yearly raw materials is the true markup.



(a) Sectors with More Than 200 Obs.



(b) Trimmed at the 0.1 Percentile Level

Figure 14: Average Markup with Differences in Trimming of Sample

Note: Figure 14a shows the average markup, estimated using sectors with more than 200 observations per year trimmed at the 1 percentile level. Figure 14b displays the average markup, trimmed at the 0.1 percentile level. Both figures are sales-weighted.

To see whether our estimation of the average markup is sensitive to the choices of trimming made to the sample, we also present our estimations using other trimming choices. As shown in Figure 14, the estimated average markup is similar to the baseline results when only sectors with more than 200 firm-year observations are included instead of 50 firm-year observations. In our baseline estimations, we drop 21,344 firm-year observations when sampling only those sectors that have at least 50 firm-year observations every year, and we drop 114,014 firm-year observations when sampling only those sectors with more than 200 firm-year observations. From a total of 75 sectors, the number of sectors included in the sample changes from 53 in our baseline results to 22 after dropping observations with less than 200 firm-year observations. This similarity of the average markups indicates that our results are robust to the choice of sampling. We can also see that the results are similar to the baseline when trimming the sample for outliers at the 0.1 percentile level compared to the one percentile level. We observe that the average markup is slightly higher, however there is no significant difference. In conclusion, the choice of trimming does not drive our results.

7 Discussion

7.1 Discussion of Main Results

The main results of this paper suggest that markups have decreased in Sweden since 1999, from 2.08 to 1.47 in 2021. Examining the distribution of markups, we find that the top 10% of firms in the markup distribution drive the variability, while 90% of the distribution shows very constant trends, albeit with a slight downward trend. Our markup estimations yield different results compared to previous findings. Although De Loecker and Eeckhout (2018) find evidence for increasing markups globally, they find that markups in Sweden have stayed relatively constant since 2000, at around 1.3. However, our methodologies differ in several ways, making a direct comparison difficult. The authors use a five-year rolling-window approach. Our estimated results using the same methodology are closer in level to those of De Loecker and Eeckhout. However, we still observe a downward trend, with results fluctuating between 1.35 and 1.55. Moreover, the estimates presented by De Loecker and Eeckhout are based on US estimates of output elasticity, which assumes that Sweden and the US are similar in terms of technologies. This could be a strong assumption for the two economies, as Sweden is a small open economy, as opposed to the US. Lastly, there is a notable difference in our samples, with ours being significantly larger, containing smaller firms, and composed of publicly and non-publicly traded firms.

Contrasting the results from De Loecker and Eeckhout (2018), Weche and Wambach (2021) find that markups have decreased in Sweden between 2007 and 2015 by 0.5, ranging between 2.4 and 2.9. This is more in line with our findings, although we have a higher variability and a more moderate decrease in the average markup during the same period. However, Weche and Wambach estimate the average markup using a translog production function, assuming a constant output elasticity of variable input.[7] This differs from our methodology, again reducing the comparability of our results.

To look at what drives the downward trend, we perform a decomposition at both the firm- and sector-level to see whether within, reallocation, or net entry effect are driving the development in the average markup. We find that the within-effect has the largest influence on the change in the average markup over time. On the firm-level, we also find that reallocation has positively affected the average markup, indicating increasing market power and reallocation of economic activity to high markup firms. When we inspect the distribution of the average markup, it is evident that the top 10% of firms completely drive the trend seen. Thus, for the majority of firms, markups are staying relatively constant, contrasting the increase seen in reallocation over time, as the average

[7] The translog production function allows for estimating firm-specific output elasticities by permitting the value added production function to be a higher order polynomial in capital and labor.

markup sees a downward trend. When inspecting the distribution, one can see that there is indeed a decrease in markups from 4.5 to 3 for the top 10% of firms between 1999 and 2004. Following 2004, these firms' markup fluctuates between 3 and 3.8. This causes a significant impact on the average markup, suggesting these firms are also those that are large in terms of market shares. Thus, the top 10% of firms drive the average markup, mainly influencing the within term. At the same time, these firms are growing in terms of market shares, which can be observed in the reallocation term. The implications in terms of the development of market power over time are less evident, as these high markup firms are indeed growing in terms of market shares, yet their markups are not increasing.

Furthermore, net entry does not affect the average markup over time, meaning that firms entering the market set similar markups as firms exiting the market. This is not in line with our expectations since we have an unbalanced panel of firms, where the number of firms in the dataset grows over time. As mentioned by De Loecker et al. (2020), this would positively affect the net entry term. As such, disregarding the effect coming from an unbalanced panel, the true net entry effect may be negative. This would instead imply that the entering firms are charging lower markups than the exiting firms, which might be consistent with decreasing markups over time. Nevertheless, as long as the distribution of firms entering is similar, this term will not be affected by the unbalanced dataset. Naturally, firms that exit the market may do so because staying in the market is no longer profitable, reasonably charging lower markups. Thus, one could assume that entering firms also set lower markups as they want to compete in the new market. To conclude, there are numerous reasons why this term has been constant over time. However, it is reasonable to assume that it does not drive the development of the average markup over time.

We observe a similar pattern at the sector-level where the within-effect drives the trend in the average markup. This is in line with the findings of De Loecker et al. (2020), who find that the rise in the average markup and market power in the US can be attributed to all sectors. Compared to the firm-level decomposition, our sector-level decomposition indicates that all sectors experience similar changes in markups over time. In relation to the between and cross terms, we see less clear patterns, where both contribute positively and negatively to the change in markups over the years. This contrasts the firm-level decomposition where reallocation was increasing over time. However, this is not necessarily contradictory since it solely implies that large firms with high markups are growing larger, whereas large sectors with high markups are not. As such, large firms across all sectors drive the changes in markups over time.

As seen in Appendix A4, the sector-specific markups are experiencing high variation over time in the majority of sectors. This questions the interpretability of the sector analysis, as the underlying markups are highly volatile. One sector where we find relatively stable results is the food processing sector. This has also been studied before in terms of markups by, for example, Gullstrand et al. (2014), Olofsdotter et al. (2011) and Wilhelmsson (2006). As seen in Appendix A4 Figure 16c, our estimations indicate that markups for the food manufacturing sector remained relatively stable at around 1.5 from 1999 to 2021, except for one year, where the results are deemed unreliable. In comparison, using data from 1997 to 2007, Gullstrand et al. (2014) and Olofsdotter et al. (2011) find lower markups, ranging between 1.2 and 1.4 across different industries within the sector. Both papers present one average markup for the entire period, thus it is difficult to assess the changes over time. Moreover, Wilhelmsson (2006) finds an average markup of 1.09 during the 1990s in the food and beverage industry, with a marginal increase following Sweden's accession to the EU.

On average, we estimate higher markups than the above-mentioned papers. This is expected since the industry experienced increases in concentration during the past 20 years (Swedish Competition Authority, 2018). However, based on the increase in concentration, we would have anticipated a rise in markups in our estimations, which is not the case. One reason for this could be that wholesalers have, during the same period, observed a similar increase in market concentration (Swedish Competition Authority, 2018). As such, this could suggest that there is no increase in market power for manufacturers of food products against their buyers. Since we only present the average markup for wholesale on an aggregated level, it is difficult to draw further conclusions on the development of markups for the grocery wholesale industry. However, Gullstrand et al. (2014) find lower markups for wholesale in the food industry, contradicting this conclusion. Nevertheless, the food sector analysis is in line with our firm and sector decomposition analysis, where we find that large firms with high markups may be growing larger, but not necessarily that markups are growing larger. As such, this is consistent with the increase in concentration presented by the Swedish Competition Authority (2018) but also with our findings that the average markup in this sector stays constant over time.

In conclusion, drawing from our firm- and sector-level analysis, it is evident that the changes in the average markup over time are not driven by a specific sector but rather by large firms spread out across sectors in the economy. This has implications for policymakers when constructing policies aimed at mitigating market power. Rather than implementing sector-specific policies, focus should be directed to large firms attaining excessive power within their respective sectors.

7.2 Limitations and Suggestions for Future Research

As with any study, it is important to discuss its limitations. One limitation stems from the variable raw materials and consumables not being included in the adjusted Serrano Database, and it was outside the scope of this study to transform this raw data in line with the adjustments (see Appendix A3). As a result, we resorted to creating a proxy from 312,586 observations, which might not be representative of the true population of 1,214,172 observations. By transforming the raw data from the Swedish Companies Registration Office, the sample would be more representative of the entire population of Swedish firms, giving more powerful estimates.

Moreover, the estimated output elasticities are highly variable, which impacts our results. As can be seen by our robustness checks, it is the estimated output elasticities of labor over time that lead to a volatile average markup with a downward trend. As mentioned previously, the proxy we use may introduce a downward bias on the output elasticities. Moreover, approximately 1% of our estimates are negative, and around 5% have output elasticities above 7 (see Appendix A2 Table 5). These two issues give rise to concerns regarding the reliability of our estimates. Interestingly, previous research generally finds that the majority of estimated output elasticities in variable inputs range between 0 and 1 (see De Loecker et al., 2020; Díez et al., 2021; Van Vlokhoven, 2023), which is consistently lower than our estimates. Given the suggested downward bias, we would expect our estimates to be lower compared to previous research. However, Díez et al. (2021) find that larger firms have smaller output elasticities up until a certain threshold of firm size. In our dataset, the average number of employees per firm is 23, which, compared to the mean of 8,363 employees in De Loecker et al. (2020), can be deemed relatively small. Consequently, our observation of higher output elasticities aligns with the findings of Díez et al., that larger firms tend to have lower output elasticities. To conclude, there is uncertainty in that the presented estimates are the true output elasticities of labor, which causes concern about the reliability of the average markup.

While we acknowledge the proxy as a limitation, we leave estimations of the true population of Swedish firms for future research. Moreover, it would be interesting to compare the development of markups to other countries using more comprehensive, country-specific datasets similar to the Serrano Database. Researchers could also investigate specific industries, as the sector-specific average markups in this paper show very heterogeneous results. Lastly, estimations of markups could be researched in relation to the development in labor share and profit share to get a more nuanced picture of the development of market power in Sweden.

8 Conclusion

This study investigates the development of markups in Sweden from 1999 to 2021 using the production function approach. We use the estimated sector-year specific production function to extract markups as the ratio between the output elasticity of labor and its cost share in sales. By decomposing the average markup at the firm- and sector-level, we can see what drives the development. We find that Sweden's average markup has decreased between the years 1999 and 2021, from 2.08 to 1.47. There is a sharp decline in the average markup at the beginning of the 21st century, after which the average markup fluctuates between 1.5 and 1.7. These findings support previous research by Weche and Wambach (2021), who find a declining markup trend over time in Sweden but contrast the conclusions drawn by De Loecker and Eeckhout (2018), suggesting that markups have remained constant. Nonetheless, adopting a methodology closer to the one used by De Loecker and Eeckhout, we still find that the average markup has been decreasing, further strengthening our, and Weche and Wambach's, findings of declining markups in Sweden.

Our findings further suggest that the top 10% of firms in the markup distribution drive the variability in markups, while the bottom 90% of firms maintain stable markups over time. The decomposition of the average markup reveals that the within-effect is the main contributor to the change in the average markup at the firm- and sector-level. This means that all firms across all sectors experience decreases in markups, keeping firms' and sectors' market shares fixed. However, it is not evident whether Swedish firms' ability to exert market power has increased during the last two decades. While the average markup has decreased, entirely driven by the within-effect, we also observe an increase in the reallocation term. This suggests that firms charge higher markups as they grow or that high markup firms grow.

Furthermore, in this paper we contribute with novelty to the current body of research by using a unique approach to estimating sector-year specific output elasticities of labor. This allows us to mitigate the influence of future technologies on our findings, a factor overlooked in prior studies. Although this results in highly fluctuating output elasticities of labor, we conduct several robustness tests where the majority of them validate our main result that the average markup is decreasing over time.

Besides our contribution to the literature, the paper has implications for policymakers who strive to make informed decisions regarding the market in which we interact. Our results indicate that market power may be prevalent but not necessarily growing at the top of the markup distribution in Sweden and that this occurs across all sectors. While this offers insight into potential areas of focus for policymakers, the topic has to be investigated further to guide them. With the inclusion of profit and labor shares, a more detailed understanding of how market power evolves in Sweden over time can be presented.

References

Ackerberg, D., Benkard, C. L., Berry, S., and Pakes, A. (2007). Econometric tools for analyzing market outcomes. *Handbook of econometrics*, 6:4171–4276. DOI: 10.1016/S1573-4412(07)06063-1.

Ackerberg, D. A., Caves, K., and Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, 83:2411–2451. DOI: 10.3982/ecta13408.

Affeldt, P., Duso, T., and Szücs, F. (2021). 25 years of European merger control. *International Journal of Industrial Organization*, 76:102720. DOI: 10.1016/j.ijindorg.2021.102720.

Agrawal, S., Gaurav, A., and Suveg, M. (2021). Markups as a hedge for input price uncertainty: Evidence from Sweden. Working Paper 2021(1418), IFN Working Paper.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., and Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, 135(2):645–709. DOI: 10.1093/qje/qjaa004.

Badinger, H. and Breuss, F. (2005). Has Austria's accession to the EU triggered an increase in competition? A sectoral markup study. *Empirica*, 32(2):145–180. DOI: 10.1007/s10663-004-8078-x.

Basu, S. (2019). Are price-cost markups rising in the United States? A discussion of the evidence. *Journal of Economic Perspectives*, 33(3):3–22. DOI: 10.1257/jep.33.3.3.

Belleflamme, P. and Peitz, M. (2015). *Industrial organization: markets and strategies*. Cambridge University Press.

Berry, S., Gaynor, M., and Morton, F. S. (2019). Do increasing markups matter? Lessons from empirical industrial organization. *Journal of Economic Perspectives*, 33(3):44–68. DOI: 10.1257/jep.33.3.44.

Bokföringsnämnden [The Swedish Accounting Standards Board] (2023a). Bokföringsnämndens Vägledning: Årsredovisning i mindre företag (K2) 2016:10 Section 1.1. Available online: link.

Bokföringsnämnden [The Swedish Accounting Standards Board] (2023b). Bokföringsnämndens Vägledning: Årsredovisning i mindre företag (K2) 2016:10 Section 4.4. Available online: link.

Carraro, C. and De Cian, E. (2013). Factor-augmenting technical change: an empirical assessment. *Environmental Modeling & Assessment*, 18:13–26. DOI: 10.22004/ag.econ.50403.

Cavalleri, M. C., Eliet, A., McAdam, P., Petroulakis, F., Soares, A., and Vansteenkiste, I. (2019). Concentration, market power and dynamism in the euro area. Working Paper Series 2019(2253), European Central Bank. DOI: 10.2866/379250.

Chakravarti, I. M., Laha, R., and Roy, J. (1967). *Handbook of methods of applied statistics. Vol. 1, Techniques of computation, descriptive method and statistical inference*. Wiley series in probability and mathematical statistics. Wiley, New York.

David, J. M. and Venkateswaran, V. (2019). The sources of capital misallocation. *American Economic Review*, 109(7):2531–2567. DOI: 10.1257/aer.20180336.

De Loecker, J. (2011). Recovering markups from production data. *International Journal of Industrial Organization*, 29(3):350–355. DOI: 10.1016/j.ijindorg.2011.02.002.

De Loecker, J. and Eeckhout, J. (2018). Global market power. Working Paper 24768, National Bureau of Economic Research. DOI: 10.3386/w24768.

De Loecker, J., Eeckhout, J., and Mongey, S. (2021). Quantifying market power and business dynamism in the macroeconomy. Working Paper 28761, National Bureau of Economic Research. DOI: 10.3386/w28761.

De Loecker, J., Eeckhout, J., and Unger, G. (2020). The rise of market power and the macroeconomic implications. *The Quarterly Journal of Economics*, 135(2):561–644. DOI: 10.1093/qje/qjz041.

De Loecker, J., Goldberg, P. K., Khandelwal, A. K., and Pavcnik, N. (2016). Prices, markups, and trade reform. *Econometrica*, 84(2):445–510. DOI: 10.3982/ecta11042.

De Loecker, J. and Warzynski, F. (2012). Markups and firm-level export status. *American economic review*, 102(6):2437–2471. DOI: 10.1257/aer.102.6.2437.

Doraszelski, U. and Jaumandreu, J. (2018). Measuring the bias of technological change. *Journal of Political Economy*, 126(3):1027–1084. DOI: 10.1086/697204.

Díez, F., Leigh, D., and Tambunlertchai, S. (2018). Global market power and its macroeconomic implications. Working Paper 2018(137). DOI: 10.5089/9781484361672.001.

Díez, F. J., Fan, J., and Villegas-Sánchez, C. (2021). Global declining competition? *Journal of International Economics*, 132:103492. DOI: 10.1016/j.jinteco.2021.103492.

European Commission (2023). Glossary: Statistical classification of economic activities in the european community (NACE) - statistics explained. Available online: link. Accessed: 2024-03-11.

FRED (2023). National accounts: National accounts deflators: Gross Domestic Product:

GDP deflator for Sweden. Available online: link. Federal Reserve Bank of St. Louis. Accessed: 2024-02-07.

Goolsbee, A., Syverson, C., and Levitt, S. (2016). *Microeconomics*. Palgrave Macmillan Books. Worth Publishers, 3rd edition.

Gullstrand, J., Olofsdotter, K., and Thede, S. (2014). Markups and export-pricing strategies. *Review of World Economics*, 150:221–239. DOI: 10.1007/s10290-013-0178-x.

Hall, R. E. (1986). Market structure and macroeconomic fluctuations. *Papers on Economic Activity*, 1986:285–338. DOI: 10.2307/2534476.

Haltiwanger, J. (1997). Measuring and analyzing aggregate fluctuations: the importance of building from microeconomic evidence. *Federal Reserve Bank of St. Louis Review*, (May):55–78. DOI: 10.20955/r.79.55-78.

Jakubik, A., Keck, A., and Piermartini, R. (2023). Trade policy implications of a changing world: Tariffs and import market power. Working Paper 2003(5), International Monetary Found. DOI: 10.30875/25189808-2022-14.

Justitiedepartementet L1 [Ministry of Justice] (1995). Årsredovisningslag 3 kap. § 3 (SFS 1995:1554) [Swedish Annual Accounts Act]. Available online: link.

Justitiedepartementet L1 [Ministry of Justice] (1999). Bokföringslag 3 kap. § 3 (SFS 1999:1078) [Swedish Bookkeeping Act]. Available online: link.

Konkurrensverket [Swedish Competition Authority] (2018). Konkurrensen i livsmedelskedjan. Report Series 2018(4).

Levinsohn, J. and Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The review of economic studies*, 70(2):317–341. DOI: 10.1111/1467-937X.00246.

Marschak, J. and Andrews, W. H. (1944). Random simultaneous equations and the theory of production. *Econometrica, Journal of the Econometric Society*, 12(3/4):143–205. DOI: 10.2307/1905432.

OECD (1993). *Glossary of Industrial Organisation Economics and Competition Law:*. CCEET series. Organisation for Economic Co-operation and Development.

Olley, G. S. and Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64(6):1263–1297. DOI: 10.2307/2171831.

Olofsdotter, K., Gullstrand, J., and Karantininis, K. (2011). Konkurrens och makt i den svenska livsmedelskedjan. Report prepared by Agrifood Economics Centre in Lund, Konkurrensverket [Swedish Competition Authority].

Raval, D. R. (2019). The micro elasticity of substitution and non-neutral technology. *The RAND Journal of Economics*, 50(1):147–167. DOI: 10.1111/1756-2171.12265.

Statistiska Centralbyrån [Statistics Sweden] (2024). Företagsregistret. Available online: link. Accessed: 2024-03-17.

Van Vlokhoven, H. (2023). Decomposing the rise in markups with measurement error. Working Paper 2022(006), Tilburg University, Center for Economic Research. DOI: 10.2139/ssrn.4338765.

Vancauteren, M. (2013). EU harmonisation of regulations and mark-ups in the Dutch food industry. *European Review of Agricultural Economics*, 40:163–189. DOI: 10.1093/erae/jbs009.

Weche, J. P. and Wambach, A. (2021). The fall and rise of market power in Europe. *Jahrbücher für Nationalökonomie und Statistik*, 241(5-6):555–575. DOI: 10.1515/jbnst-2020-0047.

Weidenman, P. (n.d.). The serrano database for analysis and register-based statistics. Swedish House of Finance Research Data Center. Available online: link. Accessed: 2024-01-16.

Wilhelmsson, F. (2006). Market power and European competition in the Swedish food industry. *Journal of Agricultural & Food Industrial Organization*, 4(1). DOI: 10.2202/1542-0485.1147.

Appendix

A1: Summary Statistics

Table 4: Summary Statistics (1998-2021)

	Acronym, var.	Mean	Median	No. Obs
Sales	Net sales, PQ	50,776	13,403	1,214,172
Labor	Personnel expenses, L	11,878	4,134	1,214,172
Capital	Tangible fixed assets, K	14,396	638	1,214,172
Intermediate inputs	Proxy for raw materials, M	21,909	4,441	1,214,172
Employees	Employees, EMP	23	9	1,214,172

Note: The data is presented in thousands of SEK and deflated with the Swedish GDP deflator from FRED (2023), the base year is 2015. The acronym refers to the name of the variable in the Serrano Database, and the variable name is the notation used in the methodology section of the paper.

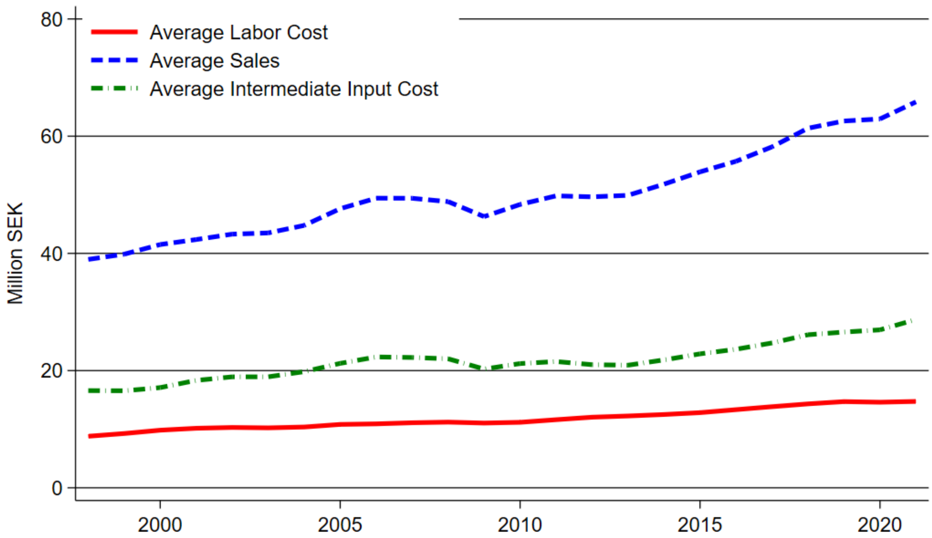


Figure 15: Average Sales and Variable Input Costs
Note: The data is presented in millions of SEK and deflated with the Swedish GDP deflator from FRED (2023), the base year is 2015.

Figure 15 displays the average sales and costs for all firms in our sample. Both sales and intermediate input costs are clearly trending upwards, whereas labor costs see a smaller increase over time.

A2: Summary Statistics of Estimated Output Elasticities of Labor

Table 5: Summary Statistics of Output Elasticity of Labor

				Percentiles				
Sample/Estimation-Method	Mean	Min	Max	1%	5%	50%	95%	99%
Baseline	3.60	-38.80	2435.41	-0.51	0.16	1.11	7.05	21.08
Rolling-Window	0.83	-2.08	13.84	-0.21	0.32	0.84	1.38	2.21
Highest Sector Aggregation	1.26	-1.33	2435.41	-0.28	0.21	0.81	1.53	2.26
Raw Materials	3.88	-3.43	179.64	-1.83	0.25	1.10	12.41	64.70

Note: The table shows the summary statistics of the estimations of output elasticity of labor using different samples or methods. Baseline corresponds to our main results, whereas rolling-window corresponds to the results of using a five-year rolling-window approach. Highest sector aggregation displays the results from estimating output elasticity of labor using the highest level of sector aggregation when estimating the sector-year specific production functions. Raw materials corresponds to the estimations using the sample that reports raw materials.

A3: Adjustments Made to Serrano

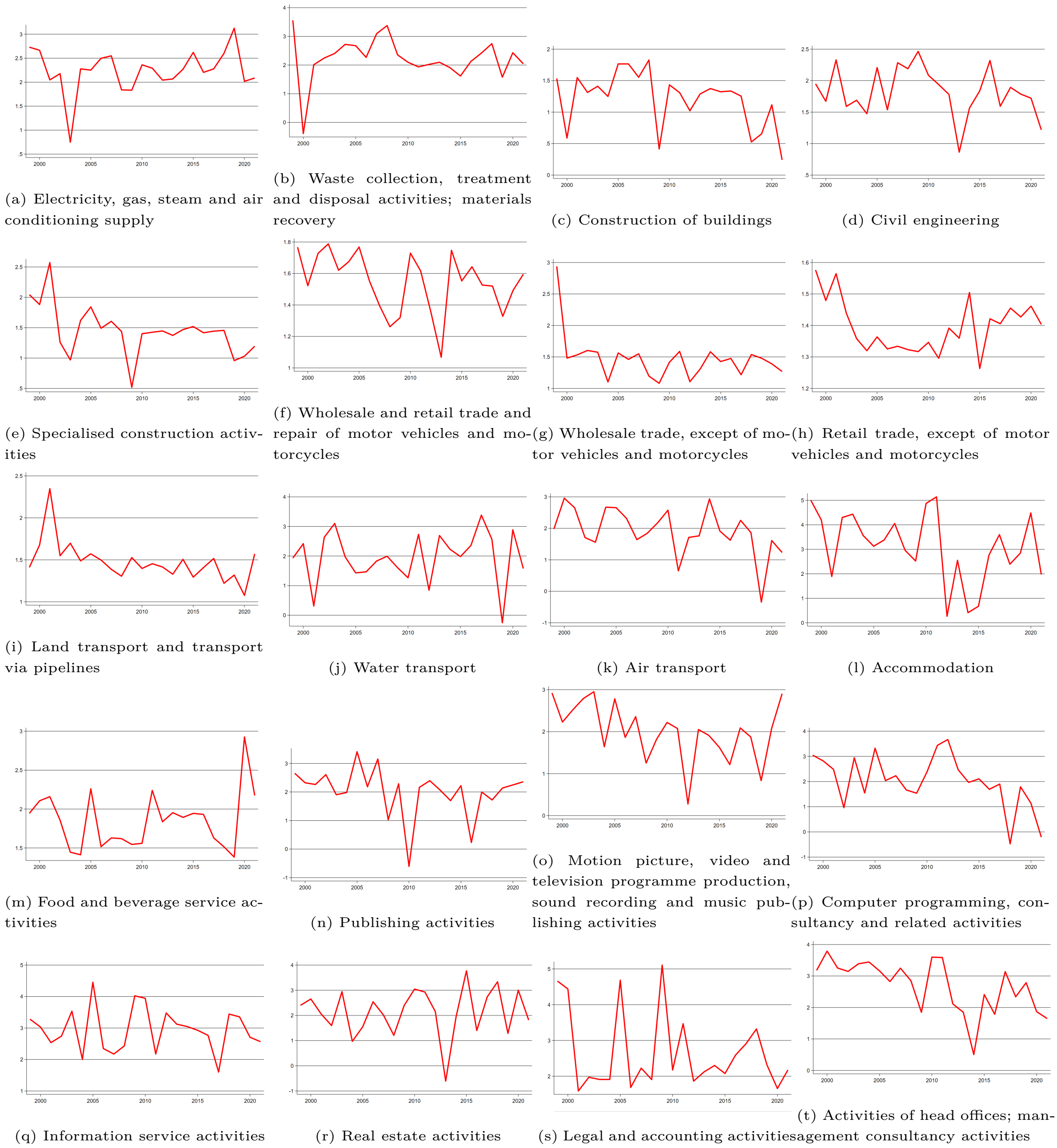
The Serrano Database adjusts and corrects its data to address various phenomena. This includes broken, short, and long accounting periods, and omissions and gaps in financial statements. Moreover, it also accounts for imputation for the latest year's calendar year values, registration and deregistration dates during a calendar year, and conversion of data to calendar year values for both stock and flow data. Lastly, it applies rules for determining active businesses and rules for newly started companies (Weidenman, n.d.).

A4: Sector-Specific Markups

(a) Forestry and logging
(b) Other mining and quarrying
(c) Manufacture of food products
(d) Manufacture of textiles
(e) Manufacture of wood and of products of wood and cork
(f) Manufacture of paper and paper products
(g) Printing and reproduction of recorded media
(h) Manufacture of chemicals and chemical products
(i) Manufacture of rubber and plastic products
(j) Manufacture of other non-metallic mineral products
(k) Manufacture of basic metals
(l) Manufacture of fabricated metal products, except machinery and equipment
(m) Manufacture of computer, electronic and optical products
(n) Manufacture of electrical equipment
(o) Manufacture of machinery and equipment n.e.c.
(p) Manufacture of motor vehicles, trailers and semi-trailers
(q) Manufacture of other transport equipment
(r) Manufacture of furniture
(s) Other manufacturing
(t) Repair and installation of machinery and equipment

Figure 16: Average Markups by Sectors

Note: The figure illustrates the average markups by sector, which are sales-weighted by year and sector, and trimmed at the 1 percentile level.



(a) Electricity, gas, steam and air conditioning supply

(b) Waste collection, treatment and disposal activities; materials recovery

(c) Construction of buildings

(d) Civil engineering

(e) Specialised construction activities

(f) Wholesale and retail trade and repair of motor vehicles and motorcycles

(g) Wholesale trade, except of motor vehicles and motorcycles

(h) Retail trade, except of motor vehicles and motorcycles

(i) Land transport and transport via pipelines

(j) Water transport

(k) Air transport

(l) Accommodation

(m) Food and beverage service activities

(n) Publishing activities

(o) Motion picture, video and television programme production, sound recording and music publishing activities

(p) Computer programming, consultancy and related activities

(q) Information service activities

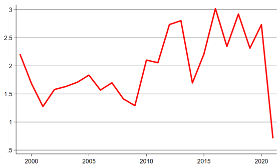
(r) Real estate activities

(s) Legal and accounting activities

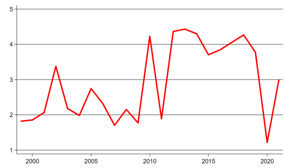
(t) Activities of head offices; management consultancy activities

Figure 17: Average Markups by Sectors

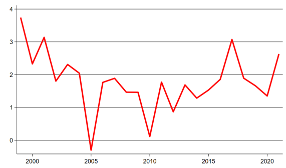
Note: The figure illustrates the average markups by sector, which are sales-weighted by year and sector, and trimmed at the 1 percentile level.



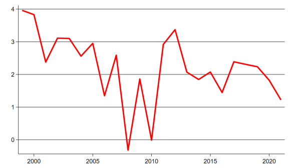
(a) Architectural and engineering activities; technical testing and analysis



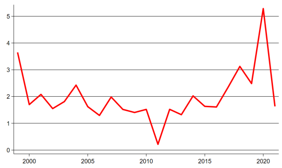
(b) Scientific research and development



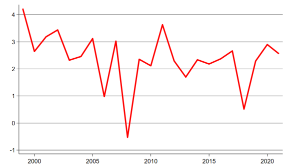
(c) Advertising and market research



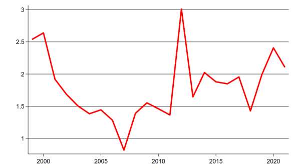
(d) Other professional, scientific and technical activities



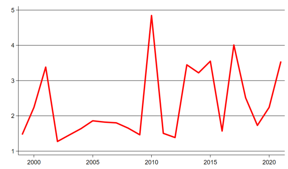
(e) Veterinary activities



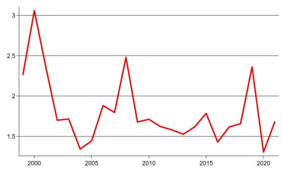
(f) Rental and leasing activities



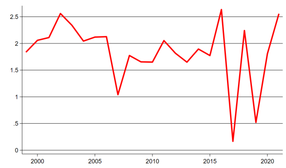
(g) Travel agency, tour operator and other reservation service and related activities



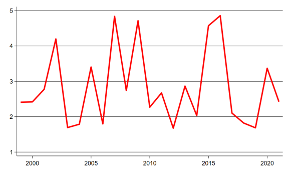
(h) Security and investigation activities



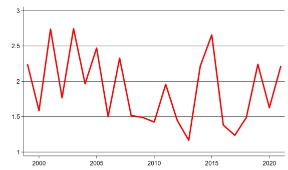
(i) Services to buildings and landscape activities



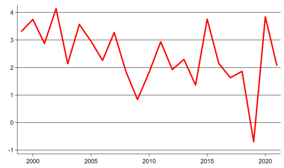
(j) Office administrative, office support and other business support activities



(k) Sports activities and amusement and recreation activities



(l) Repair of computers and personal and household goods



(m) Other personal service activities

Figure 18: Average Markups by Sectors

Note: The figure illustrates the average markups by sector, which are sales-weighted by year and sector, and trimmed at the 1 percentile level.

A5: Sector-Level Decomposition at Different Aggregation Levels

Table 6: Sectoral Decomposition of the Average Markup by Different Aggregation Levels

Year	Markup	ΔMarkup	ΔWithin	ΔBetween	ΔCross
2-digit sector					
2002	1.734	-0.342	-0.350	0.073	-0.065
2005	1.817	0.082	0.062	0.002	0.018
2008	1.494	-0.323	-0.328	-0.015	0.020
2011	1.741	0.247	0.200	0.011	0.036
2014	1.668	-0.073	-0.040	0.041	-0.074
2017	1.743	0.075	0.074	0.034	-0.033
2020	1.625	-0.118	-0.102	-0.004	-0.012
3-digit sector					
2002	1.734	-0.342	-0.349	0.065	-0.058
2005	1.817	0.082	0.064	0.002	0.016
2008	1.494	-0.323	-0.316	-0.030	0.008
2011	1.741	0.247	0.204	0.012	0.031
2014	1.668	-0.073	-0.046	0.048	-0.075
2017	1.743	0.075	0.073	0.029	-0.027
2020	1.625	-0.118	-0.108	-0.000	-0.011
4-digit sector					
2002	1.734	-0.342	-0.350	0.071	-0.065
2005	1.817	0.082	0.067	-0.011	0.008
2008	1.494	-0.323	-0.316	-0.067	0.008
2011	1.741	0.247	0.204	0.010	0.030
2014	1.668	-0.073	-0.059	0.048	-0.062
2017	1.743	0.075	0.075	0.035	-0.035
2020	1.625	-0.118	-0.108	-0.010	-0.001

Note: The table shows the 3 year change in the decomposition of the average markup at the sector level at the 2-, 3-, and 4-digit sector levels. The average markup is sales-weighted by sector and year and trimmed at the 1 percentile level.

A6: Sector-Level Decomposition at Highest Level of Aggregation

Table 7: Sectoral Decomposition of the Average Markup at the Highest Level of Aggregation

Year	Markup	ΔMarkup	ΔWithin	ΔBetween	ΔCross
2000	1.653	0.249	0.244	0.002	0.003
2001	1.585	-0.068	-0.074	0.004	0.003
2002	1.487	-0.097	-0.087	-0.006	-0.005
2003	1.556	0.068	0.078	0.010	-0.020
2004	1.349	-0.206	-0.202	0.014	-0.018
2005	1.402	0.053	0.053	-0.000	0.001
2006	1.320	-0.083	-0.103	-0.011	0.031
2007	1.415	0.096	0.097	-0.012	0.011
2008	1.295	-0.121	-0.126	0.007	-0.001
2009	1.506	0.211	0.209	0.011	-0.009
2010	1.082	-0.423	-0.482	0.002	0.056
2011	1.229	0.147	0.107	-0.079	0.119
2012	1.519	0.290	0.288	0.013	-0.012
2013	1.379	-0.140	-0.170	-0.003	0.033
2014	1.395	0.016	0.015	-0.032	0.033
2015	1.402	0.006	0.039	-0.005	-0.027
2016	1.354	-0.048	-0.049	0.025	-0.024
2017	1.272	-0.082	-0.008	-0.056	-0.017
2018	1.338	0.066	0.005	0.063	-0.002
2019	1.255	-0.083	-0.079	0.020	-0.024
2020	1.457	0.202	0.198	0.021	-0.017
2021	1.378	-0.079	-0.195	-0.011	0.128

Note: The table shows the yearly decomposition of the average markup at the highest level of aggregation of sector. The average markup is sales-weighted by sector and year and trimmed at the 1 percentile level.