FACULTY OF ECONOMICS AND BUSINESS



Essays on firms' market power: from microdata to macroeconomic performance

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Introduction

Competition in the product market forces firms to keep their prices low, in line to their marginal costs, in order to attract and retain customers. However, some firms become dominant enough to gain market power, i.e. they set prices above their marginal costs, without losing all their customers to a competitor. Over the past decades, firms' market power has substantially increased in the United States (De Loecker, Eeckhout and Unger, 2020), as well as at the global level (De Loecker and Eeckhout, 2021).[1] This secular rise in markups has stirred concerns not only about the efficiency of competition or anti-trust policy, but also about the potential effects of market power on macroeconomic outcomes (Syverson, 2019).

Firms' market power is often measured by market concentration measures. The theoretical motivation behind this idea can be derived from the general Cournot model, in which more market concentration leads to less competition, hence, more market power and higher profit levels. This might explain why the recent increase in market concentration is often interpreted as a rise of 'superstar firms', and consequently linked to the deterioration of macroeconomic outcomes (Autor et al., 2020), like for example a decrease in output market competition, falling productivity and innovation levels, and increasing inequality (OECD, 2021). Much of the research so far has focused on the United States, while less is known about market concentration in European countries, and its impact on macroeconomic outcomes.

Although market concentration is a popular proxy for market power among policy makers as well as academics, it remains a market outcome rather than a market primitive. This implies that higher market concentration is not necessarily linked to an increase in market power (Syverson, 2019). Therefore, the literature on firms' market power has heavily focused on the estimation of markups, as well as its secular trend. As mentioned, De Loecker et al. (2020) provide empirical evidence on the evolution of markups and document sizable increases in aggregate markups. This increase in markups may reflect rising market power as it is a good proxy for profitability. However, in the presence of fixed costs, rising markups may reflect a rise in fixed costs associated with production. Most of the literature tends to overlook the issue of fixed costs, by assuming that one or all inputs are entirely variable, leading to potential biased estimates on firms' market power and its evolution.

This dissertation contributes to the academic literature on two main aspects. First of all, chapters one and two study the evolution of superstar firms at the Belgian and European level, respectively, and

[1] De Loecker, Eeckhout and Unger (2020) show that the U.S. markup, i.e. defined as the ratio of price over marginal costs, rises from 21% in 1980 to 61% in 2016, while De Loecker and Eeckhout (2021) find that the aggregate markup increases from 1.15 in 1980 to 1.6 in 2016.

explore its link with macroeconomic outcomes. In particular, the first chapter investigates the link between superstar firms and the labor share, defined as the part of GDP going to labor, based on long time series of Belgian firm level data from 1985 to 2014. We provide evidence for a negative conditional correlation between the increase in market concentration and the decrease in the labor share in its two largest sectors: Manufacturing and Wholesale & Retail. This negative relation is predominantly driven by a reallocation effect, i.e. market share reallocates from high labor share firms towards low labor share firms, thereby pushing down the aggregate Belgian labor share. The Manufacturing and Wholesale & Retail sectors represent approximately half of the Belgian economy in terms of value added. We do not find evidence for the other Belgian sectors.

The second chapter looks into superstar firms at the European level, and its impact on the pass-through from productivity dispersion into wage dispersion. We make use of microdata from 14 European countries: Austria, Belgium, Denmark, Germany, Spain, Finland, France, Ireland, Italy, Luxemburg, the Netherlands, Portugal, Sweden and the United Kingdom from 2000 until 2016. We document increases in productivity dispersion, wage dispersion and market concentration, albeit with a moderating effect for wage and productivity dispersion in recent years. Beyond documenting an incomplete pass-through from productivity into wages, we present novel evidence of an even weaker pass-through in industries dominated by superstar firms. Firms in industries with limited product competition pass on fewer productivity gains to wages compared to more competitive industries. From a policy standpoint, this raises interesting questions related to the optimal degree of regulation of both product and labour markets needed to reduce wage inequality.

Next, chapters three and four move beyond the use of market concentration measures and deal with the estimation of markups, or alternatively price-cost margins. More specifically, we account explicitly for the existence of fixed costs. Chapter three introduces a novel method which estimates price-cost margins in the presence of fixed factors of production based on properties of the primal and dual revenue- and cost-based Solow residual. The estimated price-cost margin can be further decomposed into two components: a fixed costs ratio, which is needed to pay fixed costs, and the excess profitability, which captures economic profits. The main advantage of the approach is that it does not rely on the availability of an input which is entirely variable, rather, it allows for the flexible treatment of each input, i.e. fixed, variable or a combination of both. Additionally, unlike most other approaches, we do not need price deflators, as we use nominal values rather than deflated real values. To this end, we need to assume constant returns to scale on *variable* inputs, perfectly competitive *input* markets and variable input factors adjusting without frictions within a time period.

We illustrate our methodology by using a panel of Belgian firm level data from 1985 until 2014. This leads to three main results. First, we estimate aggregate price-cost margins of 25.9% on average, while fixed costs as a fraction of operating revenue and excess profitability equal 23.4% and 2.5%, respectively. Second, ignoring fixed costs in production underestimates price-cost margins and overestimates excess profit margins. Third and lastly, price-cost margins, fixed cost ratios and excess profitability have declined in the last three decades, suggesting competitive product markets.

Finally, the fourth chapter applies this novel estimation methodology to the ongoing COVID-19 pandemic. We show that the two components of price-cost margins, the part needed to cover fixed costs and the excess profits move in different directions during an economic crisis, thereby contributing to the price-cost margin cyclicality literature. The fixed cost share is countercyclical while the excess profit ratio is procyclical such that, ex-ante, the price-cost margin cyclicality is ambiguous. If fixed costs are high relative to profits, then the price-cost margin should be countercyclical. Vice versa, if excess profits are high relative to fixed costs, then the price-cost margin should be procyclical. Building on these insights, we introduce a 'vulnerability index', which identifies sectors with a high risk of inefficient exit of healthy firms during the COVID-19 crisis. The index is based on changes in operating revenue, changes in fixed cost shares and pre-crisis profitability. In particular, sectors characterized by a low pre-crisis profitability, high fixed cost shares and high revenue losses, might run rapidly into liquidity trouble. The case for government support is high in these sectors.

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Chapter 1

The impact of superstar firms on the labor share: Evidence from Belgium

1.1 Introduction

Recent research has documented a fall in the share of GDP going to labor (ILO and OECD, 2015). Karabarbounis and Neiman (2014) show that the labor share is declining in 59 out of 76 countries. Moreover, the labor share is decreasing in seven out of the largest eight economies: US, China, Japan, Germany, France, Italy and Canada. The only exception is the United Kingdom which experiences a modest increase in the labor share. The fall of the labor share is an important policy issue for at least two reasons. First, it implies that productivity is structurally growing faster than real wages, thereby shifting the benefits of economic growth from workers towards firms and capital owners (Bivens, Gould, Mishel & Shierholz, 2004).[1] Second, a declining labor share might lead to a rise in income inequality. This follows from the fact that labor income is known to be more equally distributed than capital income. A gradual shift from the former component to the latter will increase total income inequality (Dao, Das, Koczan & Lian, 2017).

Even though there is still discussion about the measurement of the labor share and the magnitude of the decline (Bridgman, 2014; Elsby, Hobijn & Sahin, 2013; Koh, Santaeulàlia-Llopis & Zheng, 2018; Rognlie, 2015; Smith, Yagan, Zidar & Zwick, 2019), consensus has emerged on the fall of the labor share. However, there is an ongoing debate on the drivers of this secular evolution. The literature has mainly looked into macroeconomic causes for this phenomenon. More recently, researchers are exploring the impact of microeconomic, granular drivers as well. Autor, Dorn, Katz, Patterson & Van Reenen (2020) relate another secular trend, namely the rise of market concentration, to the fall of the labor share. They suggest the existence of a superstar firm mechanism. Superstar firms are defined as

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** I am grateful for the financial support from Methusalem that made this study possible.
[1] Bivens et al. (2014) document the disconnect between productivity and wages for production workers in the private sector in the United States. From 1948 to 1979, productivity and wages rose respectively by 108% and 93% in real terms, but between 1979 and 2013, productivity increased by 65% while wages increased only by 8%.

large firms which 1) are expanding their market share (in terms of value added) in their industry and 2) are characterized by a low labor share. As a consequence, the aggregate labor share falls over time. They show evidence for a variety of sectors in the United States.

In this chapter, we assess whether a superstar firm mechanism also exists in other economies. We consider the Belgian economy for three reasons. First, evidence from a European country is still lacking and serves as an interesting research opportunity to investigate to what extent the U.S. findings generalize (De Loecker, Fuss & Van Biesebroeck, 2018). Second, Autor et al. (2020) also look into other countries and provide evidence which suits their hypothesis for various countries, except for Belgium for which they find a positive link between market concentration and the labor share. Third, we have a rich longitudinal Belgian firm-level data set. It covers all for-profits firms from 1985 until 2014. This allows to distinguish business cycle fluctuations from the secular labor share trend. In order to enhance comparability with the U.S results, we closely follow the methodology of Autor et al. (2020).

Our main finding is that we confirm the presence of a superstar firm mechanism in the two largest Belgian sectors: Manufacturing and Wholesale & Retail. These sectors account for approximately 53% of the Belgian economy, in terms of value added between 1985 and 2014. However, we are not able to find evidence in other Belgian sectors. We conclude that we cannot generalize the superstar firm hypothesis to all Belgian sectors. It is a sector-specific phenomenon.

This chapter fits into academic literature which looks into the drivers of the decline of the labor share. As aforementioned, one dominant strand looks to macroeconomic drivers and points to the rapid advancement of technology as well as to the globalization of trade and capital (Dao et al., 2017). Karabarbounis and Neiman (2014) emphasize the influence of technology. They relate the decline in the relative price of investment goods to the fall of the labor share. Doan and Wan (2017) support the importance of international trade. They show that exports depress the labor share whereas imports increase the labor share. Next, the literature remains inconclusive about the impact of other determinants like a decline in unionization, offshoring labor-intensive work, an increase in intellectual property rights (IPP), product market regulations, public ownership, size of the welfare state or minimum wage legislation (Dao et al., 2017). Ambiguous results arise because authors do not use one standardized method for measuring the labor share, do not agree upon the value of elasticity of substitution between capital and labor or consider different time periods.

A more recent strand in the literature focuses on microeconomic, granular drivers of the fall of the labor share. Kehrig and Vincent (2018) show that the labor share in U.S. manufacturing declines by five percentage points between 1967 and 2012 while the median labor share has even increased. This happens due to a large reallocation of production from high labor share firms towards low labor share

firms. They refer to the latter firms as hyper-productive firms. Firm size heterogeneity is key in understanding the labor share evolution. Their work relates closely to the idea of the superstar firm mechanism.

The remainder of the chapter contains five parts. Section 1.2 discusses the empirical strategy. We proceed by describing our data set in section 1.3. Section 1.4 shows and discusses the results. We provide various robustness tests in section 1.5 and conclude in section 1.6.

1.2 Empirical strategy

1.2.1 Terminology

We start by introducing some basic terminology. Define the aggregate labor share LS at time *t* as,

$$LS_t = \sum_i w_{it} * LS_{it} \,, \tag{1}$$

with w_{it} and LS_{it} representing respectively the market share (i.e. the firm weight) and the labor share of firm *i* in year *t*. The firm-specific market share is the value added produced by a firm relative to aggregate value added. The firm-specific labor share is defined as remuneration divided by value added within one firm. This ratio typically lies between zero and one.

It is crucial to weigh the firm-specific labor share by its market share in order to calculate the aggregate labor share. Calculating the simple (unweighted) average over all firm-specific labor shares, without considering the corresponding market shares, leads to a biased aggregate labor share as this implicitly assumes an equal market share for each firm. Weighting gives more (less) importance to the labor share of a large (small) firm, and therefore stresses the importance of firm size heterogeneity.[2]

The market and aggregate labor shares can be calculated at different levels of aggregation by summing over all firms *i* at this corresponding level. For example, we can aggregate at the industry, sector, country or even global level.[3]

1.2.2 The superstar firm hypothesis

Autor et al. (2020) argue that globalization and/or technological change disproportionately benefits the most productive firms. As these high-performing firms are able to increase their market share even

[2] For example, assume that firm A generates a value added of €100 and pays €60 in wage costs. Firm B has a value added of €400 and pays €140 in wage costs. The firm-specific labor shares are respectively 0.60 and 0.35 while the market shares equal respectively 0.20 and 0.80. The aggregate labor share is 0.40. This value is closer to firm B's labor share due to its higher weight. The unweighted labor share is 0.475.

[3] A country has multiple sectors like Manufacturing, Wholesale & Retail and so on. A sector consists out of various industries. For example, the Manufacturing sector combines various industries like Manufacture of Sugar, Manufacture of Beer, Printing of Newspapers and so on.

further over time, they turn into so-called superstar firms. The reallocation of market share to dominant firms increases market concentration within an industry. Besides, superstar firms are characterized by a low labor share. They achieve this through lower average costs, superior quality and/or greater innovation.

Combining the low labor share of superstar firms and its growing market share, leads to a gradual decline in the aggregate U.S. labor share over time. Value added reallocates from high towards low labor share firms. Some examples of superstar firms in the Belgian economy might be GlaxoSmithKline Biologicals and Electrabel. They are dominant firms in respectively the industry of pharmaceutical products and the industry of the trade of energy.[4]

The superstar firm hypothesis contains four testable predictions: 1) industries become increasingly concentrated, 2) industries with the highest market concentration ratio increase experience the largest drop in the labor share, 3) the between-firm component drives the fall of the labor share (rather than the within-firm component) and 4) industries with the highest market concentration ratio increase experience the largest fall in the between-firm component. We elaborate on the definition of these predictions and on our approach to test them in the remainder of this section.

Prediction 1: Industries become increasingly concentrated

We define three market concentration measures, namely C4, C10 and C20. This captures the market share of respectively the four, ten and twenty largest firms within an industry. We aggregate the industry-specific concentration measures to a sector-specific concentration measure while taking into account the different weight of each industry within a sector.[5] The market concentration measures and the corresponding weights are denoted in terms of value added. At this stage, we are only interested in providing descriptive figures which show the evolution of the market concentration measures C4, C10 and C20. We want to observe if we can identify (periods in) sectors with an increasing market concentration and a declining labor share. We try to link these evolutions in a more formal way and turn to econometrics in the next prediction(s).

[4] GlaxoSmithKline Biologicals increases its market share from 33% (1993) to 68% (2006) while its labor share stays approximately 29%. Electrabel is able to grow its market share from 65% (2007) to 92% (2014). In the same period, its labor share rises from 44% to 50%, which is below the Belgian aggregate labor share (approximately 59% in this period).

[5] For example, assume that sector A has two industries. The four largest firms in the first industry create a value added of €80 relative to a total value added of €100. The four largest firms in the second industry create a value added of €120 relative to a total value added of €400. The market concentration will be .80 in the first industry and .30 in the second industry. Taking into account the weight of each industry, this leads to an aggregate market concentration of .40 in this sector.

Prediction 2: Industries with the highest market concentration ratio increase experience the largest drop in the labor share

The second prediction suggests a negative relationship between the change in the market concentration ratio and the change in the labor share at the industry-year level. We follow the regression specification used by Autor et al. (2020) in order to test this prediction,

$$\Delta LS_{jt} = \beta_s * \Delta CONC_{jt} + \gamma_t + \varepsilon_{jt}, \quad (2)$$

with ΔLS_{jt} and $\Delta CONC_{jt}$ denoting the percentage point change in respectively the labor share and the concentration ratio C4 for an industry *j* between year *t* and *t-1*.[6] Time dummies are represented by γ_t and the error term is given by ε_{jt}. We run separate regressions for each sector, weighted by total value added at the industry level. The regression coefficient β_s is estimated uniquely for each sector.[7]

The second prediction requires that the change of the market concentration and the change of the labor share move in opposite direction. The sector-specific β_s coefficient should thus be negative and significant in order to confirm this prediction.

Prediction 3: The between-firm component drives the fall of the labor share (rather than the within-firm component)

The between-firm and within-firm component are two components resulting from the Olley and Pakes (1996) decomposition. The within-firm component captures all factors which influence firms 'in a common way'. Assume that the government promotes a specific industry such that all firms can sell ten percent more without raising wage costs. All firms in this industry are affected in the same way. The between-firm component, also called the reallocation effect, describes factors influencing firms 'in a different way'. For example, assume that a firm introduces a new, innovative product so that they capture more market share. The fact that this firm captures more market share means that other firms lose market share.

We continue with another example. Assume that all firms decrease their labor share by two percentage points. This will be completely captured by the within-firm component. Assume now that all firms increase their labor share by one percentage point while one firm decreases its labor share by five percentage points. The common one percentage point increase will be captured by the within-

[6] The robustness section (1.5) uses C10 and C20 as alternative market concentration measures in predictions 2 and 4.
[7] We use heteroscedasticity-robust standard errors in equation (2). Abadie, Athey, Imbens and Wooldridge (2017) state that we should not cluster by industry if all industries within a sector are present, even if clustering by industry would make a difference.

firm component while the deviation from this common trend by that one firm will be captured by the between-firm component.

The third prediction claims that firm-specific deviations from the common trend are more dominant than the common trend across all firms and these firm-specific deviations cause a fall of the labor share. Alternatively, a reallocation effect drives the fall of the labor share.

Olley and Pakes (1996) decompose industry productivity into two components, a within-firm and a between-firm component. The decomposition considers only surviving firms. Their method can be applied in an analogous way to decompose the evolution of the labor share. Define the aggregate labor share as,

$$LS_t = \sum_i w_{it} * LS_{it}$$

$$= \underbrace{\overline{LS}_t}_{Within-firm} + \underbrace{\sum_i (w_{it} - \overline{w}_t)(LS_{it} - \overline{LS}_t)}_{Between-firm}, \quad (3)$$

with the unweighted average firm weight $\overline{w}_t$ and the unweighted average labor share $\overline{LS}_t$.[8] Other variables are defined as before.

The within-firm component describes the evolution of the unweighted average labor share. A negative (positive) within-firm component means that firms experience a common labor share drop (increase). The between-firm component describes the sum of the covariance between the firm weight and the labor share. A decrease in the between-firm component can be caused by two different mechanisms. On the one hand, a change in the distribution of market shares towards the low labor share firms will imply a fall in the between-firm component, keeping the firm-specific labor share constant. On the other hand, an unequal change in the firm-specific labor share alters the between-firm component. It leads to a decrease of this component when the labor share of large firms increases less or decreases more than the labor share of small firms, keeping the market shares constant. The observed evolution in the between-firm component is a combination of these two mechanisms at work which might reinforce or offset each other.

In order to keep track of the evolution over time, we take the difference between year *t* and year *t-1*, expressed as,

[8] The unweighted average firm weight is the market share of a firm when all firms are assumed to be equally large. For example, an industry with five firms has an unweighted average firm weight of 20%. The unweighted average labor share takes the average over all firm-specific labor share, without adjusting for the firm weight.

$$\Delta LS_t = LS_t - LS_{t-1}$$

$$= \underbrace{\Delta\,\overline{LS_t}}_{Within-firm} + \underbrace{\Delta \sum_i (w_{it} - \overline{w}_t)(LS_{it} - \overline{LS_t})}_{Between-firm}. \quad (4)$$

Melitz and Polanec (2015) extend this method in order to capture the contribution of entry and exit of firms over time. They decompose the change in aggregate productivity as a sum of four components, a within-firm, a between-firm, a firm entry and a firm exit component. The firm exit component is positive (negative) if leaving firms have a lower (higher) labor share than surviving firms. The firm entry component is positive (negative) if entering firms have a higher (lower) labor share than surviving firms.

We define the Melitz-Polanec decomposition at time *t* as,

$$\Delta LS_t = \underbrace{\Delta\,\overline{LS_t^S}}_{Within\,(Survivors)} + \underbrace{\left\{\Delta \sum_i (w_{it} - \overline{w}_t)(LS_{it} - \overline{LS_t})\right\}^S}_{Between\,(Survivors)} + \underbrace{w_{t-1}^X\left(LS_{t-1}^S - LS_{t-1}^X\right)}_{Exit\,term} + \underbrace{w_t^E(LS_t^E - LS_t^S)}_{Entry\,term}, \quad (5)$$

with the superscripts *S*, *X* and *E* denoting respectively survivors, exiting firms and entrants. A survivor is a firm that operates in the same industry in both year *t* and year *t-1*. An exiting firm operates only in year *t-1* and an entrant only operates in year *t*. The terms w_{t-1}^X and w_t^E represent the total value added of respectively exiting firms in period *t-1* and entrants in period *t* relative to total value added in the corresponding year. The term LS_t^* represents the weighted labor share in period *t* with the * referring to one of the mutually exclusive subgroups of survivors (*S*), exiting firms (*X*) or entrants (*E*).

We extend the decomposition by calculating the standard errors and significance levels associated with each component based on Hyytinen, Ilmakunnas and Maliranta (2016). Providing standard errors is becoming common practice in the field of productivity decompositions (Fuss & Theodorakopoulos, 2018) but barely done in labor share decomposition papers.

Prediction 4: Industries with the highest market concentration ratio increase experience the largest fall in the between-firm component

We use a similar approach as in prediction 2 and use the following regression specification,

$$\Delta Between_{jt} = \beta_s * \Delta CONC_{jt} + \gamma_t + \varepsilon_{jt}, \quad (6)$$

with $\Delta Between_{jt}$ defined as the percentage point change of the between-firm component for industry *j* between year *t* and *t-1*. All other terms are defined as before. Again, regressions and coefficients are

estimated separately for each sector, weighted by total value added at the industry level. The regression coefficient should be significantly negative in order to confirm the fourth hypothesis.

We thus expect that industries characterized by an increasing market concentration are those industries which experience a fall of the labor share due to a reallocation of value added from high towards low labor share firms.

1.3 Data

We source our Belgian firm-level data from the National Bank of Belgium. This data set ranges from 1985 to 2014, a particular long time dimension, and covers all for-profit firms which file an annual income statement. We use the variables remuneration, value added and employment. We identify firms by their Belgian VAT number. NACE codes are used to assign a firm to a sector (NACE 1-digit) and to an industry (NACE 4-digit) within a sector.[9] We have 4.016.033 unique firm-year combinations (of which 73.659 in 1985 and 162.333 in 2014). We refer to the data appendix (section 1.7.1) for more detailed information about the data set. Table 1.1 shows some summary statistics for our variables of interest: remuneration, value added, firm labor share, employment and market concentration.

Table 1.1 Summary statistics

Variable	**mean**	**sd**	**p25**	**p50**	**p75**	**min**	**max**
Remuneration	553,258	9,454,051	19,013	57,697	187,567	0.08	2,171,158,016
Value Added	914,000	676,355	44,744	112,186	308,355	0.00	2,927,595,520
Firm Labor Share	0.60	0.37	0.36	0.60	0.80	0.00	2.00
Employment	13.12	226.90	1.00	2.00	6.00	0.00	57,964
Market Concentration	0.45	0.24	0.24	0.40	0.64	0.02	0.99

Notes: *This table includes summary statistics (mean, standard deviation, 25th percentile, 50th percentile, 75th percentile, minimum value and maximum value) for our variables of interest. The observations are pooled over our time period (1985-2014) and are not adjusted for inflation in this table.*

This reveals that the mean value for remuneration and value added is larger than the median (50th percentile). This implies that the distribution of remuneration and value added is not normally distributed, but heavily skewed towards large firms. The highest value for remuneration is €2.2 billion while the largest for value added equals €2.9 billion. The mean and standard deviation of the firm-specific labor share equal respectively 0.60 and 0.37.

Finally market concentration ranges from 0.02 to 0.99. Some industries are not concentrated at all whereas other industries are completely dominated by the four largest firms. The mean and the

[9] NACE is the industry standard classification system used in the European Union. It is the acronym of the French translation of the Statistical Classification of Economic Activities in the European Community. The first four digits are common across all European countries. We refer to the NACE 1-digit and 4-digit level as respectively a sector and an industry.

median values are respectively 0.45 and 0.40 indicating that the four largest firms produce roughly 40%-45% of value added in an average industry.

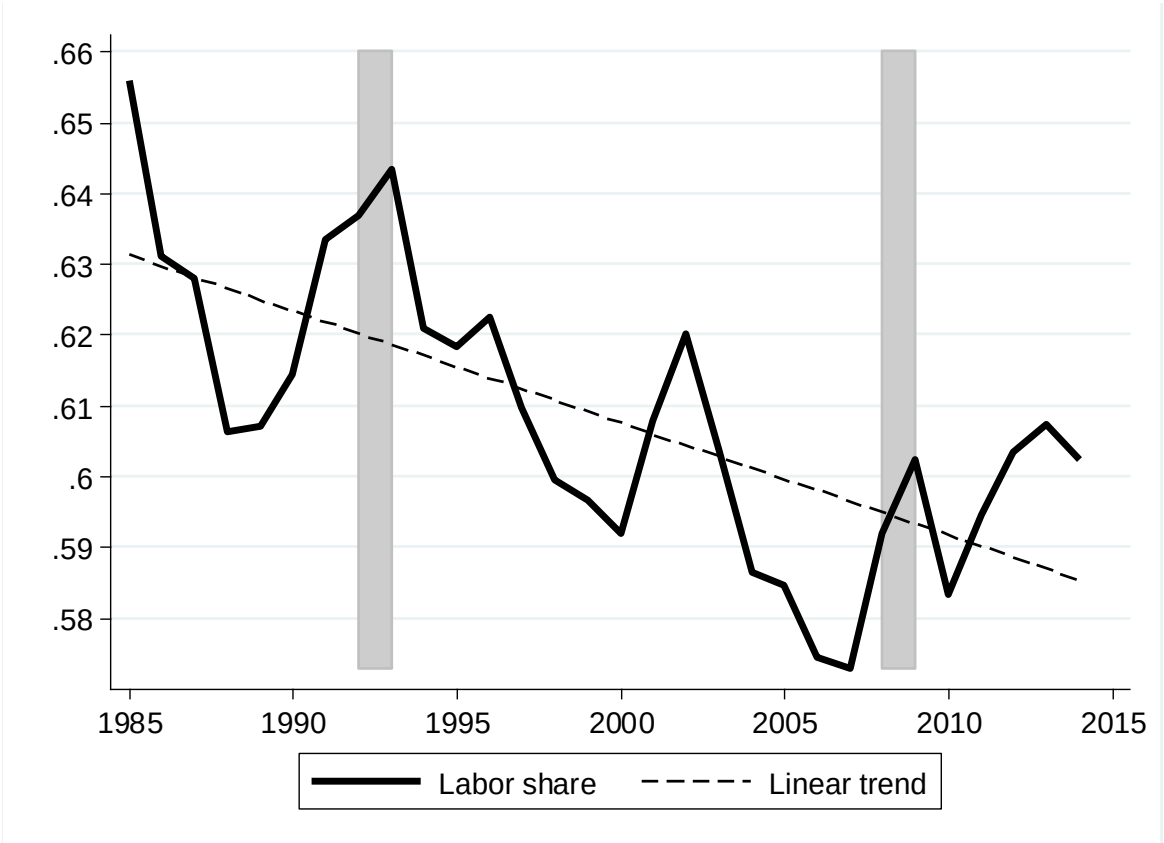
Our main empirical analysis is done at the sectoral level. We only keep sectors which have a sectoral market share of at least five percent in at least one year. We retain eight sectors which represent 82.5% and 88.0% of value added in respectively 1985 and 2014. Sectoral market shares and sectoral summary statistics are respectively shown in (appendix) Figure 1.8 and (appendix) Table 1.3. We observe that the sectoral market share of Manufacturing is shrinking whereas it is increasing in various other sectors like Wholesale & Retail.

1.4 Results

1.4.1 Descriptive statistics: Country level

We start by plotting the evolution of the Belgian labor share in Figure 1.1. We add a linear trend to capture the secular trend of the labor share and shaded grey areas to indicate recession years, as indicated by the OECD (2020).

Figure 1.1 Decline of the Belgian labor share



Notes: *This figure plots the evolution of the Belgian labor share (1985-2014). The firm-specific labor share is weighted by its value added in order to calculate the weighted aggregate labor share.*

This leads to five main results. First, the Belgian labor share is declining. It shrinks from less than 0.66 in 1985 to 0.60 in 2014, a drop of more than five percentage points. Second, both the absolute level and the decreasing trend are reasonably similar to the evolution observed in the United States. The U.S. labor share decreases from roughly 0.65 in 1977 to 0.59 in 2010 (Autor et al., 2020). Third, the slope of the secular trend line equals -0.00156.[10] This means that the labor share drops on average by 0.156 percentage point per year. A back-of-the-envelope calculation converts this into an economically meaningful number. A Belgian worker would lose on average €139 of labor income per year.[11]

Fourth, the labor share appears to evolve countercyclically over time. It reaches a peak during periods of recessions, while it decreases again during periods of recovery and economic upturn.[12] This countercyclical pattern is in line with research done by Rios-Rull and Santaeulàlia-Llopis (2010).[13]

Finally, the evolution of the Belgian labor share is more volatile than the evolution of the U.S. labor share. A plausible explanation for this phenomenon might be labor hoarding. Belgian firms might be less tempted to hire and fire workers in respectively good and bad times due to, for example, stronger labor unions. De Mulder and Druant (2011) document the case of labor hoarding in Belgium.

Next, the labor share is defined as the ratio of remuneration and value added. We delve further into the evolution of each component separately. Figure 1.2 describes the evolution of total remuneration and total value added at the aggregate Belgian level. Panel 1.2A shows the aggregate evolution.[14] We observe that both the remuneration and value added factors grow over time. However, the value added component increases relatively more than the wage component. Hence, the labor share drops.

Alternatively, panel 1.2B visualizes the evolution of the average value added and average remuneration per worker.[15] We can interpret this as average real productivity and average real wage. We observe that the wage (+25%) and productivity (+35%) rise over time. Nevertheless, the increasing

[10] We regress the aggregate Belgian labor share on year. The estimated coefficient equals -.00156 (se = 0.00031 ; p-value < 0.01).

[11] Based on Eurostat data from 2014, Belgian GDP and its labor force equals respectively ±€400 billion and 4 497 200 employees. Dividing Belgian GDP by its labor force leads to an average value added per worker of €88 944. Multiplying this ratio by the regression coefficient of -0.00156 leads ceteris paribus to the estimated yearly loss of €139 per employee.

[12] The Belgian economy seems to be in a similar point in the business cycle in 1985 in comparison to the economy in 2014. According to the World Bank (2020), GDP grew by 1.7% and 1.3% in respectively 1985 and 2014 after having experienced a recession in earlier years. In particular, the Belgian economy decreased by 0.3% in 1981 while it fell by 2.3% in 2009.

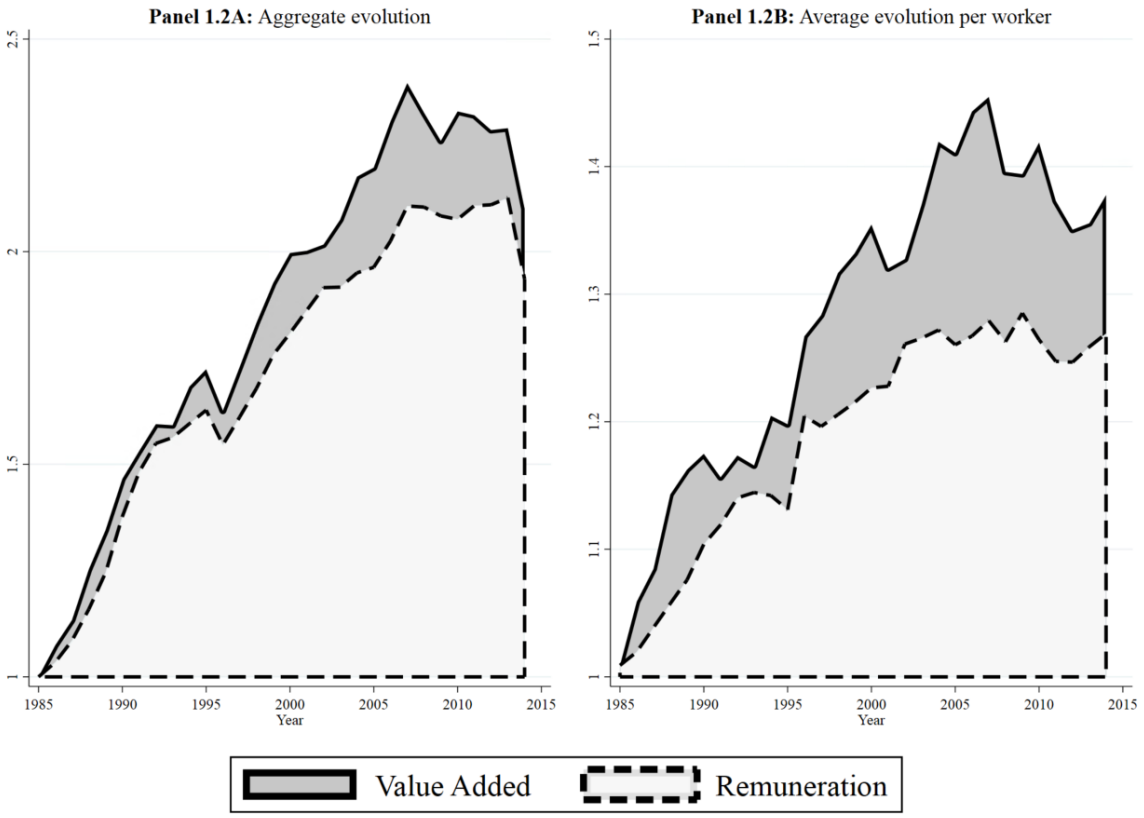
[13] Our data shows that value added per worker is more volatile than remuneration per worker. The standard deviation of the cyclical component from the Hodrick-Prescott filter is higher for value added per worker (0.025) than for remuneration per worker (0.012). Both variables move together as their correlation is 0.97.

[14] The Belgian labor share can be defined as $LS = \frac{w*L}{VA_.} = \frac{w/p*L}{VA_./p} = \frac{(\bar{w}*L)}{\overline{VA}}$ with w, L, p and VA denoting respectively nominal mean wage per worker, total employment, the CPI price index and nominal value added . Nominal variables are deflated by the CPI index so that we obtain real variables. Variables with a bar are denoted in real terms.

[15] Decomposing the Belgian labor share further leads to $LS = \frac{w*L}{VA} = \frac{w/p*L}{VA_./p} = \frac{\bar{w}}{\overline{VA}/_L}$. The nominator $\bar{w}$ is the mean real wage per worker. The denominator $\overline{VA}/_L$ represents the average real value added per worker.

real wage per worker is unable to follow the faster increase in real value added per worker. Furthermore, we observe that the average real wage per worker increases until the early '00s after which it becomes rather stable.[16]

Figure 1.2 Evolution of remuneration and value added



Notes: *All observations for remuneration and value added are divided by their corresponding value in 1985. Hence, the value observed in 1985 serves as a reference level. Observations are inflation-adjusted.*

1.4.2 Descriptive statistics: Sectoral level

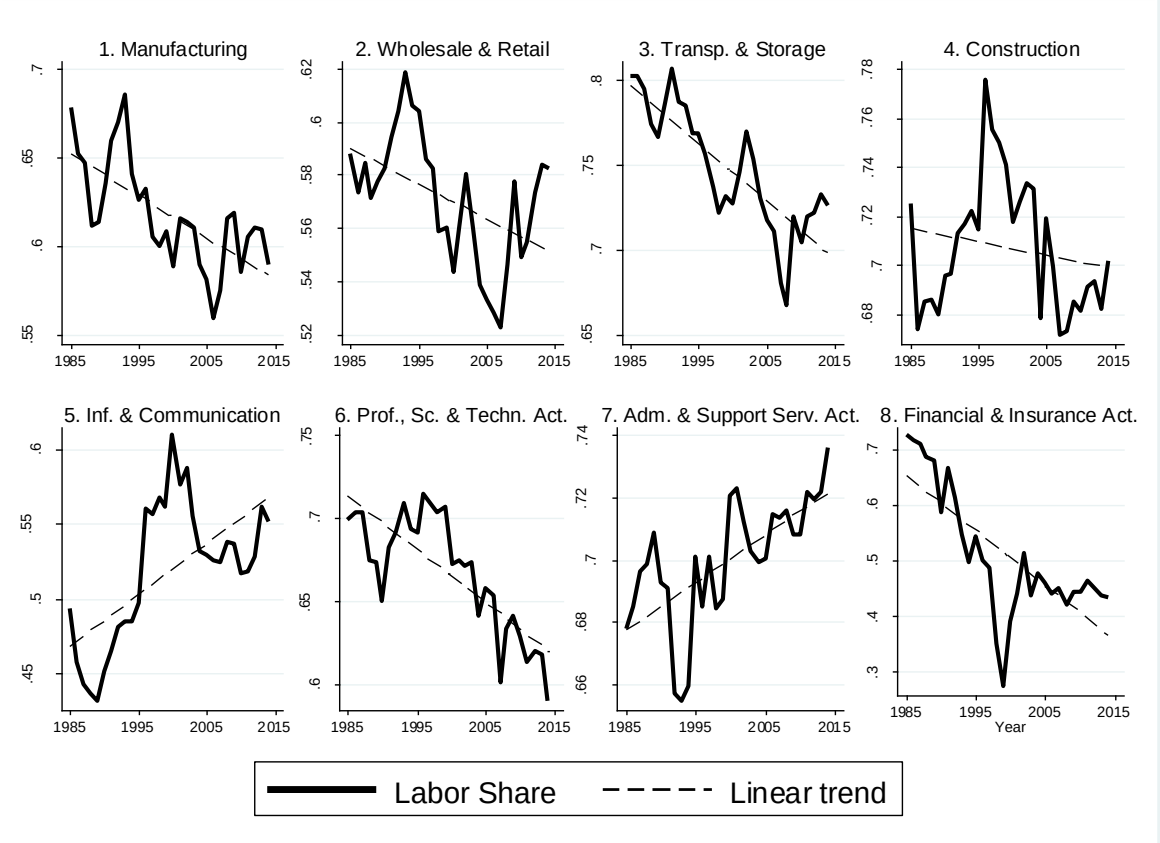
Following Autor et al. (2020), we perform our analysis at the sectoral level. We show the evolution of the sectoral labor shares in Figure 1.3. Sectors are ranked by their market share in terms of total value added in 1985. In particular, Manufacturing is the largest sector while Financial & Insurance Activities is the smallest of the eight sectors.

Figure 1.3 shows considerable differences among the eight largest sectors in Belgium. First of all, the absolute labor share level differs notably among sectors. For example, the labor share stands at 0.60

[16] In the U.S., the Bureau of Labor Statistics (BLS, 2020) documents that the real wage of goods-producing worker tracked the productivity increase from the late '40s until the early '70s. However, the real wage remained approximately the same between the early '70s and the late '00s while productivity more than doubled.

in Manufacturing in 2014. We observe a higher labor share in Construction in the same year as it equals 0.70. On the other hand, the labor share equals only 0.45 in Financial & Insurance Activities.

Figure 1.3 Evolution of sectoral labor share



Notes: *Each panel plots the evolution of the labor share for a specific sector with its trend. Panels are shown in descending order of sectoral value added in '85. The sectoral labor share is weighted by value added within a sector-year combination.*

Further, we find that the secular labor share trend decreases in six sectors while it increases in two other sectors. It decreases in the four largest sectors: Manufacturing, Wholesale & Retail, Transportation & Storage and Construction. We also observe a decrease in Professional, Scientific & Technic Activities and Financial & Insurance Activities while the labor share increases in Information & Communication and Administrative & Support Service Activities.[17]

Finally, one spike deserves more attention. We observe a huge drop in the labor share in Financial & Insurance Activities in ’98 and ’99 after which it recovers again. This remarkable spike might be related

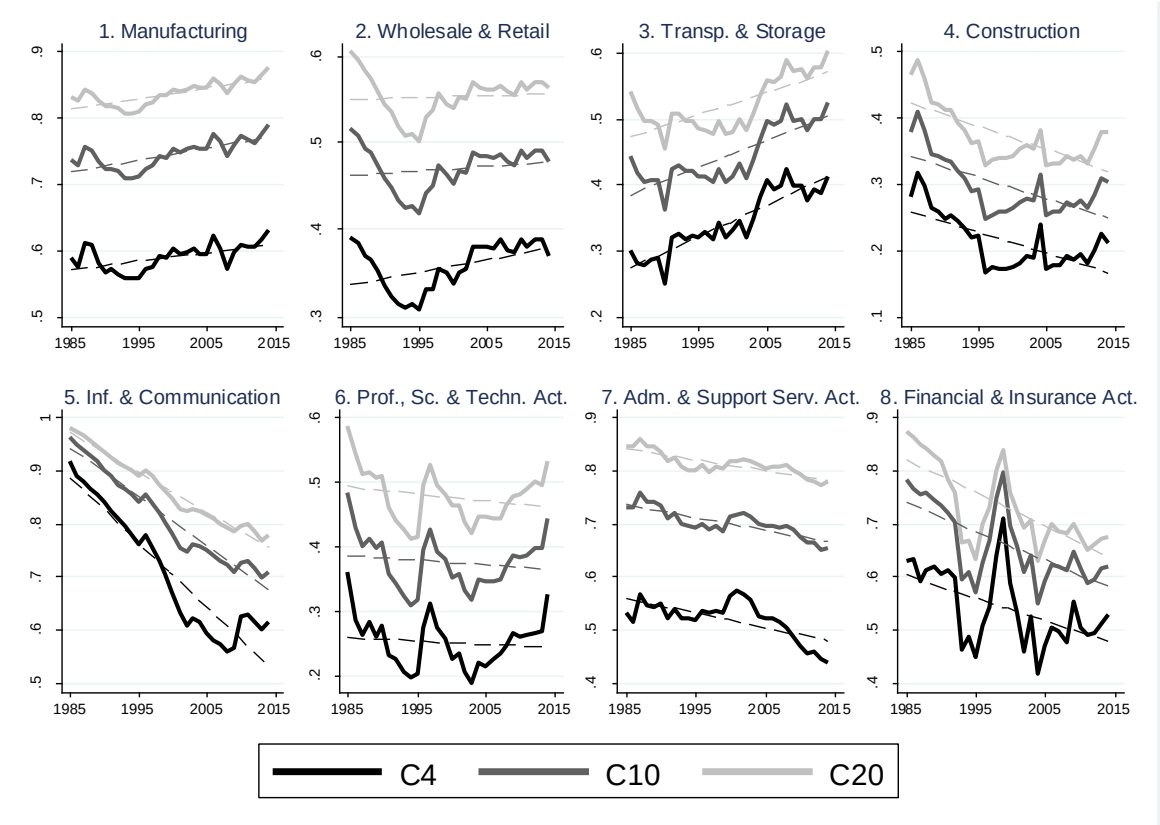
[17] We regress the sectoral labor share on year and show the estimation results in (appendix) Table 1.4. These linear trends are always significant, except for Construction. In this sector, we observe an initial increase until the end of the ‘90s offset by a subsequent fall of the labor share.

to the dot-com bubble.[18] Value added rose extremely in this sector in these years after which the bubble burst and the labor share evolution reversed back to its secular, decreasing, trend.

1.4.3 The superstar firm hypothesis in Belgium

In this part, we test whether the rise of superstar firms can be related to the fall of the labor share at the sectoral level. We test the predictions of the superstar firm hypothesis step by step.

Figure 1.4 Evolution of sectoral market concentration



Notes: *Each panel plots the evolution of C4. This represents the share of value added generated by the four largest firms within an industry. We then aggregate this into a sectoral concentration ratio.*

<u>Prediction 1:</u> Industries become increasingly concentrated

Figure 1.4 plots the sectoral evolution of the market concentration ratios C4, C10 and C20 in Belgium.[19] The three concentration measures move in parallel. The market share of the four largest firms is what

[18] The dot-com bubble refers to the period from 1997 until 2000 in which the economy was growing rapidly. Many internet-based companies were founded during these years. Investors speculated heavily on the value of these companies. The BEL20 index rose from roughly 1800 points in '97 to 3600 points in '99. Afterwards, this turned out to be a speculative bubble which burst around '00. The index returned to 2500 points again (Yahoo! Finance, 2020).

[19] We use market concentration measures in terms of value added. An alternative might be to define the concentration measures in terms of employment. We show the evolution of C4 (value added) and C4 (employment) in (appendix) Figure 1.9. We find that market concentration tends to be lower in terms of employment suggesting that the largest firms are more productive than other firms. The secular trend goes in the same direction in all sectors but Manufacturing. In this sector, the superstar firms are able to capture more market share in terms of value added while decreasing their market share in terms of employment. Note that the four largest firms in terms of value added are not necessarily the same four firms which are largest in terms of employment.

drives the evolution of the three market concentration measures. We use C4 to test the four predictions. In the robustness section, we also use C10 and C20 as concentration measure.

C4 increases in Manufacturing and in Transportation & Storage. It is also rising in Wholesale & Retail although we initially observe a rapid decrease until the mid '90s. Considering Professional, Scientific & Technic Activities, the market concentration ratio displays a decrease until the mid '90s after which it starts growing again. The market concentration ratio decreases in the four other sectors.[20] Autor et al. (2020) show that market concentration is increasing in each sector in the United States.

Combining Figure 1.3 and Figure 1.4 allows us to find suggestive evidence for a negative link between the evolution of the market concentration and the evolution of the labor share. For example, this seems to be the case in Manufacturing as the two evolutions move in opposite directions. We aim to link the evolution of the labor share and the market concentration in a more formal way in the next prediction.

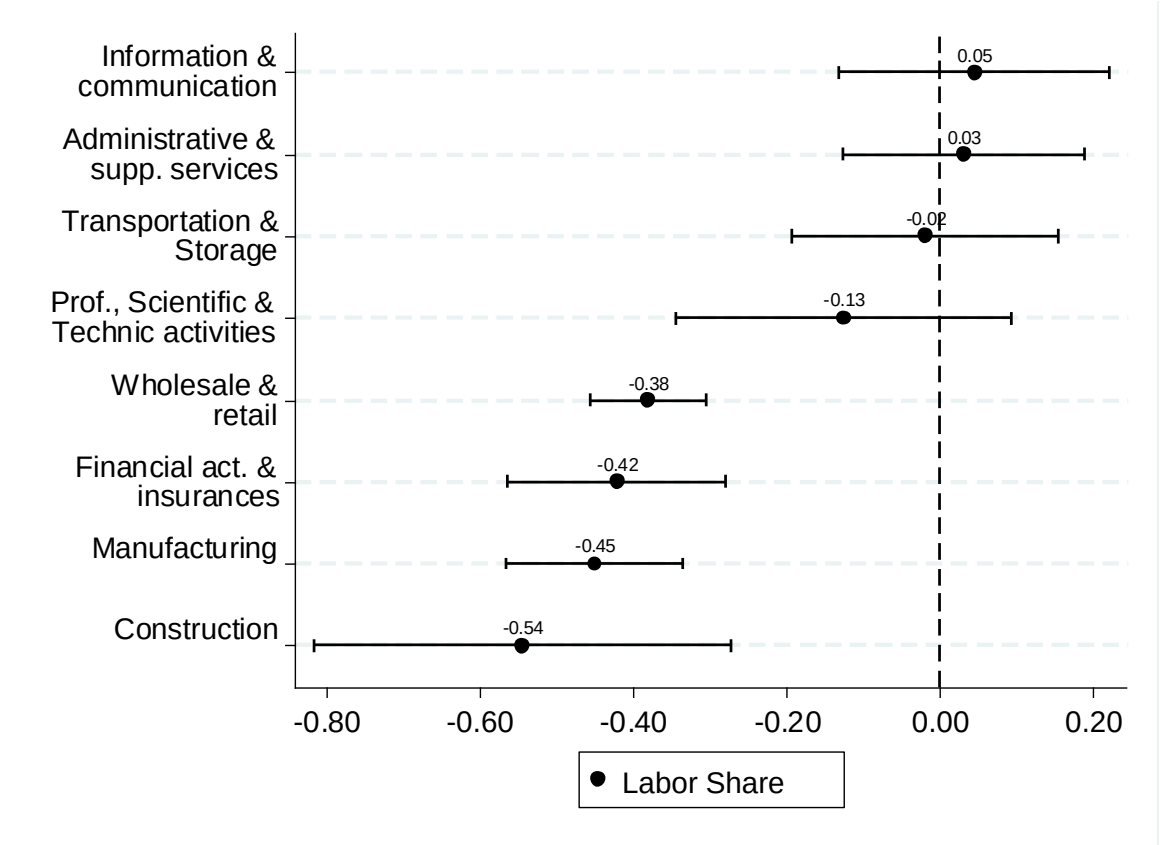
> Prediction 2: Industries with the highest market concentration ratio increase experience the largest drop in the labor share

Figure 1.5 shows one coefficient for each sector. This coefficient results from estimating the sector-specific β_s from equation (2). We display the coefficient with the corresponding 95% confidence interval.

The regression coefficient is significantly negative in four sectors: Construction, Financial & Insurance Activities, Manufacturing and Wholesale & Retail. In Manufacturing, an increase of one percentage point in the concentration ratio would lead to an estimated decrease of 0.45 percentage points in its labor share. The regression coefficient is not significant in the four other sectors: Prof. Sc. & Technical Activities, Administrative and Support Services, Transportation & Storage and Information & Communication. The change of the concentration ratio can thus be linked to a decrease of the labor share in some sectors but not all.

[20] We regress the sectoral market concentration C4 on year and show the estimation results in (appendix) Table 1.5. These linear trends are always significant, except for Professional, Scientific & Technic Activities. This is due to the fact that market concentration falls at first, after which it increases over time. These effects offset each other such that we do not identify a significant linear trend.

Figure 1.5 The link between market concentration (C4) and the labor share



Notes: *This figure plots the regression coefficients from equation (2). Each coefficient follows from a separate regression. Robust standard errors are used to calculate the 95% confidence interval and shown around the point estimate in the figure.*

Disaggregating the regression coefficient into year-specific regression coefficients in (appendix) Figure 1.10 allows us to delve deeper into possible time trends. The regression coefficients for Manufacturing, Construction and Wholesale & Retail seem to become more negative over time. The regression coefficients for Transportation & Storage, Information & Communication, Financial & Insurance Activities, Professional, Scientific & Technic Activities and Supportive and Administrative Services do not reveal any trend towards (more) negative regression coefficients.

Prediction 3: The between-firm component drives the fall of the labor share (rather than the within-firm component)

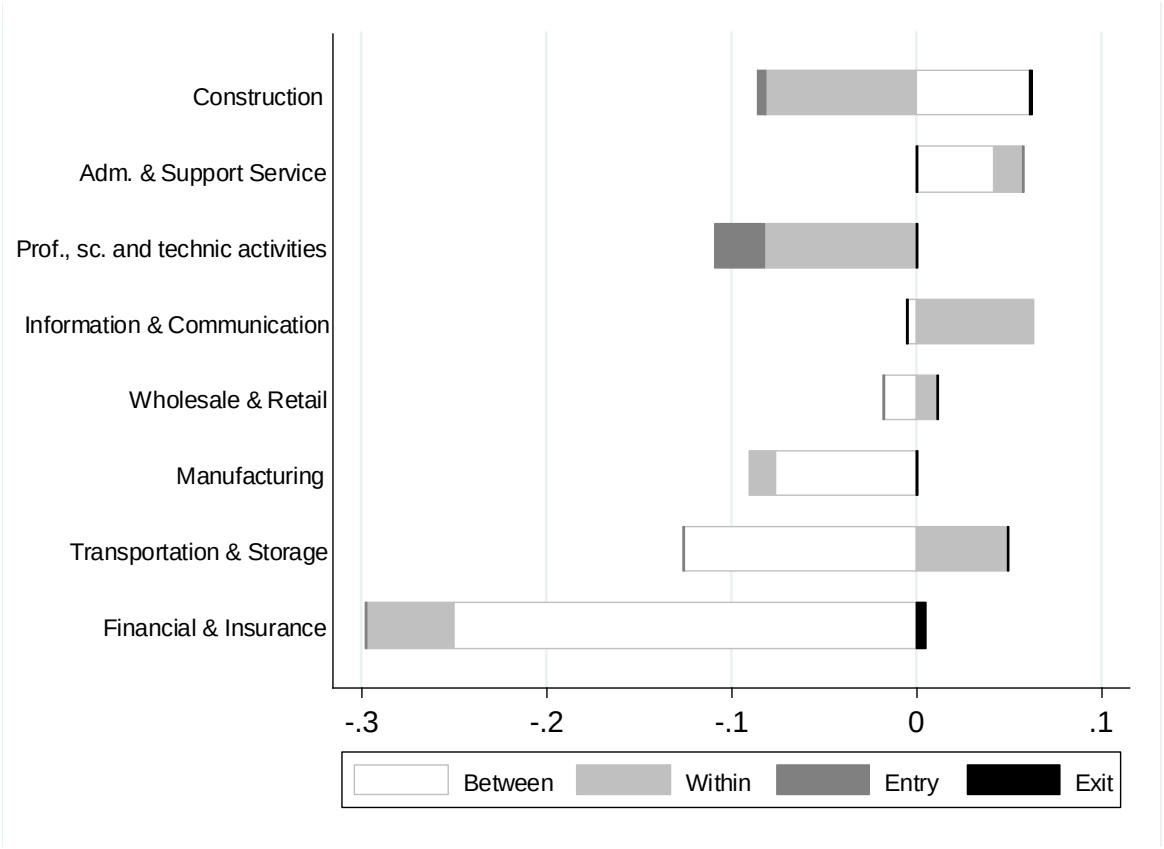
The results of the Melitz-Polanec decomposition are shown in Figure 1.6. The decomposition is based on equation (5). The corresponding standard errors and significance levels are shown in (appendix) Table 1.6.

The between-firm component drives the fall of the labor share in Manufacturing, Wholesale & Retail, Transportation & Storage and Financial & Insurance Activities. This means that the between-firm component is 1) the largest component of the four components in absolute magnitude, 2) negative

and 3) significantly different from the within-firm component.[21] For example, the between-firm component (-7.62%) is the largest component, negative and easily offsets the within-firm component (1.37%) in Manufacturing. The difference between the within-firm and the between-firm component is shown in the last column of (appendix) Table 1.6. It is statistically significant.

Combining these findings, we conclude that the reallocation effect drives the fall of the labor share in four sectors: Transportation & Storage, Manufacturing, Wholesale & Retail and Financial & Insurance Activities. The third prediction does not hold in the four other sectors: Construction, Information & Communication, Prof., Sc. And Technic Activities and Administrative and Support Services.

Figure 1.6 Melitz-Polanec decomposition of the change in the labor share



Notes: *Each bar shows the cumulated sum over 30 years for each labor share component of the Melitz-Polanec decomposition. Results are ranked from the largest between-firm component to the lowest between-firm component.*

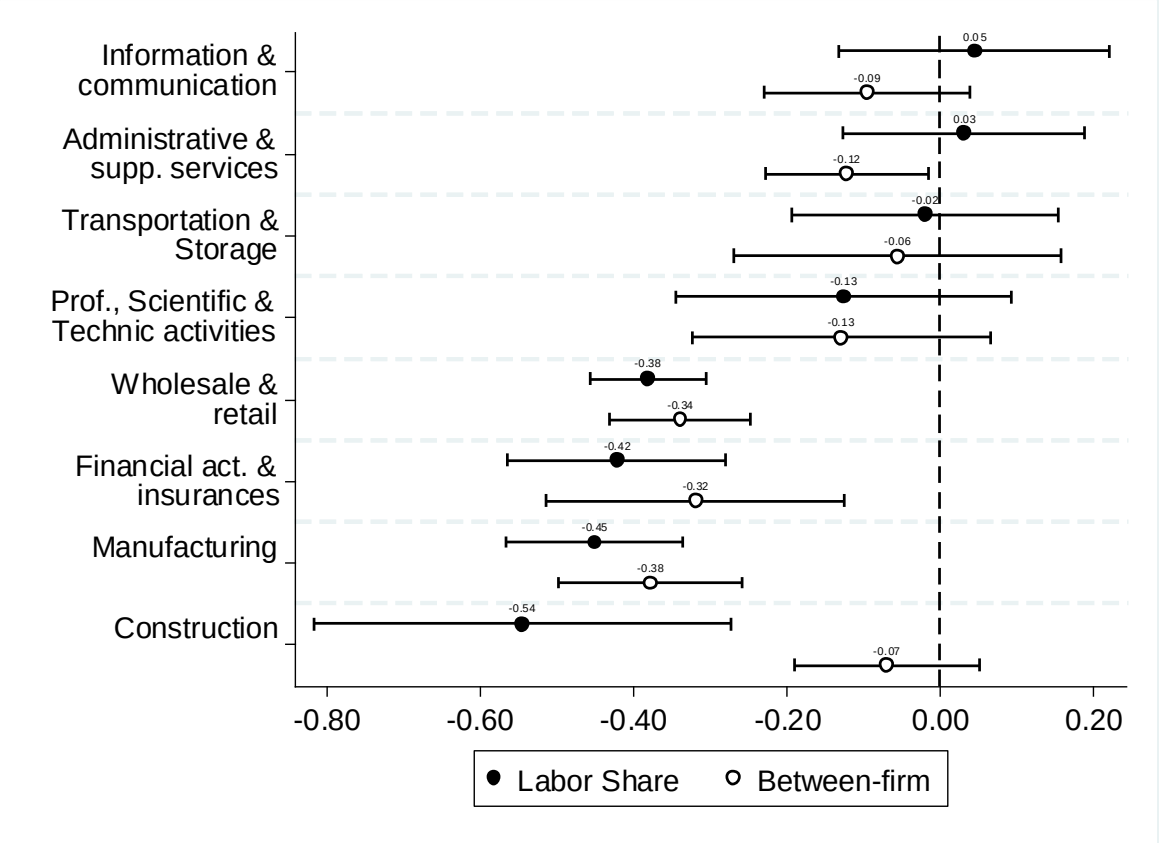
Our results in (appendix) Table 1.6 also indicate that the within-firm component is significant in all sectors but there is no pronounced common trend apparent. Half of the sectors has a positive coefficient while the other half has a negative coefficient. At last, the firm entry and firm exit components play a negligible role as both are nearly always insignificant and very small.

[21] The between-firm component is 6.3, 1.1, 2.1 and 3.1 times as big as the within-firm component in respectively Manufacturing, Wholesale & Retail, Transportation & Storage and Financial & Insurance Activities.

Prediction 4: Industries with the highest market concentration ratio increase experience the largest fall in the between-firm component

We extend Figure 1.5 with a second regression coefficient which comes from equation (6) and show this in Figure 1.7. The second regression coefficient displays the effect from the change in market concentration on the change in the between-firm component.

Figure 1.7 The link between market concentration (C4) and the between-firm component



Notes: *This figure plots the regression coefficients from equation (2) and (6). Each coefficient follows from a separate regression. Robust standard errors are used to calculate the 95% confidence interval and shown around the point estimate in the figure.*

The regression coefficient is significant and negative in Manufacturing, Financial & Insurance Activities, Wholesale & Retail, and Administrative & Support Services. We thus observe a reallocation effect in these four sectors. An increase of one percentage point in the market concentration ratio in Manufacturing lowers the labor share on average by .38 percentage point through the between-firm component. The regression coefficients are also negative in the four other sectors but insignificant.

We observe that the two regression coefficients by sector are very close to each other for various sectors. This implies that an increase in the concentration ratio lowers the labor share predominantly through a decrease in the between-firm component (and remarkably less through the three other components).

Disaggregating the regression coefficients into yearly coefficients, displayed in (appendix) Figure 1.11, reveals that the regression coefficients in Manufacturing and Wholesale & Retail display a downward trend over time. This means that increasing market shares leads to an even stronger reallocation effect. In recent years, the coefficients are becoming less negative again.

We summarize the results of the four predictions in Table 1.2 for the eight different Belgian sectors. Our analysis shows that the superstar firm hypothesis is present in some sectors but not in all. We show that the four predictions hold in Manufacturing as well as in Wholesale & Retail. The other sectors do not satisfy the four predictions. Manufacturing and Wholesale & Retail are the two largest sectors and account for roughly half of the Belgian economy.[22]

Table 1.2 Summary table

	Man.	**W&R**	**T&S**	**Constr.**	**I&C**	**PS&T**	**A&S**	**F&I**
Average sector share (1985-2014)	33%	20%	9%	7%	6%	5%	5%	4%
Labor share is falling	YES	YES	YES	YES	NO	YES	NO	YES
P1: Concentration is rising.	YES	YES	YES	NO	NO	NO	NO	NO
P2: ΔConcentration $\bar{\Rightarrow}$ ΔLS	YES	YES	NO	YES	NO	NO	NO	YES
P3: Reallocation effect drives the fall of the labor share	YES	YES	YES	NO	NO	NO	NO	YES
P4: ΔConcentration $\bar{\Rightarrow}$ ΔBetween-firm component	YES	YES	NO	NO	NO	NO	YES	YES
Conclusion: Superstar firm hypothesis?	YES	YES	NO	NO	NO	NO	NO	NO

Notes: *This Table summarizes the four predictions. The second row shows the average sectoral market share in terms of value added between 1985 and 2014.*

Finally, we decompose the results in two time periods: 1985-1998 and 1998-2014.[23] Looking at Manufacturing and Wholesale & Retail, we observe that the labor share has decreased in both periods in Manufacturing whereas it decreases only in the first period in Wholesale & Retail. Further, market concentration has risen in both periods in Manufacturing. In Wholesale & Retail, we observe an initial drop after which market concentration is on the rise from the mid '90s onwards.

(Appendix) Figures 1.12 and 1.13 show the results for the second and fourth prediction for respectively the periods 1985-1998 and 1998-2014. The second prediction relates the change in market concentration to the change in labor share. We find a significant negative coefficient for this in Manufacturing, Wholesale & Retail, Financial & Insurance Activities and Construction in both time periods. The effects becomes more negative in the former three sectors. It becomes less negative in the latter one. The coefficient is insignificant in the other four sectors. The fourth prediction links the

[22] Manufacturing and Wholesale & Retail account respectively for 33% and 20% of aggregate value added in Belgium between 1985 and 2014, as indicated in Table 1.2.

[23] We choose 1998 as intermediate point because this year is in a comparable point in the business cycle as 1985 and 2014. According to the World Bank (2020), GDP grows by 2.0% in 1998 after having experienced a recession (-1.0% in 1993) in earlier years.

change in market concentration to the change in the between-firm component. We observe that this coefficient is negative and significant in Manufacturing, Wholesale & Retail, Financial & Insurance Activities and Administrative & Support Service Activities between 1985 and 1998. The coefficient becomes more negative in the three former sectors whereas it becomes insignificant in the latter one. It is insignificant in the other sectors.

Next, we decompose the results of the Melitz-Polanec decomposition in (appendix) Figures 1.14 and 1.15. These decompositions show the results for respectively 1985-1998 and 1998-2014. We find that the reallocation effect pushes the labor share downwards in Financial & Insurance Activities, Transportation & Storage, Manufacturing and Wholesale & Retail between 1985 and 1998. It is the largest component in the former three sectors. Considering the period 1998 until 2014, we observe a negative reallocation effect in Information & Communication, Prof., Sc. & Technic Activities, Transportation & Storage, Manufacturing, Wholesale & Retail and Administrative & Support Service Activities. The latter five of these sectors have a positive within-firm effect which moderates, or even dominates, the reallocation effect such that the labor share remains rather stable in this period. This is in line with Kehrig and Vincent (2018). They find that the labor share of the median firm has increased, which increases the aggregate labor share. On the other hand, market share reallocates to the large low labor share firms. This effect lowers the aggregate labor share.

1.5 Robustness tests

We elaborate on two robustness tests. First, we use C10 and C20 as alternative market concentration measure. (Appendix) Figure 1.16 and (appendix) Figure 1.17 show the results of the second and fourth prediction with respectively C10 and C20 as concentration measure. We see that the first regression coefficient of equation (2) is significantly negative in Manufacturing, Wholesale & Retail, Construction and Financial & Insurance Activities. This is in line with the original results. The third prediction does not depend on the definition of the concentration measure. The second regression coefficient of equation (6) is significantly negative in Financial & Insurance Activities, Manufacturing and Wholesale & Retail for C10. It is significantly negative in Construction, Manufacturing and Wholesale & Retail for C20. This robustness confirms our findings for the two sectors, Manufacturing and Wholesale & Retail, which display a superstar firm mechanism.

Second, we use C4 again as our measure of market concentration but consider five-year and ten-year changes instead of one-year changes. We show the results of regressing the five-year and ten-year changes of the labor share (between-firm component) on respectively the five-year and ten-year changes in market concentration in (appendix) Figure 1.18 and (appendix) Figure 1.19. Looking first at five-year changes, we confirm a negative relationship for the second and fourth prediction for Financial

Activities & Insurances, Manufacturing and Wholesale & Retail. Considering ten-year changes, we find again a negative relationship for the second and fourth prediction for Manufacturing and Wholesale & Retail but not for the other sectors. Results are thus robust for Manufacturing and Wholesale & Retail.

1.6 Conclusion

In this chapter, we investigate whether an increase in market concentration can be linked to a fall of the labor share in the Belgian economy. Autor et al. (2020) show evidence for the presence of a superstar firm mechanism for various sectors in the United States. The hypothesis states that value added reallocates from high labor share firms to low labor share firms, hence, the aggregate labor share falls over time. We use longitudinal Belgian-firm level data from 1985 until 2014.

Our main finding is that we confirm the superstar firm hypothesis in the two largest Belgian sectors: Manufacturing and Wholesale & Retail. This implies that: 1) industries become increasingly concentrated, 2) industries with the highest market concentration ratio increase experience the largest drop in the labor share, 3) the reallocation effect drives the fall of the labor share rather than the within-firm component and 4) industries with the highest market concentration ratio increase experience the largest fall in the between-firm component. These sectors account for approximately 53% of the Belgian economy, in terms of value added between 1985 and 2014. However, we are not able to find evidence in other Belgian sectors. Our research demonstrates that the superstar firm hypothesis cannot be generalized to all sectors outside the United States.

Additional research is required to understand why some sectors exhibit a superstar firm mechanism while others do not. Next, alternative macroeconomic or microeconomic explanations can be consistent with the superstar firm hypothesis, and might reinforce or offset this. For example, an increase in monopsony power in the labour market has recently been linked to a fall of the labor share (Brooks, Kaboski, Li & Qian, 2019). Finally, one might want to link firms to their global ultimate owner rather than their domestic ultimate owner in order to delve deeper into firm ownership linkages.

1.7 Appendix

1.7.1 Data appendix

Our empirical analysis uses Belgian firm-level data obtained from the National Bank of Belgium (1985-2014). The data set includes all firms which have to file an annual income statement. 'Small firms' do not have to file this although they can voluntarily choose to do so.[24] Further, self-employed people are not included. We make use of the following balance-sheet variables: remuneration, value added and employment. Remuneration (62) is defined as the total amount of the wage bill. This includes salaries, wages, social security payments and pension payments. Value added (9800) is defined as operating revenue (70/74) minus trade goods, raw materials and excipients (60) and services and diverse goods (61). Employment is defined as full-time equivalents (9087) from 1996 onwards. It is defined as the number of jobs (9086) before 1996. The numbers between parentheses refer to the codes in the Belgian financial statement.

The data is distributed over 485 industries in Manufacturing (234), Construction (23), Wholesale & Retail (99), Transportation & Storage (23), Information & Communication (27), Financial & Insurance Activities (22), Professional, Scientific & Technic Activities (21) and Administrative & Support services (36) sector.

Next, our unconsolidated firm-level data structure does not take into account that firms might belong to a parent company. Each firm has its own legal VAT number but multiple firms can belong to the same parent company. We use an example to illustrate how this might impact our analysis. Assume an industry with ten supermarkets. The four largest firms produce a value added of €50, €40, €30 and €20. Suppose that the six other supermarkets produce a value added of €10 each. Our concentration measure C4 would be 0.70 (= 140/200). However, if the six other supermarkets belong to the same parent company, then this group of firms produces a total value added of €60. The parent company combines the market shares of each of its subsidiaries and will suddenly become the largest 'firm' in the industry. This alters the concentration ratio. This firm will have more market power than each of its subsidiaries separately. We follow Goutsmet, Lecocq & Volckaert (2017) in order to match firms with their corresponding parent company. Firms are linked to a parent company by exploiting information about the domestic ultimate owner, as defined by Bel-first.[25] We aggregate subsidiaries

[24] We refer to Bijnens and Konings (2018) for more detailed information on the filing requirements. Small firms are firms that fulfill all the following criteria: average number of employees above 50 FTE, €7.3 million for turnover and €3.65 for balance sheet total (2014 levels).

[25] We thank Goutsmet et al. (2017) for providing us data on the domestic ultimate owner of Belgian firms. Firm A is the domestic ultimate owner of firm B if it owns at least 50% of the shares. A firm is its own domestic ultimate owner if nobody owns more than 50% of the shares.

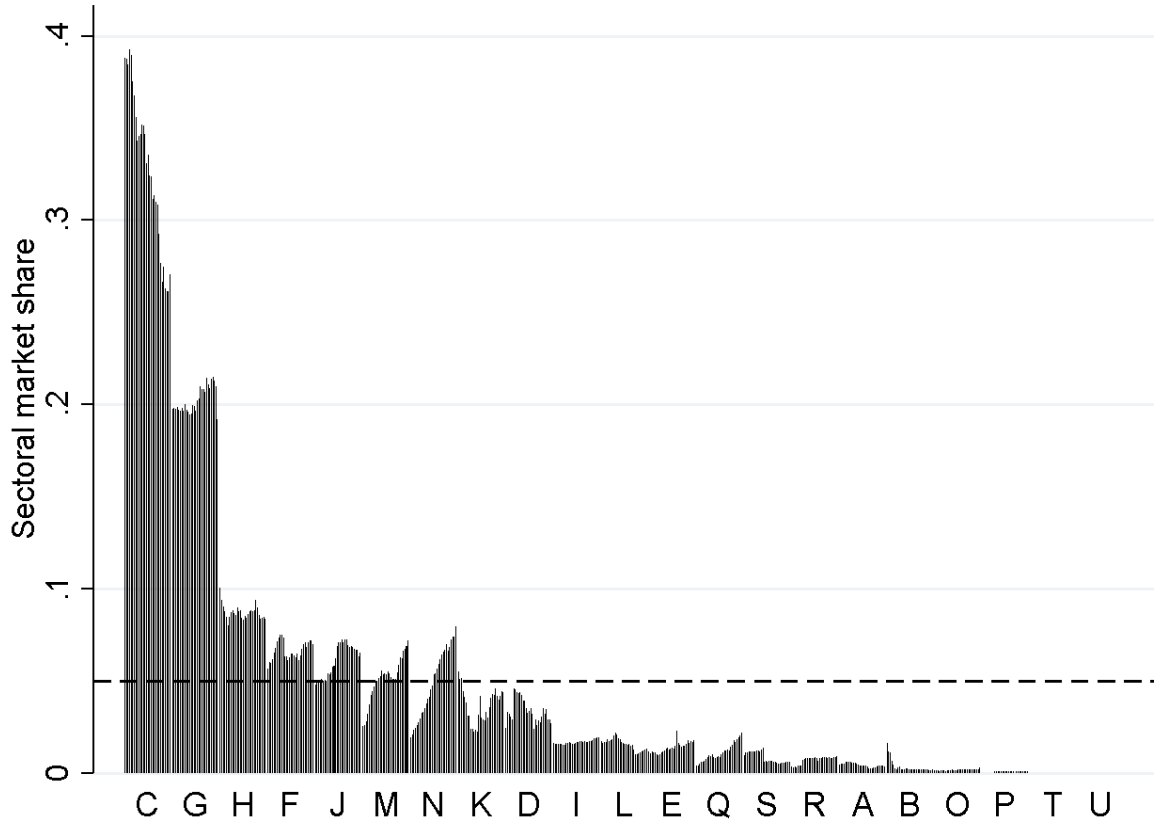
belonging to the same parent company up until the level of an industry, thereby following Autor et al. (2020).

Further, we encounter the issue of a broken book year for remuneration, value added and employment. In order to do analyses with yearly data, the reported book year should match the corresponding calendar year. A book year should start on 01/01 and end on 31/12. However, this is only the case in 78% of our observations. How do we solve this issue? If a book year spans n calendar years in our data set, then we duplicate that row n-1 times. We allocate the part of the original observation to the corresponding calendar year based on the number of months. Assume a firm produces €100 during a book year going from 01/04/2004 till 31/03/2005. We then separate this row into a row for 2004 with €75 (9 out of 12 months) and a row for 2005 with €25 (3 out of 12 months). If the firm produces €200 during the book year going from 01/04/2005 to 31/03/2006, we separate this row again in a row with €150 for 2005 and €50 for 2006. Next, we sum the information within the same year. We get a value of €175 for 2005. We can only do this if that year has information for 12 months. For example, the year 2004 has only 9 months of information. We extrapolate this and get a value of €100 for 2004. The same approach applies for 2006. Note that our method shifts some data to 1984 (if the book year in 1985 spans more than one book year). We drop this information as it is not representative for the Belgian economy. We keep only data from 1985 till 2014 after adjusting for the broken book year issue. The calendar and adjusted book year now match in 100% of the cases.

Lastly, the definition of the labor share causes two technical issues. First, the labor share is negative if value added or remuneration is lower than zero. We drop observations with a negative value added or a negative remuneration. We also drop observations with a value of zero for value added or remuneration. Second, if value added of a firm approaches zero, then the labor share goes to infinity. This is not a problem when we weigh our calculations by value added but it leads to a distorted Melitz and Polanec (2015) decomposition. We solve this by limiting the labor share at a value of two.

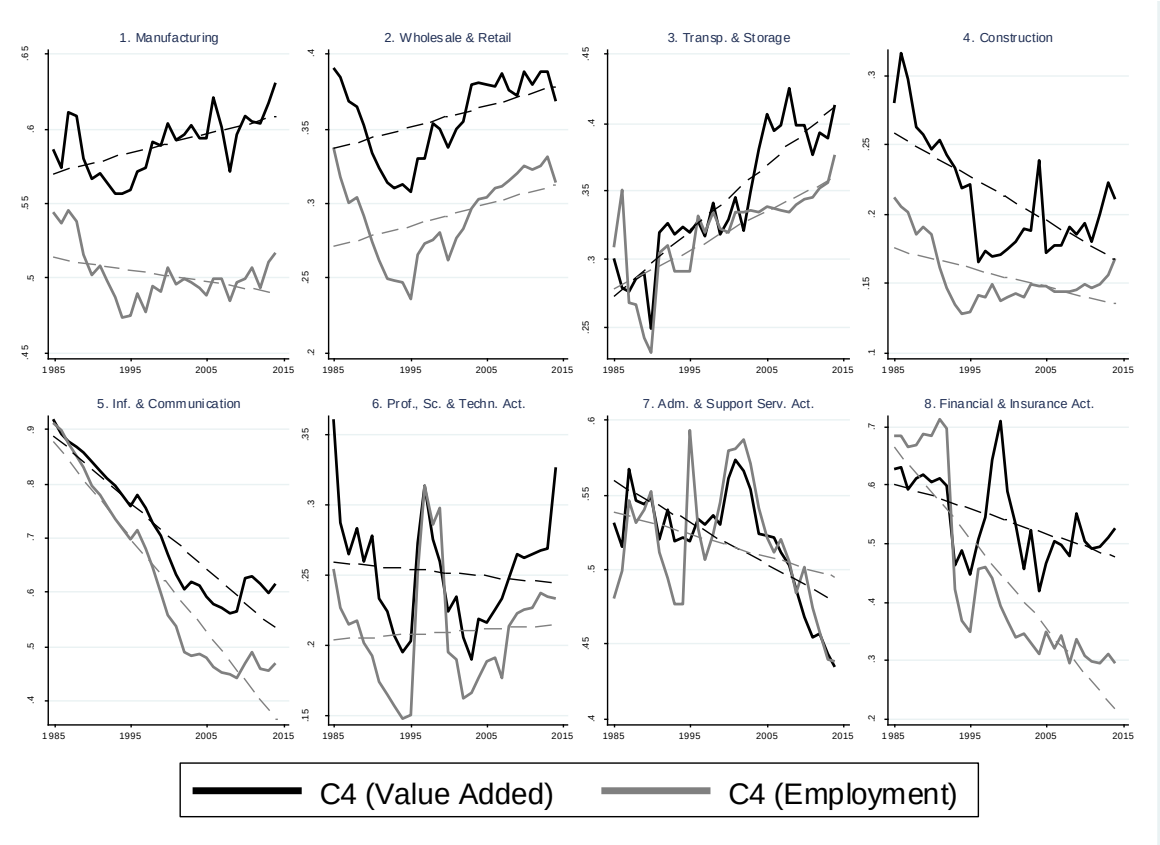
1.7.2 Figures appendix

Figure 1.8 Sectoral market share in total value added



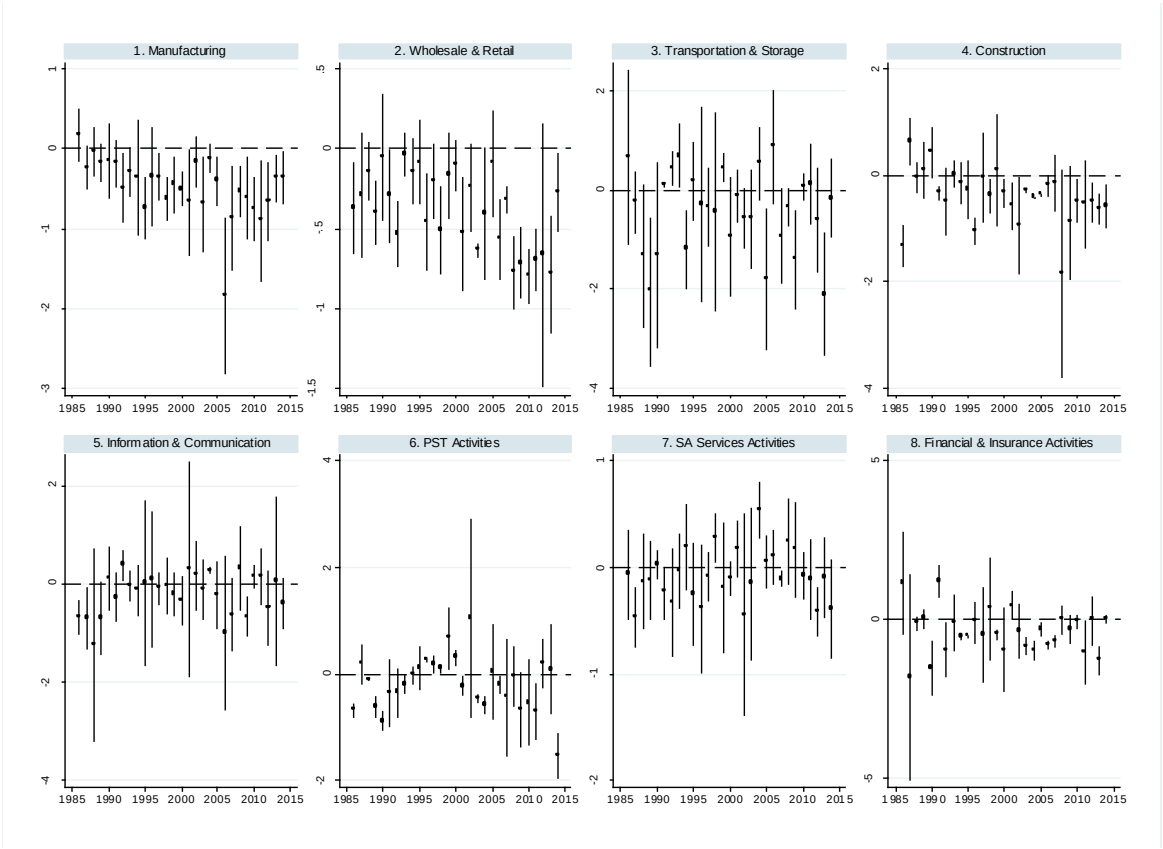
Notes: The market share evolution is plotted from 1985-2014 for each sector. Each sector is represented by its section code as used in NACE Rev. 2. The horizontal line represents the cut-off value of five percentage market share. The market share is calculated within a year. The eight largest sectors are Manufacturing (C), Wholesale & Retail (G), Transportation & Storage (H), Construction (F), Information & Communication (J), Professional, Scientific and Technic Activities (M), Administrative & Support services (N) and Financial & Insurance Activities (K).

Figure 1.9 Evolution of sectoral market concentration: Value added and employment



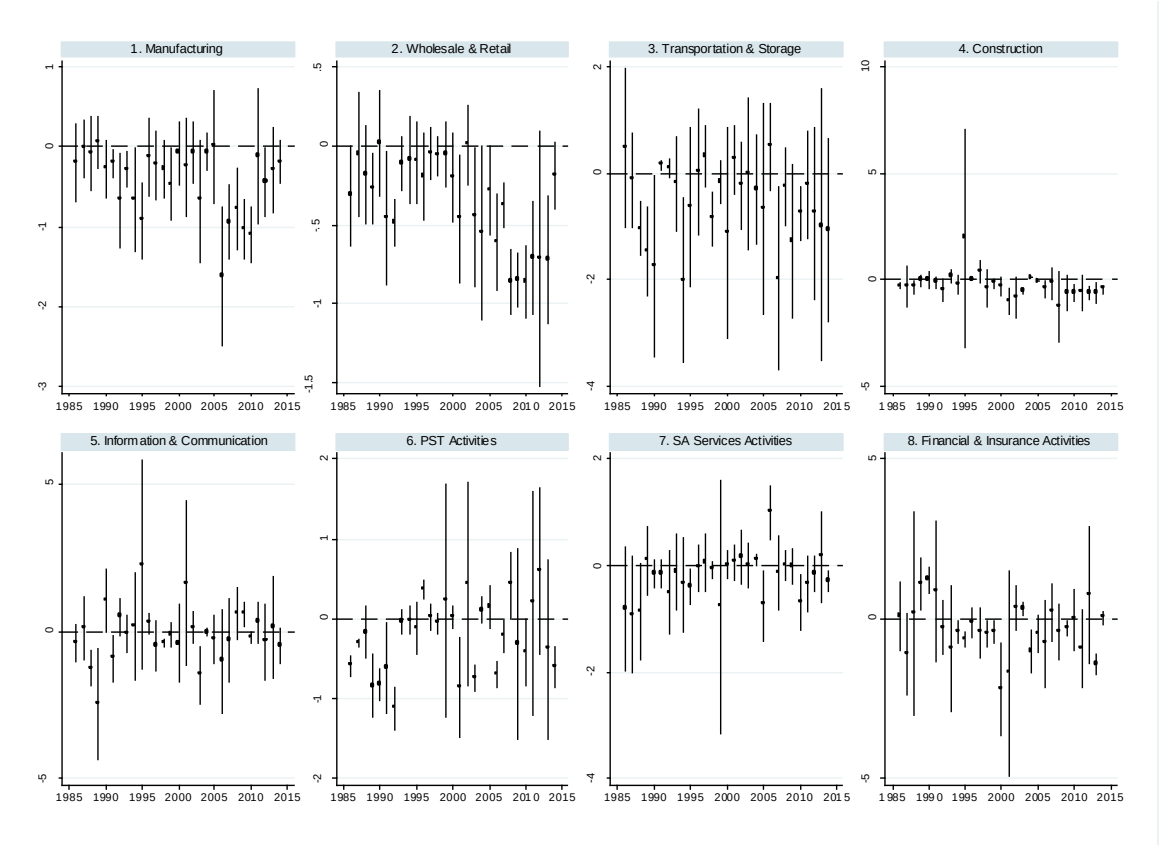
Notes: *Each panel plots the evolution of C4, once in terms of value added and once in terms of employment.*

Figure 1.10 The link between market concentration (C4) and the labor share: Yearly



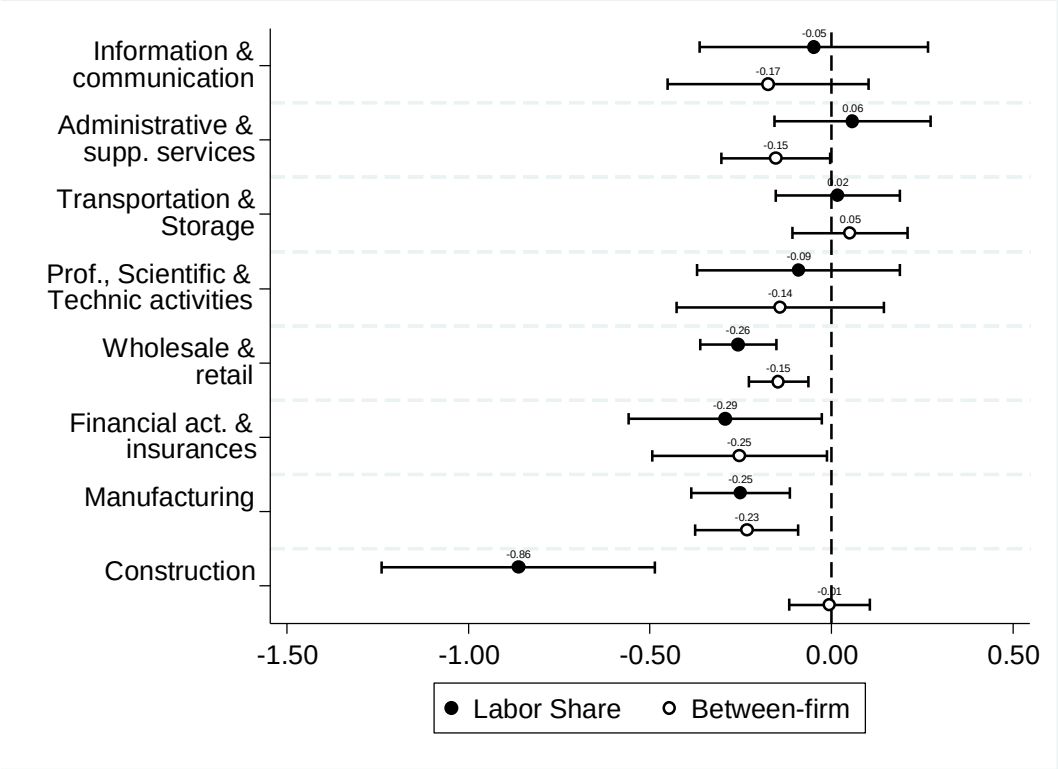
Notes: *This figure plots the yearly coefficient from equation (2) by sector. Robust standard errors are used to calculate the 95% confidence interval and shown around the point estimate in the figure.*

Figure 1.11 The link between market concentration (C4) and the between-firm component: Yearly



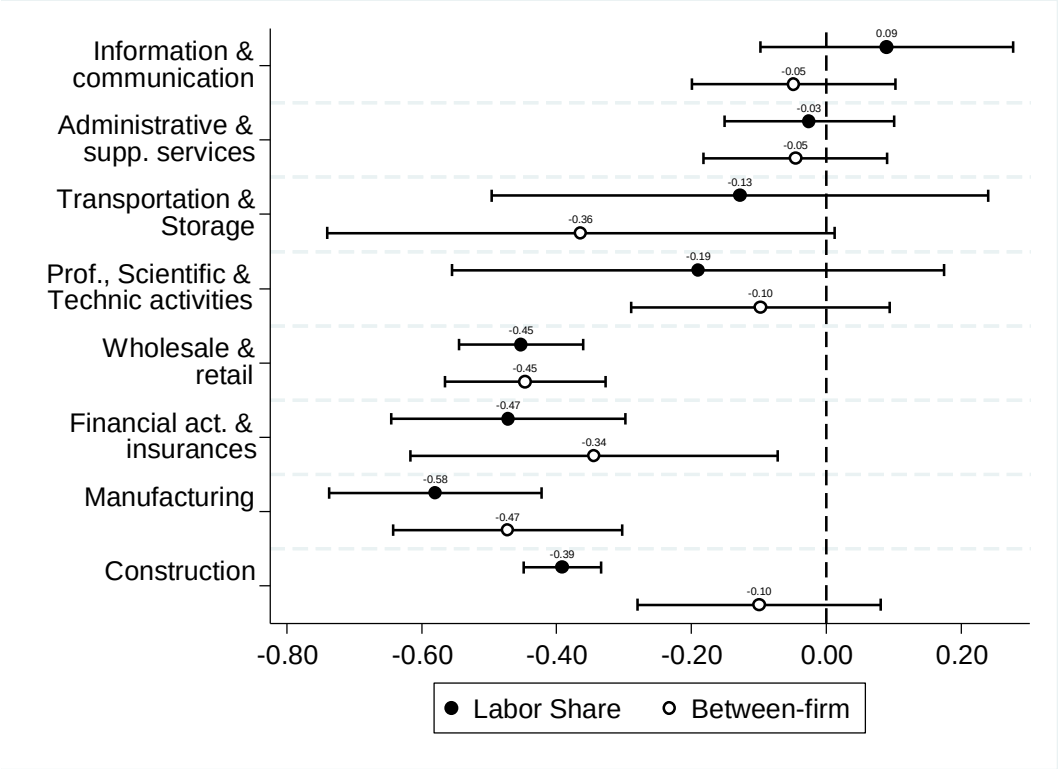
Notes: *This figure plots the yearly coefficient from equation (6) by sector. Robust standard errors are used to calculate the 95% confidence interval and shown around the point estimate in the figure.*

Figure 1.12 The link between market concentration (C4) and the labor share and between-firm component: 1985-1998



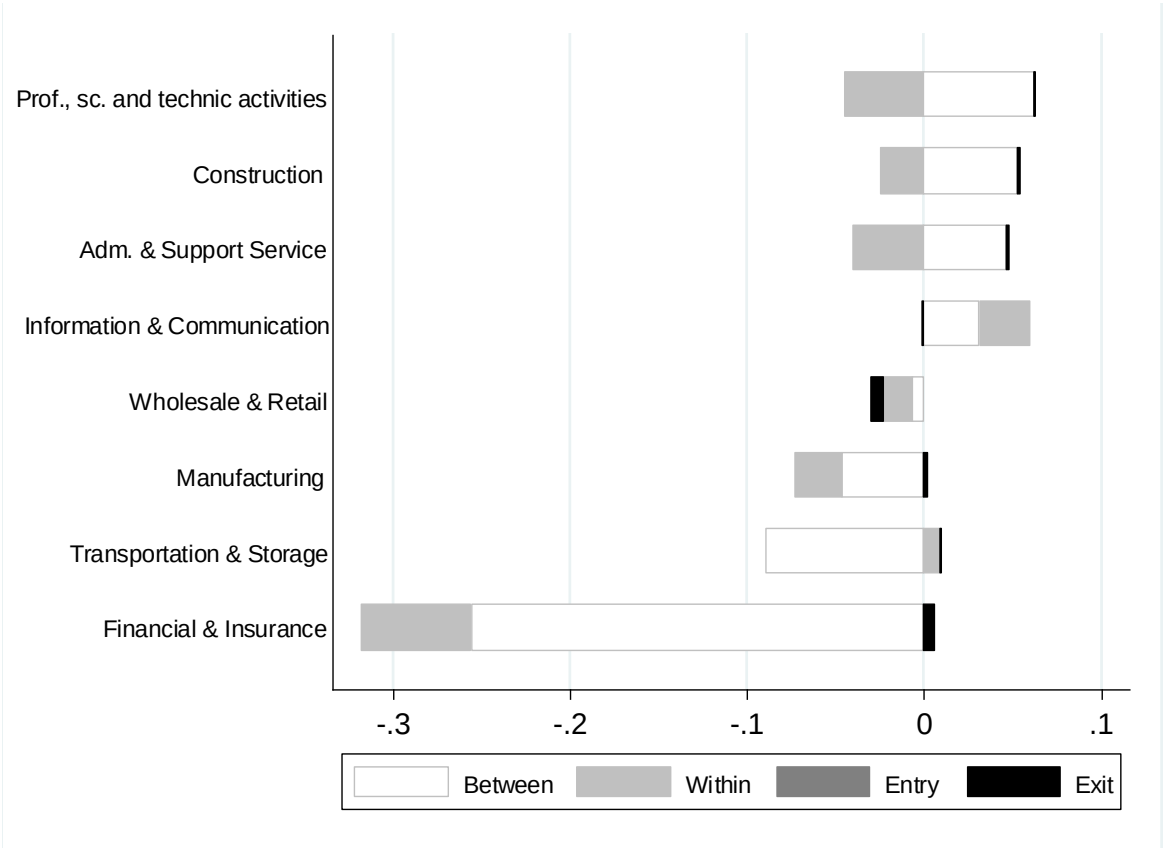
Notes: *This figure plots the regression coefficients from equation (2) and (6) for the period 1985-1998. Each coefficient follows from a separate regression. Robust standard errors are used to calculate the 95% confidence interval and shown around the point estimate in the figure.*

Figure 1.13 The link between market concentration (C4) and the labor share and between-firm component: 1998-2014



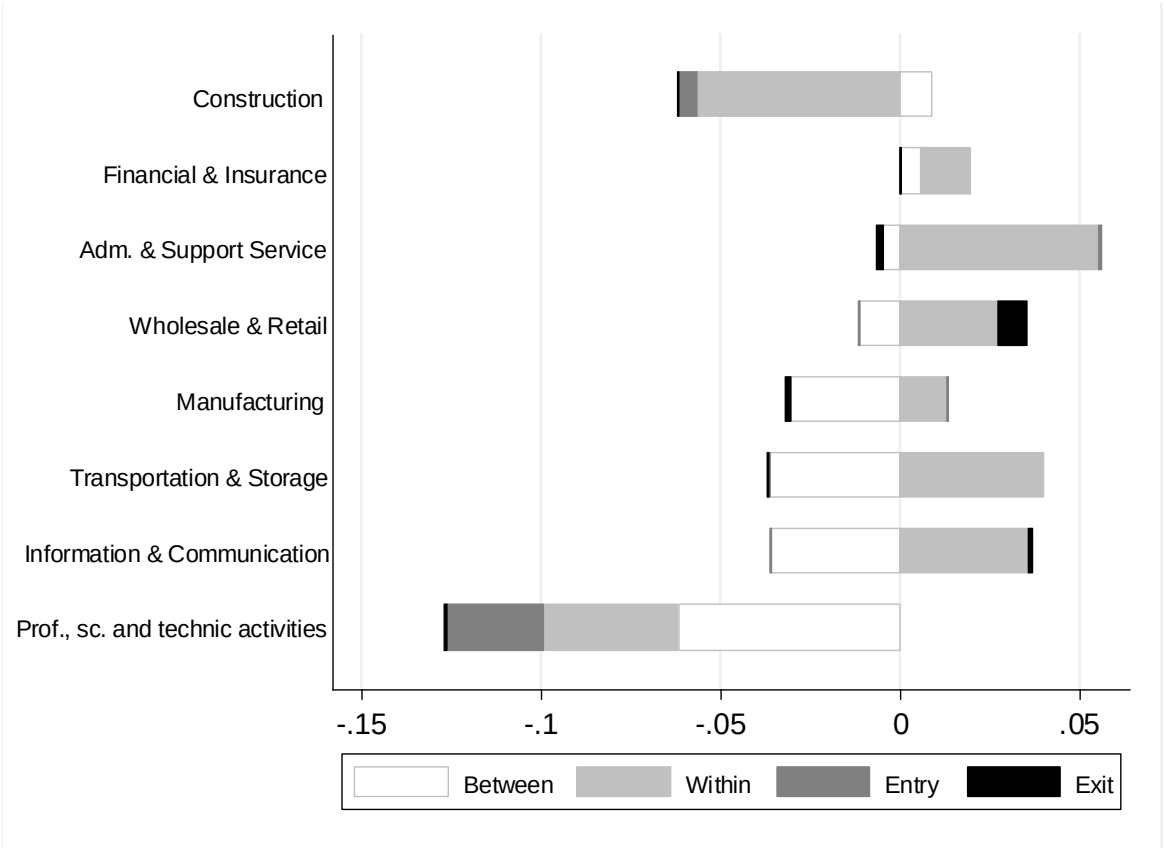
Notes: *This figure plots the regression coefficients from equation (2) and (6) for the period 1998-2014. Each coefficient follows from a separate regression. Robust standard errors are used to calculate the 95% confidence interval and shown around the point estimate in the figure.*

Figure 1.14 Melitz-Polanec decomposition of the change in the labor share (1985-1998)



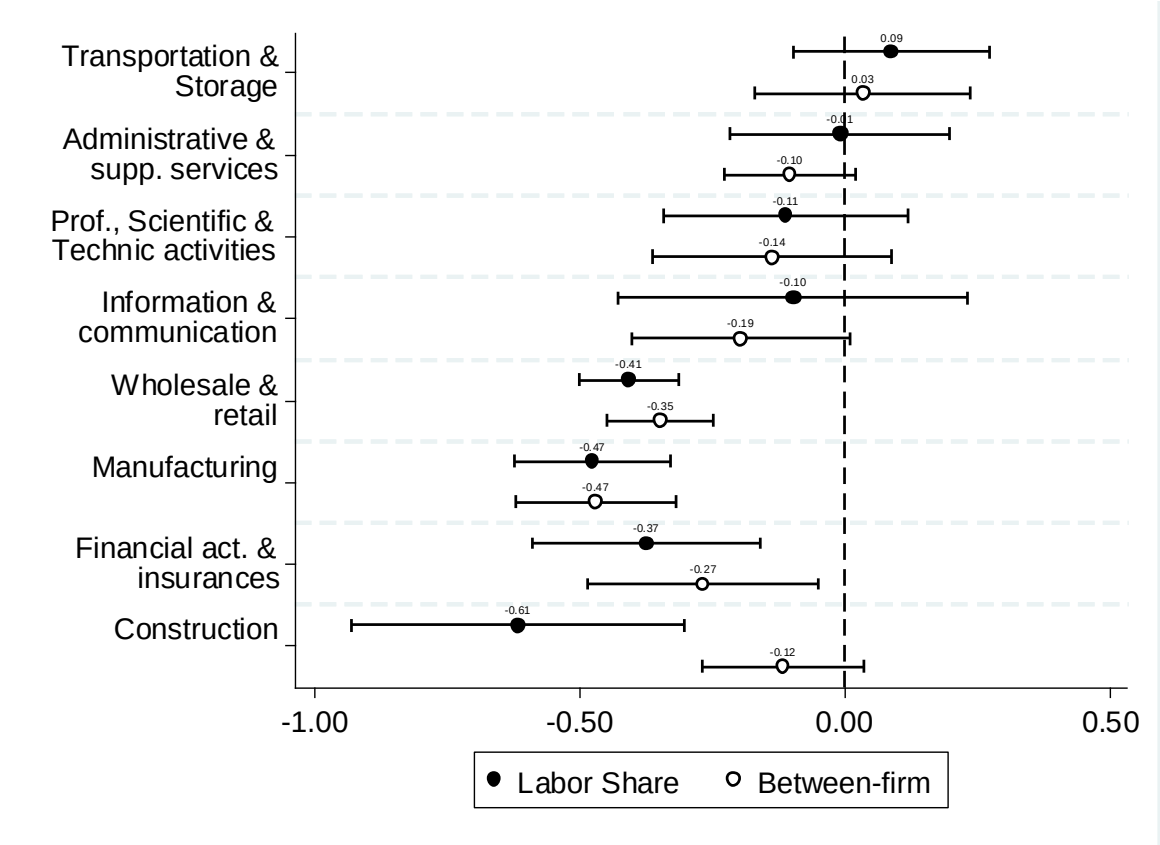
Notes: *Each bar shows the cumulated sum between 1985-1998 for each labor share component of the Melitz-Polanec decomposition. Results are ranked from the largest between-firm component to the lowest between-firm component.*

Figure 1.15 Melitz-Polanec decomposition of the change in the labor share (1998-2014)



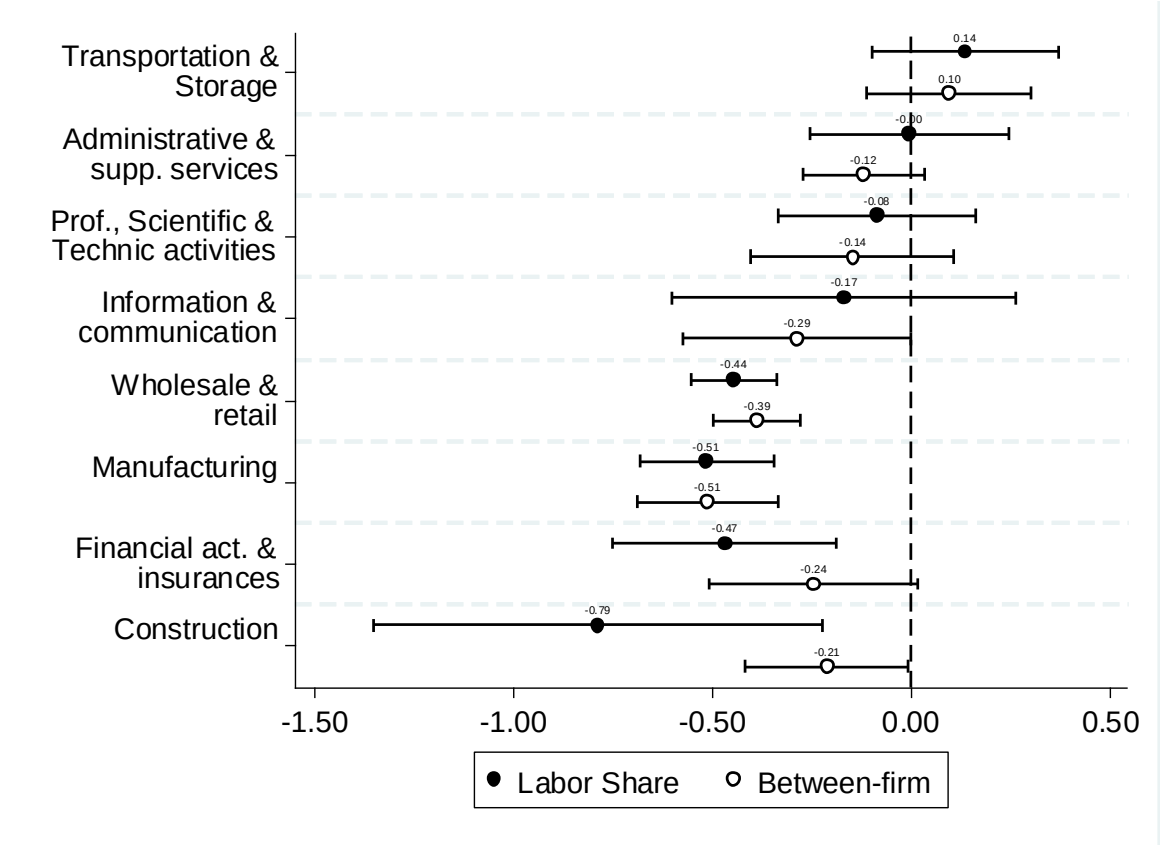
Notes: *Each bar shows the cumulated sum between 1998 and 2014 for each labor share component of the Melitz-Polanec decomposition. Results are ranked from the largest between-firm component to the lowest between-firm component.*

Figure 1.16 The link between market concentration (C10) and the labor share



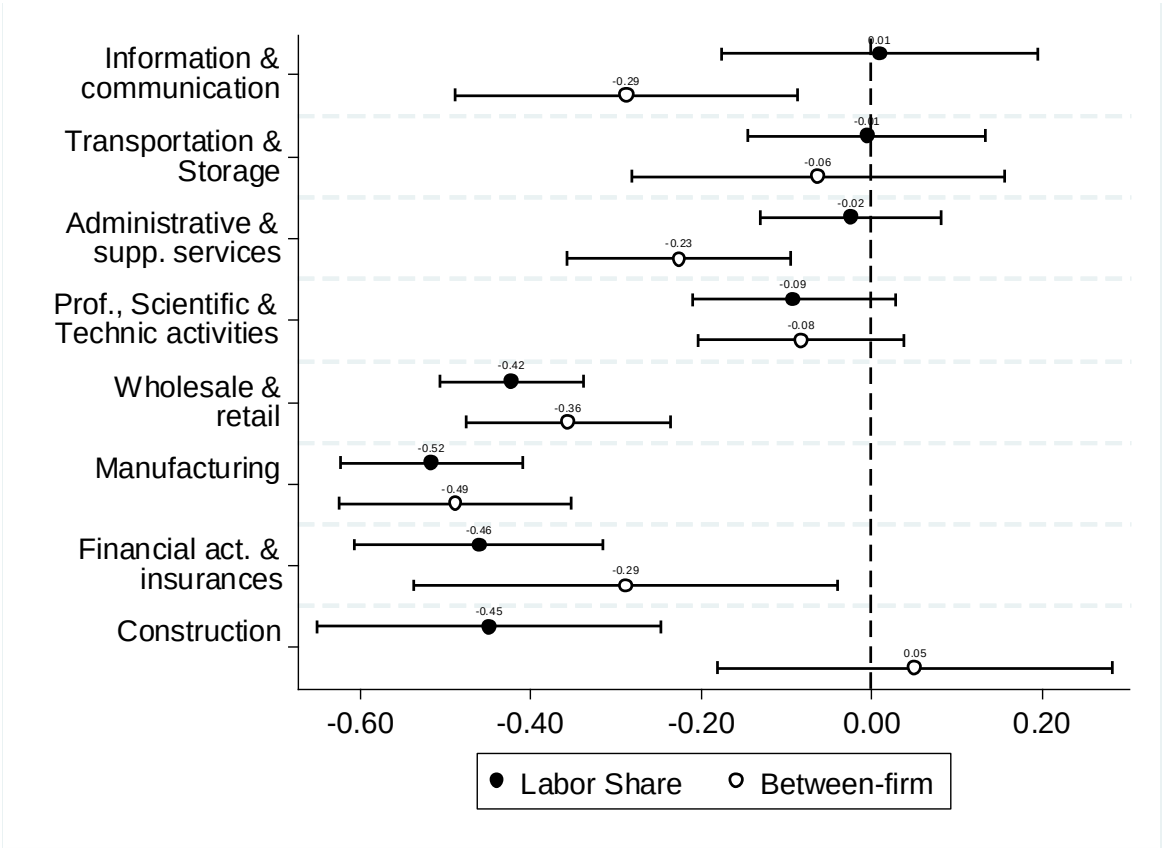
Notes: *This figure plots the regression coefficients from equation (2) and (6). Each coefficient follows from a separate regression. Robust standard errors are used to calculate the 95% confidence interval and shown around the point estimate in the figure.*

Figure 1.17 The link between market concentration (C20) and the labor share



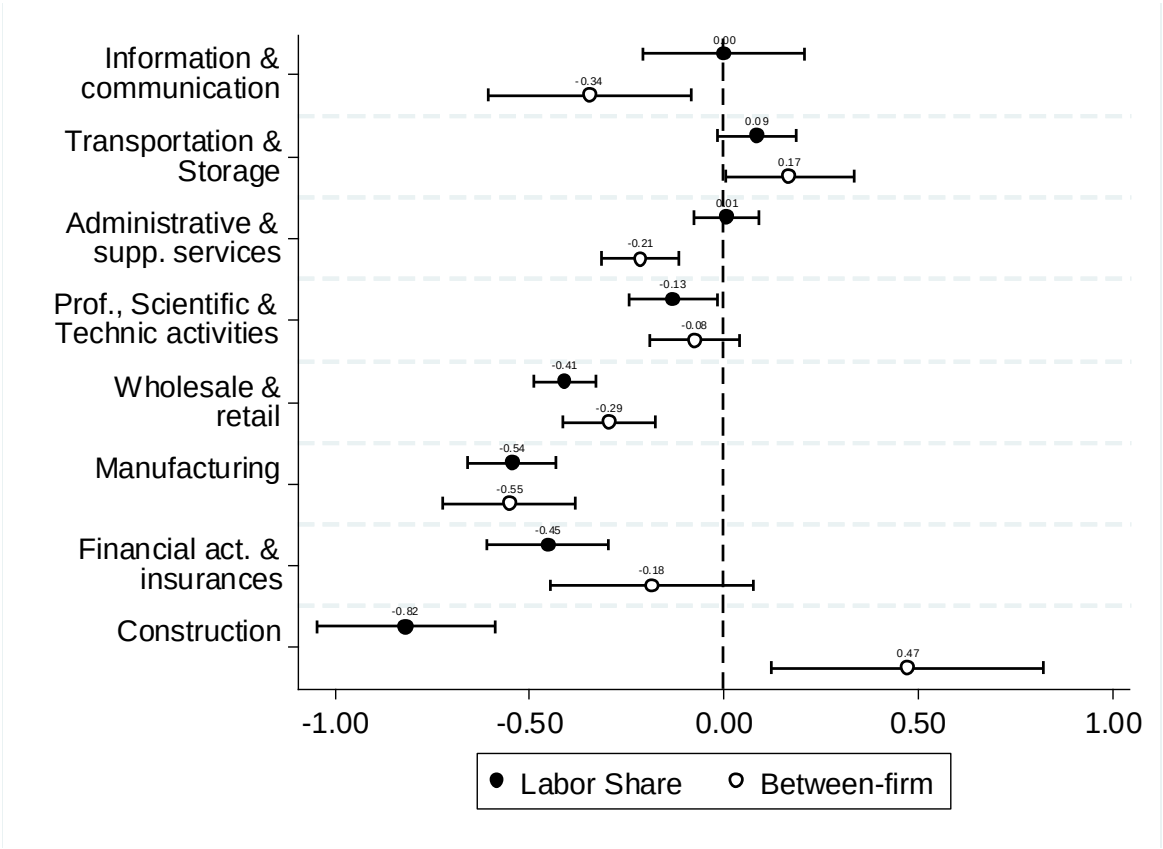
Notes: *This figure plots the regression coefficients from equation (2) and (6). Each coefficient follows from a separate regression. Robust standard errors are used to calculate the 95% confidence interval and shown around the point estimate in the figure.*

Figure 1.18 The link between market concentration (C4 - Δ5yr) and the labor share



Notes: *Each panel shows the coefficient from equation (2) and (6) for 5 year differences. Robust standard errors are used to calculate the 95% confidence interval and shown around the point estimate in the figure.*

Figure 1.19 The link between market concentration (C4 - Δ10yr) and the labor share



Notes: *Each panel shows the coefficient from equation (2) and (6) for 10 year differences. Robust standard errors are used to calculate the 95% confidence interval and shown around the point estimate in the figure.*

1.7.3 Tables appendix

Table 1.3 Summary statistics by sector

Manufacturing	mean	sd	P25	P50	P75	min	max
Remuneration	1,640,483	12,192,740	48,440	162,783	590,829	0	821,774,336
Value Added	2,673,775	24,641,142	87,606	254,287	869,551	4	2,822,272,256
Labor Share	0.66	0.32	0.48	0.66	0.82	0.00	2.00
Employment	36	226	2	6	18	0	16,583
Concentration	0.55	0.22	0.39	0.54	0.74	0.09	0.98
Construction	mean	sd	P25	P50	P75	min	max
Remuneration	310,629	1,961,372	26,802	76,754	207,822	0	220,944,144
Value Added	440,408	3,104,495	50,516	119,559	293,326	2	621,241,984
Labor Share	0.65	0.32	0.47	0.69	0.84	0.00	2.00
Employment	9	42	1	3	7	0	5,530
Concentration	0.25	0.21	0.13	0.17	0.30	0.03	0.88
Wholesale & Retail	mean	sd	P25	P50	P75	min	max
Remuneration	339,857	3,961,017	21,021	58,507	173,302	0	702,623,488
Value Added	598,246	8,949,667	44,571	110,883	290,250	0	1,769,869,568
Labor Share	0.62	0.38	0.38	0.59	0.78	0.00	2.00
Employment	9	97	1	2	6	0	16,817
Market Concentration	0.34	0.19	0.20	0..30	0.44	0.04	0.98
Transportation & Storage	mean	sd	P25	P50	P75	min	max
Remuneration	1,305,531	29,364,743	35,920	132,895	433,405	0	2,171,158,016
Value Added	1,771,806	33,095,405	74,789	229,377	674,666	11	2,319,222,784
Labor Share	0.62	0.32	0.43	0.62	0.78	0.00	2.00
Employment	32	778	1	4	12	0	57,964
Concentration	0.48	0.28	0.22	0.41	0.75	0.04	0.97
Information & Communication	mean	sd	P25	P50	P75	min	max
Remuneration	1,200,136	17,552,635	16,498	62,023	274,170	0	1,481,415,424
Value Added	2,244,266	43,703,975	40,147	111,995	409,052	0	2,927,595,520
Labor Share	0.64	0.42	0.35	0.63	0.85	0.00	2.00
Employment	21	387	1	2	6	0	29,067
Concentration	0.58	023	0.38	0.61	0.74	0.13	0.98
Financial & Insurance Activities	mean	sd	P25	P50	P75	min	max
Remuneration	407,117	6,197,947	18,770	45,912	116,175	0	576,028,992
Value Added	836,304	12,794,137	51,227	108,024	237,914	1	2,187,632,128
Labor Share	0.53	0.37	0.28	0.48	0.71	0.00	2.00
Employment	8	202	1	1	3	0	27,509
Concentration	0.48	0.22	0.25	0.51	0.66	0.04	0.95
Professional, Scientific & Technic Activities	mean	sd	P25	P50	P75	min	max
Remuneration	335,688	3,116,067	13,659	40,655	129,648	0	478,589,376
Value Added	512,283	4,742,415	39,035	92,292	240,069	2	735,589,440
Labor Share	0.55	0.38	0.28	0.53	0.77	0.00	2.00
Employment	6	46	1	1	4	0	9,682
Concentration	0.32	0.18	0.16	0.27	0.43	0.08	0.97
Administrative & Support Services	mean	sd	P25	P50	P75	min	max
Remuneration	1,004,241	14,713,819	18,071	59,675	212,369	0	1,276,472,576
Value Added	1,414,321	16,120,062	45,052	121,061	360,700	1	1,364,642,304
Labor Share	0.60	0.39	0.31	0.59	0.84	0.00	2.00
Employment	31	464	1	2	6	0	44,437
Concentration	0.47	0.22	0.30	0.44	0.61	0.07	0.97

Notes: *This table includes summary statistics (mean, standard deviation, 25th percentile, 50th percentile, 75th percentile, minimum value and maximum value) for our variables of interest by sector. The observations are pooled over our time period (1985-2014) and are not adjusted for inflation in this table.*

Table 1.4 Labor share trend by sector

	(1) Manufacturing	(2) Wholesale & Retail	(3) Transportation & Storage	(4) Construction	(5) Information & Communication	(6) Prof., Sc. & Technic Activities	(7) Administrative & Support Services	(8) Financial & Insurance Activities
year	-0.00238***	-0.00134**	-0.00344***	-0.000544	0.00342***	-0.00323***	0.00153***	-0.00983***
	(0.000482)	(0.000454)	(0.000443)	(0.000573)	(0.000789)	(0.000469)	(0.000317)	(0.00162)
constant	5.369***	3.255**	7.620***	1.796	-6.328***	7.122***	-2.355***	20.17***
	(0.964)	(0.907)	(0.886)	(1.146)	(1.578)	(0.938)	(0.633)	(3.235)
N	30	30	30	30	30	30	30	30

Notes: *This Table shows the results for regressing sectoral labor share on year. Standard errors in parentheses (* p < 0.05, ** p < 0.01, *** p < 0.001).*

Table 1.5 Concentration trend by sector

	(1) Manufacturing	(2) Wholesale & Retail	(3) Transportation & Storage	(4) Construction	(5) Information & Communication	(6) Prof., Sc. & Technic Activities	(7) Administrative & Support Services	(8) Financial & Insurance Activities
year	0.00131***	0.00144**	0.00482***	-0.00316***	-0.0123***	-0.000520	-0.00278***	-0.00430**
	(0.000354)	(0.000512)	(0.000422)	(0.000662)	(0.000857)	(0.000842)	(0.000583)	(0.00128)
constant	-2.029**	-2.523*	-9.302***	6.540***	25.31***	1.292	6.069***	9.142**
	(0.708)	(1.023)	(0.845)	(1.324)	(1.714)	(1.683)	(1.165)	(2.554)
N	30	30	30	30	30	30	30	30

Notes: *This Table shows the results for regressing sectoral market concentration ratio on year. Standard errors in parentheses (* p < 0.05, ** p < 0.01, *** p < 0.001).*

Table 1.6 Melitz & Polanec decomposition by sector

Sector	Within		Between		Entry		Exit	Δ(Between and Within)	
Manufacturing	-1.37% (0.30)	***	-7.62% (1.48)	***	0.01% (1.67)		0.02% (1.21)	-6.24% (1.51)	***
Construction	-8.16% (0.25)	***	6.15% (2.99)	***	-0.47% (1.30)		0.08% (1.00)	14.30% (3.00)	***
Wholesale & Retail	1.10% (0.20)	***	-1.78% (1.70)		-0.02% (1.11)		0.09% (0.76)	-2.87% (1.72)	*
Transportation & Storage	4.93% (0.44)	***	-12.57% (3.57)	***	-0.09% (2.86)		0.06% (2.92)	-17.50% (3.60)	***
Information & Communication	6.35% (0.95)	***	-0.49% (4.86)		-0.03% (2.65)		-0.01% (4.00)	-6.84% (4.95)	
Financial & Insurance Activities	-4.75% (0.68)	***	-25.00% (3.91)	***	-0.01% (2.42)		0.59% (2.21)	-20.25% (3.97)	***
Prof.. sc. and technic Activities	-8.22% (0.41)	***	0.02% (4.96)		-2.71% (1.03)	***	0.03% (1.50)	8.25% (4.98)	*
Adm. & Support Service	1.55% (0.99)	***	4.20% (3.65)		0.06% (2.09)		0.00% (3.65)	2.65% (3.78)	

Notes: *This table shows the coefficients behind Figure 6. Standard errors are shown between parentheses. We refer to the corresponding 10%, 5% and 1% significance level with *, ** or ***. The final column calculates the difference between the within and between component. It also tests the significance of this difference.*

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Chapter 2

Productivity dispersion, wage dispersion and superstar firms

2.1 Introduction

Although often studied separately,[1] productivity and wage dispersion are found to have notably similar evolutions (Dunne et al., 2004; Faggio et al., 2010; Barth et al., 2016).[2] This positive relationship arises under a range of models based on various theoretical foundations (Lentz and Mortensen, 2010; Manning, 2011).[3] Overall, changes in productivity and wage dispersion are shown to be closely linked.[4] As such, a host of structural factors and policies are expected to impact the wage distribution not only directly,[5] but also indirectly through the link between productivity and wage dispersion, i.e. the extent to which the distribution of productivity gains are passed on to wages. In line with the above, such structural factors and policies range from globalisation and technological change to minimum wage and labour unions (for an empirical exploration of a range of factors see Berlingieri et al., 2017).

While each of these factors are compelling explanations, they jointly appear to have contributed to the emergence of a global secular trend: the rise of "superstar firms." Superstar firms refer to a

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[1] Recent research has documented increases in productivity dispersion and wage dispersion in several countries. Studies which explore changes in productivity dispersion include Syverson (2004); Aghion et al. (2009); Andrews et al. (2015) and Andrews et al. (2016), among others. For research related to increases in wage dispersion see Autor et al. (2008); Bagger et al. (2013); Card et al. (2013, 2014, 2016, 2018); Song et al. (2019).

[2] This complements mounting empirical evidence documenting that worker compensation is strongly correlated with various measures of firm performance. Note that these findings are in line with both worker sorting in more productive firms and also rent-sharing behaviour of firms (see Card et al., 2018).

[3] For example, search costs in the labour market prevent the arbitrage of wage differences across jobs or locations. Thus, an incomplete pass-through of productivity to wages emerges (Pissarides, 2011). See Layard et al. (2009) for a review of models with: search costs; efficiency wage; union bargaining; and rent-sharing.

[4] This is in line with evidence on imperfect propagation of productivity shocks to wages (Juhn et al., 2018; Berger et al., 2019; Kline et al., 2019).

[5] Two factors are typically cited as potential explanations: globalisation (Helpman, 2016) and technological change (Acemoglu and Autor, 2011). Both have been shown to have differential effects on wages for various types of labour and skills. This explains increases in the wages of skilled relative to unskilled workers and thus rising wage dispersion within and between firms. While less eminent, a series of other explanations include: the relative supply of highly-educated workers (Card and Lemieux, 2001); union power (Machin, 2016); centralisation of wage bargaining (Dahl et al., 2013); and minimum wage (DiNardo et al., 1996).

handful of large entities which dominate product market shares in their industries (Autor et al., 2020). These firms are known to be the most productive, technologically advanced, and globally engaged (Mayer and Ottaviano, 2008; Andrews et al., 2015); set higher mark-ups (Autor et al., 2020); and have a lower firm-specific labour share despite paying above-average wages (Gouin-Bonenfant, 2018). The rise of superstar firms is a global phenomenon already used to interpret emerging trends such as: declining labour share (Abraham and Bormans, 2020; Autor et al., 2020) and rising markups (De Loecker et al., 2020).

In a world where a handful of firms increasingly control the market, it is important to understand how this structural change might affect the extent to which productivity gains are passed on to wages. The importance of this question is underscored by recent anecdotal evidence from Amazon opening a warehouse in South Carolina. Despite creating approximately 4,000 jobs, Amazon's dominance in the local labour market translated to a decrease in average annual wages by roughly 30% (The Economist, 2018). This behavior supports theoretical considerations proposed by Gouin-Bonenfant (2018) about the link between productivity and wage dispersion. In particular, as productivity dispersion increases high productivity firms enjoy increased profit margins while being shielded from local wage competition. Therefore, increased monopsony power of firms at the top of the distribution leads to a gradual moderating effect in workers' wages—to levels below their marginal value of revenue. Such effects, however, are not limited to the top of the distribution. They could also arise at the bottom of the distribution through structural changes in the labour market due to increased concentration, as evidenced in the case of Amazon. Overall, a rise in market concentration is expected to weaken the link between productivity and wage dispersion, which we empirically examine in this chapter.

The contribution of this chapter is twofold. First, using a rich firm-level dataset for 14 EU countries between 2000-2016 we complement evidence of the increasing evolution of productivity and wage dispersion. A key difference between our analysis and others is the time period covered, with most previous studies ending around 2012. While we confirm increases in productivity and wage dispersion throughout the sample period, we also observe a moderating effect in more recent years. This novel evidence posits that trends in productivity and wage dispersion might be non-secular. Moreover, these evolutions are primarily driven by changes at the bottom of the distribution. In the case of productivity dispersion, these findings are consistent with increases in misallocation of resources

towards the least productive firms.[6] In the case of wage dispersion, results support the presence of increased downward pressure on labour and wages at lower parts of the distribution.[7]

Further, we confirm a rather incomplete link between productivity and wage dispersion. Otherwise stated, while we find that industries with higher productivity dispersion are associated with higher wage dispersion, the correlation is less than one. Unpacking these results, we show that this link is considerably stronger at the bottom of the distribution. Intuitively, firms at the bottom seem to transfer a relatively larger share of their productivity gains to wages compared to firms at the top. This finding can be reconciled with theoretical considerations of firms' differential levels of labour market power, where larger and more productive firms have more labour market power markdowns, and thus put relatively more downward pressure on wages (Berger et al. 2019).

Second, we explore the emergence of superstar firms and their potential impact on the link between productivity and wage dispersion. In doing so, we establish a rise of superstar firms in our sample, in line with Autor et al. (2020). In turn, we provide novel evidence that high market concentration industries—a proxy for superstar firms—are associated with a weaker link between productivity and wage dispersion.[8] As such, superstar firms appear to induce a larger disconnect between productivity and wages, and hence a more incomplete pass-through.

Interestingly, this effect holds both at the top and bottom parts of the distribution, pointing to possibly different mechanisms at play. At the top part of the distribution, such effects provide positive affirmation of the mechanism referred to above: highly productive firms enjoy increased profit margins from access to globalisation while being shielded from local wage competition through increased domestic labour market power. This allows them to pass a smaller share of their productivity gains to wages (Gouin-Bonenfant, 2018). At the bottom part of the distribution, such effects might be present through the overall impact on the market structure. Specifically, the emergence of superstar firms reduces competitive pressure in the labour market which allows even the least productive firms to have some monopsony power which translates to low wages (Azkarate-Askasua and Zerecero,

[6] Factors which engender this mechanism include: declining business dynamism (Decker et al., 2016); falling real interest rates (Gopinath et al., 2017); zombie firms (Andrews and Petroulakis, 2019); and stalling technological diffusion (Andrews et al., 2016); among others.

[7] Structural changes in firms' operating environments which generate this result include: import competition from low-wage countries (Autor et al., 2013); increases in firms' monopsony power (Burdett and Mortensen, 1998); openness in capital markets (Huber et al., 2020); and automation (Acemoglu and Restrepo, 2019); among others.

[8] Market concentration is an adequate measure of market power under certain circumstances, i.e. stable markets and when firms compete à la Cournot (De Loecker et al., 2020). In a standard Cournot oligopoly model, a positive relationship exists between market concentration and the average market power. More market concentration translates into less market competition. Once these assumptions are not fulfilled, it is not necessary the case that higher market concentration links positively to more market power (Syverson, 2019). Nevertheless, market concentration is nowadays often being used as proxy for superstar firms thereby investigating how changes in market concentration impact, for example, the labor share (see for example Autor et al., 2020).

2019; Berger et al., 2019). Upon deeper examination, we also show that this result is most prominent for services sectors. This is of particular interest, given rapidly expanding research on the structural differences between services and manufacturing, including each sector's overall dynamism.

Our analysis relies upon firm-level data from Orbis Global which allows us to construct measures for productivity dispersion, wage dispersion, and market concentration at the country-industry-year-level. The broad set of 14 European countries considered differs across various dimensions—geography, economic development, institutions, trade openness/integration, etc. Such variation lends itself to strong external validity of our main analysis. On the other hand, limitations on the coverage of this database for smaller-sized firms are well-known. We thus provide a series of cross-validation checks in terms of the data at hand to overcome these constraints and implement a broad set of robustness checks on the construction of our measures of interest (see section 2.5). In all cases, results remain robust, reaffirming the main conclusions from our baseline analysis. Finally, while all interpretations are based on conditional correlations, our findings remain robust against a rich set of fixed effects that guard against potential unobserved heterogeneity along various dimensions.

The remainder of this chapter is structured as follows. Section 2.2 discusses the construction of the main variables of interest and the choice of the empirical specifications. Section 2.3 describes the dataset used in the empirical analysis. Section 2.4 presents results and section 2.5 provides robustness checks. Section 2.6 concludes.

2.2 Empirical methodology

This section discusses the construction of our main variables and empirical strategy used in the chapter. We first describe how we measure productivity and wages at the firm-level as well as the construction of measures which capture productivity and wage dispersion at the country-industry-year level. This leads to an examination of the evolution of these measures over time. Subsequently, we provide a theoretical background which supports the introduction of the empirical specification which links productivity dispersion to wage dispersion. Finally, we elaborate on the construction of proxies which reflect the evolution of superstar firms. With these at hand, and in line with the theoretical background, we present the empirical specification used to assess: a) the direct effect of superstar firms on wage dispersion and b) the mediating effect of superstar firms on the link between productivity and wage dispersion.

2.2.1 Measuring productivity and wages

Productivity reflects how efficient firms are in transforming inputs into output. For our baseline analysis, we use labour productivity, *P*, defined as:

$$P_{jcit} = \frac{VA_{jcit}}{L_{jcit}} \quad (1)$$

where VA_{jcit} is value added and L_{jcit} is employment (in full-time equivalents) for firm *j* in country *c*, industry *i*, and year *t*.[9] This measure is advantageous because it is straightforward to compute and interpret, and information on value added and employment—necessary to calculate the measure—are well reported in the financial statements of firms. The main drawback of this measure is that it attributes all changes in labour productivity to a single factor of production, labour.[10]

For wages we rely on the average firm wage, *W*, calculated as:

$$W_{jcit} = \frac{TLC_{jcit}}{L_{jcit}} \quad (2)$$

where TLC_{jcit} captures the total labour cost for firm *j* in country *c* and industry *i* at time *t*. This measure is well reported in firms' financial statements across sectors and countries[11], however, by construction, it assumes that all employees earn the same wage within the firm.[12] Nonetheless, using average firm wages still captures a sizeable part of the wage dispersion both at the cross-section and over time.[13] As such, results in this chapter focus on between-firm wage differentials which remain meaningful in understanding the evolution of overall wage dispersion (for an in depth discussion see Berlingieri et al., 2017).

2.2.2 The evolution of productivity and wage dispersion

To proxy productivity dispersion for each country-industry-year group of firms (*cit*) we use the natural logarithm of the ratio of the 90th over the 10th percentile of the firm-level productivity distribution,

[9] We follow Berlingieri et al. (2017) as we define the relevant market at the country-industry-year combination.

[10] Implicitly, we assume a single input production function with labor being the only input. For robustness, we also use total factor productivity where labour, capital, and materials are considered. Implicitly, this assumes a production function with these three inputs. However, the additional data requirements in terms of variables required results in a 22% sample reduction, encompassing dropping all observations for Denmark, Ireland and the United Kingdom.

[11] Orbis Global (BvD, 2020a) standardizes the data across the countries. See Orbis Global (BvD, 2020b) for an overview of the exact definition of the total labor cost by country. For example, for Belgium, cost of employees is defined as the sum of remuneration, social security costs and pensions.

[12] Therefore, we cannot capture potential wage dispersion among employees/occupations within the firm, since firms are not requested to file such granular information in standard financial statements. Criscuolo et al. (2021) use a new cross-country dataset of linked employer-employee data showing that differences across firms are mainly explained by differences in the firm wage premium rather than the workforce composition. The firm wage premium is based on firms' characteristics. In this chapter, we do not have individual worker data.

[13] Specifically, recent studies using employer-employee data provide evidence that between-firm wage differentials account for most of the evolution in wage dispersion (Dunne et al., 2004; Barth et al., 2016; Helpman et al., 2017; Song et al., 2019).

denoted by $PD_{cit}^{90/10} = \ln(P_{cit}^{90}/P_{cit}^{10})$.[14] This ratio tells us how many times more productive the firm at the 90th percentile is relative to the firm at the 10th percentile of the distribution.

To capture the evolution of productivity dispersion, we estimate:

$$PD_{cit}^{90/10} = D_t\beta_t + FE_{ci} + \varepsilon_{cit} \quad (3)$$

where D_t is a vector of year dummies, FE_{ci} is a set of country-industry fixed effects, and ε_{cit} is an *i.i.d.* error term. Country-industry fixed effects eliminate all cross-sectional variation and thus account for any compositional differences in dispersion between country-industries. As such, β_t captures intertemporal changes within each country-industry. Specifically, β_t is the parameter vector of interest measuring the average dispersion in each year *t* relative to the reference year at the start of the sample. We weight the regression by the natural logarithm of total value added at the country-industry-year level.

Analogously, wage dispersion is computed as $WD_{cit}^{90/10} = \ln(W_{cit}^{90}/W_{cit}^{10})$ and its evolution is estimated as:

$$WD_{cit}^{90/10} = D_t\beta_t + FE_{ci} + \varepsilon_{cit} \quad (4)$$

where now β_t captures the estimated changes of wage dispersion in each year relative to the reference year. All other controls and the regression weighting approach remain the same as in (3). To uncover potential underlying heterogeneity, we repeat the analysis by focusing on different sub-sections of the entire distribution (see section 2.4.1).

2.2.3 The link between productivity and wage dispersion

To focus ideas, we start by introducing the theoretical background on how (labour) productivity translates into wages. Specifically, we rely on the model introduced by Wong (2021) which has two key ingredients: labour market frictions and firm heterogeneity.[15] This framework allows to structurally decompose firm-specific wages into four components:

$$W_{jcit} = P_{jcit} * LEO_{jcit} * \frac{\eta_{jcit}}{\mu_{jcit}} \quad (5)$$

[14] We rank all firms within a country-industry-year combination and calculate the productivity dispersion as the 90th percentile divided by the 10th percentile. An alternative might be to look at the ratio of the productivity of the top-n firms relative to the productivity of all firms outside this set, as is done by Andrews et al. (2015). A disadvantage of the latter approach is that outliers in terms of average productivity might have a substantial impact on this ratio, and its evolution.

[15] This model includes firm heterogeneity in terms of labour productivity and markdowns, as is common in standard labour market friction models such as Burdett and Mortensen (1998). Additionally, firms can differ in terms of their labour elasticity of output and markups. See Wong (2021) for a detailed discussion of the underlying assumptions.

where P_{jcit} is labour productivity (defined as before), $LEO_{jcit} \equiv \frac{\partial lnVA_{jcit}}{\partial lnL_{jcit}}$ is the labour elasticity of output, $\eta_{jcit} \equiv \frac{\varepsilon^L_{jcit}}{1+\varepsilon^L_{jcit}}$ is the markdown (with ε^L_{jcit} being the labour supply elasticity), and $\mu_{jcit} \equiv \frac{\varepsilon^D_{jcit}}{\varepsilon^D_{jcit}-1}$ is the markup (with ε^D_{jcit} capturing the price elasticity of demand).

Each of these components can be interpreted as follows. First, ceteris paribus, more productive firms pay higher wages as shown by the productivity term. Second, the labour elasticity of output shows the percentage increase in value added resulting from a one percentage increase in employment. Firms with a high labour elasticity of output pay higher wages, all else equal, because they have higher labour demand. Third, firms in a monopsonistic environment have upward-sloping labour supply curves, creating a wedge between the workers' wage and their marginal value of production. The lower the labour supply elasticity, the less competition a firm faces on the labour market. Fourth, firms might have price-setting power in the product market which disappears as the price elasticity of demand goes to infinity. Such a markup allows to set prices above marginal costs. Wong (2021) shows that the labour supply elasticity and the price elasticity of demand might depend on the firms' market share, with more dominant firms having more labour and product market power.

This structural framework has a general production function and does not require defining the specific microeconomic foundations for the price elasticity of demand or the labour supply elasticity, and nests various settings of frictions that lead to upward-sloping labour supply curves. For example, labour markets might be characterized by a random search wage-bargaining framework in which search frictions are present and wages are set via bargaining over the surplus.[16] In turn, the labour supply elasticity is a function of relative bargaining power and workers' value of outside options. Other possibilities which could generate an upward-sloping labour supply curve include a random search wage-posting framework, a directed search wage-posting framework or a monopsonistic model with workplace differentiation.[17]

To look into the link between productivity and wage dispersion, we consider a high productivity firm (*H*) and a low productivity firm (*L*), and express the logarithmic ratios of their firm-specific wages in equation (5) as:

$$WD^{H/L}_{cit} = PD^{H/L}_{cit} + ln\left(\frac{LEO_{Hcit}}{LEO_{Lcit}}\right) + ln\left(\frac{\eta_{Hcit}/\mu_{Hcit}}{\eta_{Lcit}/\mu_{Lcit}}\right) \quad (6)$$

[16] See Budd et al. (2005) and Abraham et al. (2009) on rent sharing models and Card et al. (2014) on wage bargaining models.
[17] Appendix E of Wong (2021) provides detailed derivations under various specific microeconomic foundations.

Under the assumptions of homogeneous markups and markdowns and the same labour elasticity of output at the country-industry-year cells, we look at the ratio of the 90th over the 10th percentile of the productivity and wage distribution to obtain the following empirical specification (also used in Berlingieri et al. 2017):

$$WD_{cit}^{90/10} = \beta * PD_{cit}^{90/10} + FE_{ci,ct,it} + \varepsilon_{cit} \quad (7)$$

where all components are as previously defined, but now with $FE_{ci,ct,it}$ also accounting for a set of country-year (*ct*) and industry-year (*it*) fixed effects. These controls capture any unobserved country- and industry-specific growth rates, e.g. business cycle variation across countries and industrial technological progress. β identifies the conditional correlation between productivity dispersion and wage dispersion. The regression is weighted by the natural logarithm of total value added at the country-industry-year level.

Moving from equation (6) to (7) implies the existence of a monotonic relationship between the productivity and wage ranking. In (Appendix) Figure 2.4, we rank the average productivity by percentile and plot it against the corresponding average wage to show that a positive monotonic relationship holds in the data. Specifically, percentiles with higher labour productivity are characterized by higher average wages.[18] Furthermore, we implicitly assume that the relevant market for the product and labor market coincide, which is not necessarily always the case, however, this assumption is needed to link the productivity distribution to the wage distribution within a country-industry-year combination.

Under the maintained assumptions, we expect a complete pass-through from productivity to wages, i.e. β equal to one. However, this setting is rather unrealistic in practice and based on equation (6) we expect β to be smaller than one. Many reasons can generate this imperfection, e.g. the presence of market inefficiencies or frictions (Van Biesebroeck, 2015). Hence, we test whether $\beta = 1$ under the null hypothesis or $\beta < 1$ under the alternative. In line with the above, we expect a statistically significant value less than one, which would suggest an incomplete pass-through.

[18] At the tails of the distribution, i.e. below the 5th and above the 95th percentile, we observe larger variation due to outliers. For example, at the top of the distribution, the average productivity becomes larger for smaller firms where all value-added is assigned to a small number of employees. Similarly, at the bottom of the distribution, the average productivity becomes very small for firms which are close to break-even. Such data irregularities also underscore why, both in the literature and in our main analysis, the focus is on firms between the 10th and 90th percentiles followed by robustness tests between the 5th and 95th percentiles. The right panel also confirms that this monotonic relationship holds when focusing on firms between the 5th and 95th percentiles. In the robustness section we also provide an alternative way to account for monotonicity by fixing the distributions.

2.2.4 Superstar firms and their mediating role

Although many factors might be driving this incomplete pass-through, it appears that the emergence of superstar firms is directly or indirectly intertwined with these factors. In particular, superstar firms are known to be more productive, have larger product and labour market power (i.e. set lower markdowns and higher markups), and have lower labour shares (Autor et al., 2020; Wong 2021).

To proxy the evolution of superstar firms we rely on the evolution of market concentration, in line with Autor et al. (2020). The gist of the argument is that superstar firms are becoming increasingly dominant within their industries, thereby controlling a larger share of the product market. Therefore, we use an index of market concentration, CNn_{cit}, calculated as the market share of the *n* largest firms within a country-industry-year combination. For the baseline specifications, we consider $CN4_{cit}$ and for robustness we use $CN10_{cit}$ and $CN20_{cit}$. Market shares are in terms of value added in line with productivity dispersion measures.

To examine the overall evolution of superstar firms in the economy, we construct an aggregate measure of market concentration at the yearly level by regressing the country-industry-year market shares on a full set of year dummies and use total value added as weights. The estimated coefficients represent the aggregate weighted market concentration at the yearly level.

Finally, we explore whether superstar firms affect wage dispersion by augmenting specification (7):

$$WD_{cit}^{90/10} = \beta * PD_{cit}^{90/10} + \gamma * CN4_{cit} + \delta(PD_{cit}^{90/10} * CN4_{cit}) + FE_{ci,ct,it} + \varepsilon_{cit} \quad (8)$$

where γ captures the direct effect which estimates whether superstar firms increase $(\gamma > 0)$ or decrease $(\gamma < 0)$ wage dispersion. δ captures the indirect effect on wage dispersion, which indicates whether superstar firms strengthen $(\delta > 0)$ or weaken $(\delta < 0)$ the link between productivity and wage dispersion captured in β. All other components are defined as before and regressions are weighted by the natural logarithm of total value added at the country-industry year level.

2.3 Data

We source data from Orbis Global, a product of Bureau van Dijk Electronic Publishing (2020a) (BvDEP). Orbis Global collects firms' financial statements from national sources and standardizes them for cross-country comparability (Bureau van Dijk Electronic Publishing 2020b). We use the balance sheet information of firms which file unconsolidated accounts from 2000-2016 in 14 European countries: Austria; Belgium; Denmark; France; Finland; Germany; Ireland; Italy; Luxembourg; Netherlands; Portugal; Spain; Sweden; and United Kingdom. For each firm identifier we retain firm-year observations which report strictly positive values of: value added; number of employees; and total

cost of employees. For the country-industry-level analysis we group firms by their NACE Rev. 2 2-digit industries.[19] To explore sectoral heterogeneity, we focus on manufacturing (10-33) and business services (49-82).

Cross-country comparability—a large advantage of this dataset (Kalemli-Ozcan et al., 2015; Merlevede et al., 2015)—comes at the expense of reduced coverage for smaller-sized firms for which there are simplified reporting obligations (European Commission, 2020). Nonetheless, the sample captures on average 67% of total private employment across the 14 EU countries considered.[20] The firm-level dataset includes 20,210,495 observations which represent an unbalanced panel of 3,601,418 firms used to compute the country-industry-year-level measures of interest. The data appendix (section 2.7.1) provides a detailed discussion of the steps followed to construct the firm-level sample and its representativeness across countries, industries, and over time. Overall, we find that the average firm in our sample produces value added of approximately 2.3 million Euro, employs 31 workers and pays an average wage of 33,359 Euro (see Appendix Table 2.7).[21]

Importantly, we thoroughly check against the data limitations discussed above through a battery of robustness checks. In short, these include: (1) comparing the trends in productivity and wage dispersion with those reported in Berlingieri et al. (2017) under a representative sample; (2) using a balanced sample to ensure that results are not driven by the entry and exit of country-industry combinations; (3) using a sample which excludes country-industry groups with irregular changes in the number of reported firms between years to account for issues related to the time-varying coverage of our sample; and (4) implementing the suggestions in Bajgar et al. (2020) to further improve the representativeness of Orbis Global. All of these exercises are detailed in robustness section 2.5.

With the sample of selected firm-level variables we can now compute the country-industry-year-level measures of productivity dispersion, wage dispersion, and market concentration. Table 2.1 provides summary statistics of these variables. In the upper panel of the table we see that, on average across all countries, industries, and years in the sample, a firm in the 90th percentile of the productivity distribution is approximately $e^{1.74} = 5.7$ times more productive than the 10th percentile firm. We observe that dispersion is larger for the top part of the productivity distribution $PD_{cit}^{90/50}$ than the

[19] Orbis covers all non-farm business sectors, corresponding to NACE 2-digit codes 10-82 (Bajgar et al., 2020).

[20] For further details on cross-country representativeness, see (Appendix) Table 2.6.

[21] As an additional check of the firm-level dataset, we regress the logarithm of average firm wage on the logarithm of labour productivity, weighted by the logarithm of the number of employees. Reassuringly, we find an estimated coefficient of 0.61, i.e. more productive firms are associated with paying higher wages, which is in line with existing studies, such as Criscuolo et al. (2020), among others.

bottom $PD_{cit}^{50/10}$. In particular, the top firm is on average 2.6 times more productive than the median firm while the median firm is 2.2 times more productive than the bottom firm.

Next, in the middle panel of the table we observe that the wage dispersion is smaller compared to the productivity dispersion on average. The average wage in the top firm is 3.3 times larger than the average wage in the bottom firm $WD_{cit}^{90/10}$. Interestingly, in contrast to productivity dispersion, wage dispersion is more pronounced at the bottom part of the distribution. The wage in a top firm is 1.7 times larger than the wage of the median firm $WD_{cit}^{90/50}$, while the wage of the median firm is almost twice as large than the wage of the bottom firm $WD_{cit}^{50/10}$.

Table 2.1 Summary statistics

				Percentiles			
	Mean	St. dev.	Min	25th	50th	75th	Max
$PD_{cit}^{90/10}$	1.74	0.72	0.37	1.27	1.56	2.01	7.68
$PD_{cit}^{90/50}$	0.96	0.53	0.21	0.65	0.81	1.07	6.95
$PD_{cit}^{50/10}$	0.78	0.30	0.14	0.56	0.73	0.94	3.10
$WD_{cit}^{90/10}$	1.20	0.52	0.13	0.85	1.10	1.44	7.24
$WD_{cit}^{90/50}$	0.54	0.25	0.05	0.39	0.50	0.64	3.55
$WD_{cit}^{50/10}$	0.66	0.36	0.03	0.43	0.59	0.81	5.14
$CN4_{cit}$	0.38	0.23	0.02	0.19	0.34	0.51	1.00
$CN10_{cit}$	0.51	0.25	0.03	0.31	0.50	0.71	1.00
$CN20_{cit}$	0.62	0.25	0.05	0.41	0.62	0.84	1.00

Notes: Productivity dispersion (*PD*), wage dispersion (*WD*), and market concentration (*CN*) measures are computed across 10,280 country-industry-year (*cit*) pairs. For *PD* and *WD*, measures capturing the entire (90/10), upper (90/50) and bottom (50/10) parts of the distribution are presented. For *CN*, measures capturing the market concentration of the largest 4, 10 or 20 firms in each *cit* are presented.

Finally, in the lower panel of the table we show that *CN*4 market concentration in the 'average industry' is 0.38. This implies that, on average, the four largest firms in a country-industry-year pair capture 38% of the total value added in the sample. Some industries are less concentrated while others are dominated by a few firms. For example, at the 25th percentile, market concentration is 0.19. At the 75th percentile it is 0.51. This suggests that the degree of competition varies across industries which appear to be monopolies/oligopolies versus those which exhibit more competitive behaviour. Finally, market concentration becomes larger, by construction, when we consider more firms in the concentration index. In particular, it is on average 0.51 for *CN*10 and 0.62 for *CN*20.

2.4 Results

This section describes the main findings of our analysis. First, we present results on the evolution of aggregate productivity and wage dispersion. We then split these evolutions for the top and bottom parts of the distribution and for the manufacturing and services sectors. Next, we examine the extent to which the pass-through of productivity dispersion into wage dispersion is incomplete. Finally, we

document the evolution of market concentration, a proxy for superstar firms, and how they impact the link between productivity and wage dispersion.

2.4.1 The rise and fall of productivity and wage dispersion

Productivity dispersion.—To examine the evolution of productivity dispersion we estimate equation (3). Figure 2.1 plots the estimated parameters for each year (β_t) for the period 2000-2016. The top left panel shows that the average country-industry productivity dispersion $PD_{cit}^{90/10}$ has statistically significantly increased between 2004 and 2012. Specifically, frontier firms at the top of the productivity distribution are, on average, increasing the productivity gap with laggard firms at the bottom.[22] These results complement existing findings in the literature of increasing productivity dispersion by providing additional external validity for a broader set of countries. For the most recent years 2013-2016 we observe a reversal of this pattern.

The increase in productivity dispersion weakens, yet remains significantly larger relative to 2000. Notwithstanding the short period that this decline is observed, results remain intriguing given their coincidence with the European debt crisis recovery period. However, additional information on later years is needed to further examine whether this is a temporary trough or a more persistent downward trend.

To guard against concerns about the representativeness of our sample which is skewed towards larger-sized firms, we compare our findings with those from Berlingieri et al. (2017) (dashed line). Their dataset is representative for the population of firms in 14 OECD countries[23]—some of which are included in our sample—and available for the period 2001-2012.[24] For the overlapping years, the evolution of productivity dispersion moves roughly in parallel in all panels. This provides further assurance that our selected sample generates similar aggregate trends to those presented in the literature to date.

Next, we explore whether this increase happens at the top or bottom of the productivity distribution. In line with the analysis above, we thus estimate the yearly coefficients β_t for the upper $PD_{cit}^{90/50}$ and lower $PD_{cit}^{50/10}$ parts of the productivity distribution. Results are plotted in the second and third row of the first column in Figure 2.1, respectively. We find that the widening of productivity dispersion

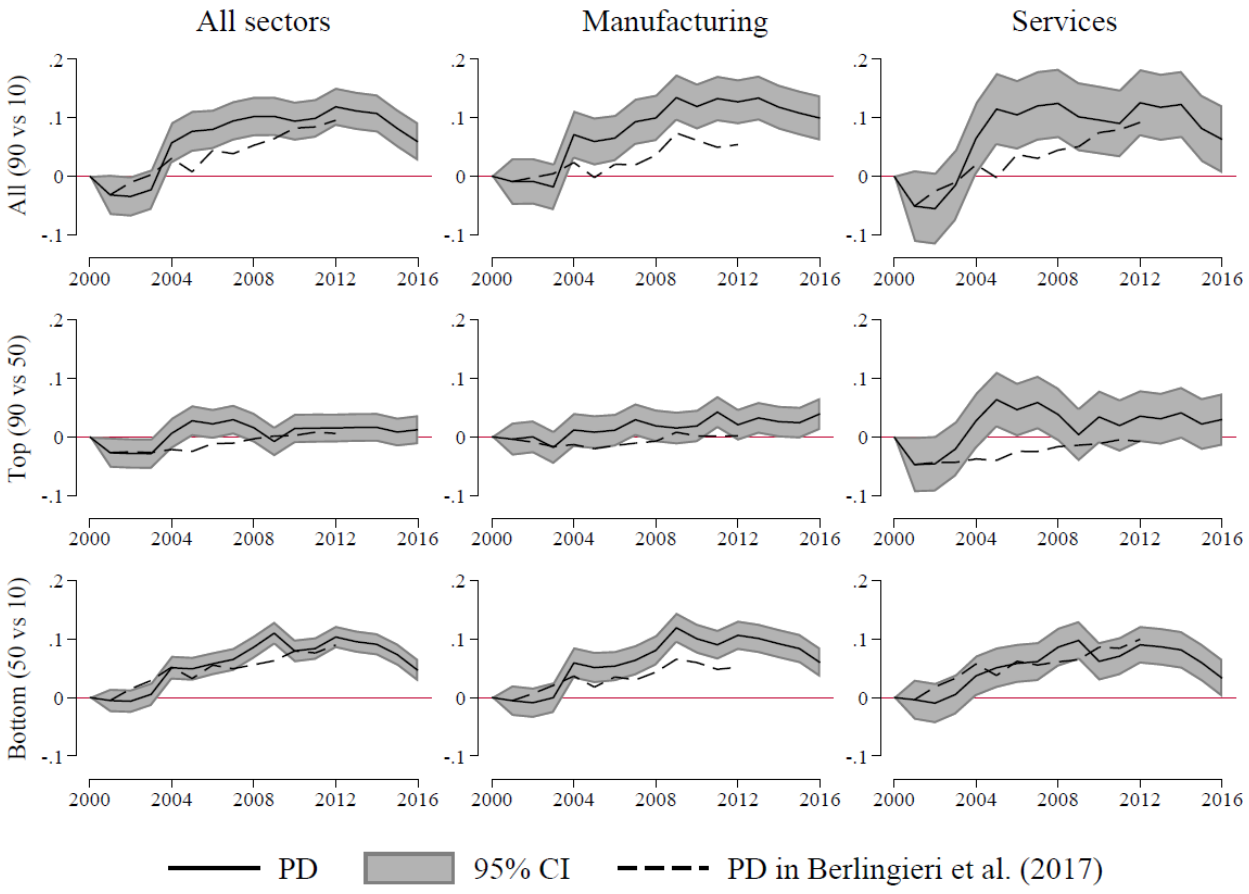
[22] (Appendix) Figure 2.5 plots the evolution of the mean and median productivity relative to the base year. We find that average productivity increased faster than median productivity. This difference increased over time with a notable spike just before the 2008 financial crisis and exhibited a relatively stable gap thereafter.

[23] Australia; Austria; Belgium; Chile; Denmark; Finland; France; Hungary; Italy; Japan; the Netherlands; Norway; New Zealand; and Sweden.

[24] We thank the authors of Berlingieri et al. (2017) for sharing the underlying values presented in each of the respective figures in their paper.

occurs at the bottom of the distribution rather than the top. Specifically, the evolution of productivity dispersion at the top hovers around zero, but remains statistically insignificant in nearly all years (middle-left panel). In contrast, large and statistically significant increases in productivity dispersion at the bottom take place between 2004-2012 (bottom-left panel). Despite a moderating effect in more recent years, we still find a significant and positive increase for the period 2013-2016. Overall, the evolution of productivity dispersion for the entire distribution is driven by changes at the bottom where firms appear to diverge over time from the median firm.

Figure 2.1 Evolution of productivity dispersion (PD)



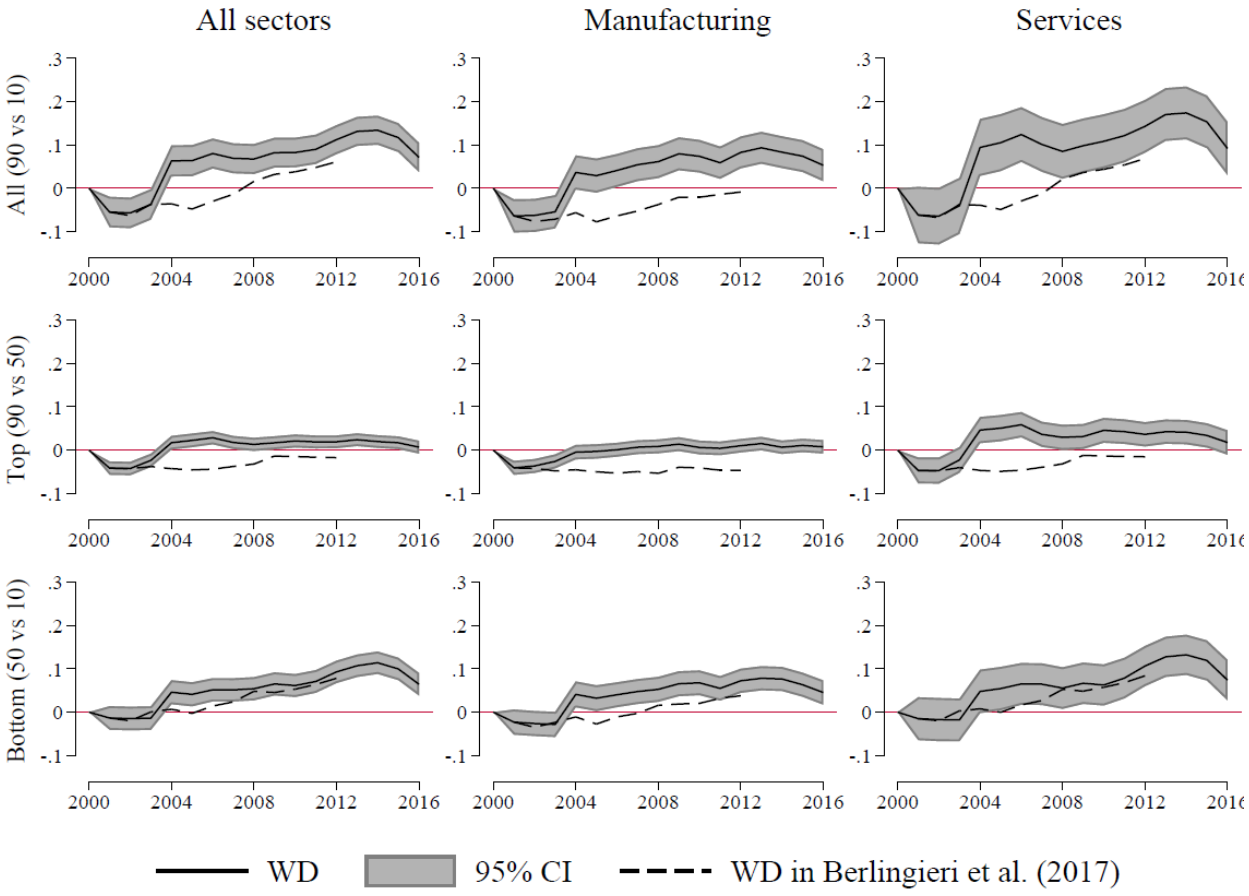
Source: Authors' estimations using Orbis Global database.
Notes: The solid line connects the estimated coefficients from regressing productivity dispersion (PD_{cit}) on a set of year dummies, i.e. parameter set β_t in equation (3). The chosen base year is 2000. All regressions include country-industry (*ci*) fixed effects and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. The dispersion measures considered in the top, middle and bottom row panels capture the entire 'All (90 vs 10)', upper 'Top (90 vs 50)' and bottom 'Bottom (50 vs 10)' parts of the distributions, respectively. The shaded area represents the clustered at the country-industry (*ci*) level 95% confidence interval. Left, middle and right column panels use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The dashed line in the top-left panel corresponds to PD_{cit} found in Berlingieri et al. (2017).

These findings are consistent with a host of mechanisms proposed in the literature which support mounting evidence of increased misallocation of resources towards the least productive firms. Such mechanisms include: a decline in business dynamism which results in a limited degree of churning in the economy (Decker et al., 2016); falling real interest rates which cause misallocation of capital inflows towards relatively unproductive firms (Gopinath et al., 2017); zombie firms which hoard

productive inputs and prevent their optimal allocation (Andrews and Petroulakis, 2019); and stalling technological diffusion/adoption which prevents laggard firms from catching up (Andrews et al., 2016).

Next, we examine the sectoral decomposition of these results. We repeat the analysis from above (first column) for firms in the Manufacturing (second column) and Services sector (third column). Panels from the last two columns in Figure 2.1 indicate that the productivity dispersion increases in roughly the same way in both sectors. In line with the previous findings, this rise seems to occur predominantly at the bottom rather than the top part of the distribution. As such, increases in the evolution of productivity dispersion in the entire economy do not appear to be driven by sectoral heterogeneity.

Figure 2.2 Evolution of wage dispersion (WD)



Source: Authors' estimations using Orbis Global database.
Notes: The solid line connects the estimated coefficients from regressing wage dispersion (WD_{cit}) on a set of year dummies, i.e. parameter set β_t in equation (4). The chosen base year is 2000. All regressions include country-industry (*ci*) fixed effects and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. The dispersion measures considered in the top, middle and bottom row panels capture the entire 'All (90 vs 10)', upper 'Top (90 vs 50)' and bottom 'Bottom (50 vs 10)' parts of the distributions, respectively. The shaded area represents the clustered at the country-industry (*ci*) level 95% confidence interval. Left, middle and right column panels use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The dashed line in the top-left panel corresponds to WD_{cit} found in Berlingieri et al. (2017).

Wage dispersion.—To document the evolution of wage dispersion $WD_{cit}^{90/10}$ we follow the same roadmap. Specifically, we estimate the set of parameters β_t from equation (4) which captures the average wage dispersion in each year *t* relative to 2000. Results are plotted in Figure 2.2. The top-left panel shows that the initial fall of wage dispersion between 2000-2002 is dominated by a subsequent rise until 2014. Similar to the productivity dispersion, this pattern weakens towards the end of our sample, but remains significantly higher compared to its 2000 level.[25] Reassuringly, the upward evolution in wage dispersion is similar to that in Berlingieri et al. (2017) under the same representative sample considered in their productivity dispersion measures discussed above (dashed line). Results are also in line with Cortes and Tschopp (2020) who document a rise in wage inequality in a broad set of countries over recent decades.[26]

We now examine how the evolution of wage dispersion emerges in different segments of the distribution. In Figure 2.2, the mid-left and bottom-left panels repeat the analysis for the top $WD_{cit}^{90/50}$ and bottom $WD_{cit}^{50/10}$ parts of the wage distribution, respectively. On the one hand, wage dispersion at the top hovers above zero and remains weakly statistically significant (at the 95% level) from 2004 onwards. On the other hand, wage dispersion at the bottom increases significantly between 2004-2014, after which it diminishes slightly (but remains higher compared to 2000). These findings suggest that while the gap between high- and median-wage firms has only modestly increased since 2000, low-wage firms were unable to offer more competitive salaries that would mitigate increases in wage inequality.

These findings might be explained by changes in firms' operating environment which place downward pressure on labour and wages. This is especially true for low-wage firms which are typically more labour intensive (Abowd et al., 1999); likely to exit the market (Bossavie et al., 2019); financially constrained (Babina et al., 2018); vulnerable to increased competition (Autor et al., 2014); and less productive (Bernard et al., 2012) overall. Changes in firms' operating environment could include: increased import competition from low-wage countries (Autor et al., 2013; Dauth et al., 2014); top firms exploiting their monopsony power (Burdett and Mortensen, 1998); increasing openness in capital markets (Huber et al. 2020); and increasing automation in production (Acemoglu and Restrepo, 2019); among others.

Next, we look into sectoral differences in Manufacturing and Services. Results from the second and third columns reveal similar patterns in both sectors, i.e. an increase in wage dispersion at the bottom

[25] (Appendix) Figure 2.6 plots the evolution of the mean and median wage relative to the base year. We find that the average wage increased faster than the median wage. This difference increased over time with a notable reduction around the 2008 financial crisis.

[26] Belgium; Croatia; Finland; France; Hungary; Italy; Lithuania; Portugal; Romania; Slovenia; Spain; and Sweden.

dominates the (marginally significant) increase in wage dispersion at the top of the distribution. Quantitatively, the increase in wage dispersion is larger in Services versus Manufacturing.

2.4.2 The link between productivity and wage dispersion

To examine the link between productivity and wage dispersion we estimate equation (7) and present results in Table 2.2. The parameter of interest β captures the conditional correlation between productivity and wage dispersion after controlling for unobserved heterogeneity at the country-industry, country-time and industry-time dimensions. Column (1) shows this estimate while columns (2) and (3) repeat the analysis for the top and bottom parts of the productivity and wage dispersion, respectively. Columns (4)-(6) and (7)-(9) repeat the analysis in (1)-(3) for the Manufacturing and Services sectors, respectively. Additionally, we test whether each estimated coefficient is significantly smaller than one and present the corresponding test p-values at the bottom of the table.[27]

Table 2.2 The link between wage and productivity dispersion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All sectors			Manufacturing			Services		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.40***			0.37***			0.40***		
	(0.03)			(0.04)			(0.04)		
$PD_{cit}^{90/50}$		0.26***			0.23***			0.29***	
		(0.03)			(0.02)			(0.04)	
$PD_{cit}^{50/10}$			0.57***			0.49***			0.59***
			(0.05)			(0.06)			(0.06)
$H_0: \beta - 1$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.892	0.881	0.851	0.911	0.869	0.891	0.880	0.875	0.840
Obs.	10,268	10,268	10,268	3,757	3,757	3,757	4,727	4,727	4,727

Notes: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), i.e. β parameter in equation (7). The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distributions. All regressions include country-industry (*ci*), country-year (*ct*), and industry-year (*it*) fixed effects, and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. Standard errors are clustered at the country-industry (*ci*) level and reported in parentheses below point estimates. H0:$\beta-1$ presents the *p*-value from testing whether the estimated coefficient is significantly smaller than one. Columns (1)-(3), (4)-(6), and (7)-(9) use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively.

In column (1), we find that industries with higher productivity dispersion are associated with higher wage dispersion. However, the pass-through is incomplete as it is significantly smaller than one. Wage dispersion is thus positively linked to productivity dispersion, but not perfectly. These findings complement other existing empirical evidence (Berlingieri et al. 2017) and point to the presence of imperfect labour markets (Pissarides, 2011; Van Biesebroeck, 2015).[28]

[27] When fixed effects are nested within clusters, maintaining groups with one observation, i.e. singletons, can overstate statistical significance and lead to incorrect inference. We use the Stata package 'reghdfe' by Correia (2015) that iteratively drops singletons from the estimation. For example, in columns (1)-(3), (4)-(6), and (7)-(9) we drop 12, 9 and 9 observations, respectively.

[28] In (Appendix) Figure 2.7 we repeat the analysis in column (1) for each country separately and plot the estimated coefficients. Results remain valid across all countries.

Columns (2) and (3) suggest that the link between productivity and wage dispersion is considerably stronger at the bottom of the distribution versus at the top. Intuitively, firms at the bottom transfer a relatively larger share of their productivity gains to wages compared to firms at the top. This finding can be reconciled with the labour market power of firms. Specifically, firms at the top of the productivity distribution have larger markdowns compared to firms at the bottom and thus gradually pay wages which are relatively lower than the marginal revenue product of labour (Berger et al., 2019).

These findings are confirmed at the sectoral level as well: productivity and wage dispersion are positively linked, though the pass-through appears to be incomplete and larger at the bottom part of the distribution. Note that the pass-through is higher in the Services sector (columns 7-9), and especially so at the bottom part of the productivity distribution.

2.4.3 The rise of superstar firms

We proceed by documenting the evolution of superstar firms, proxied by the three concentration measures described in Section 2.2. Figure 2.3 shows their evolution for the total economy (left panel), Manufacturing sector (middle panel) and Services sector (right panel).

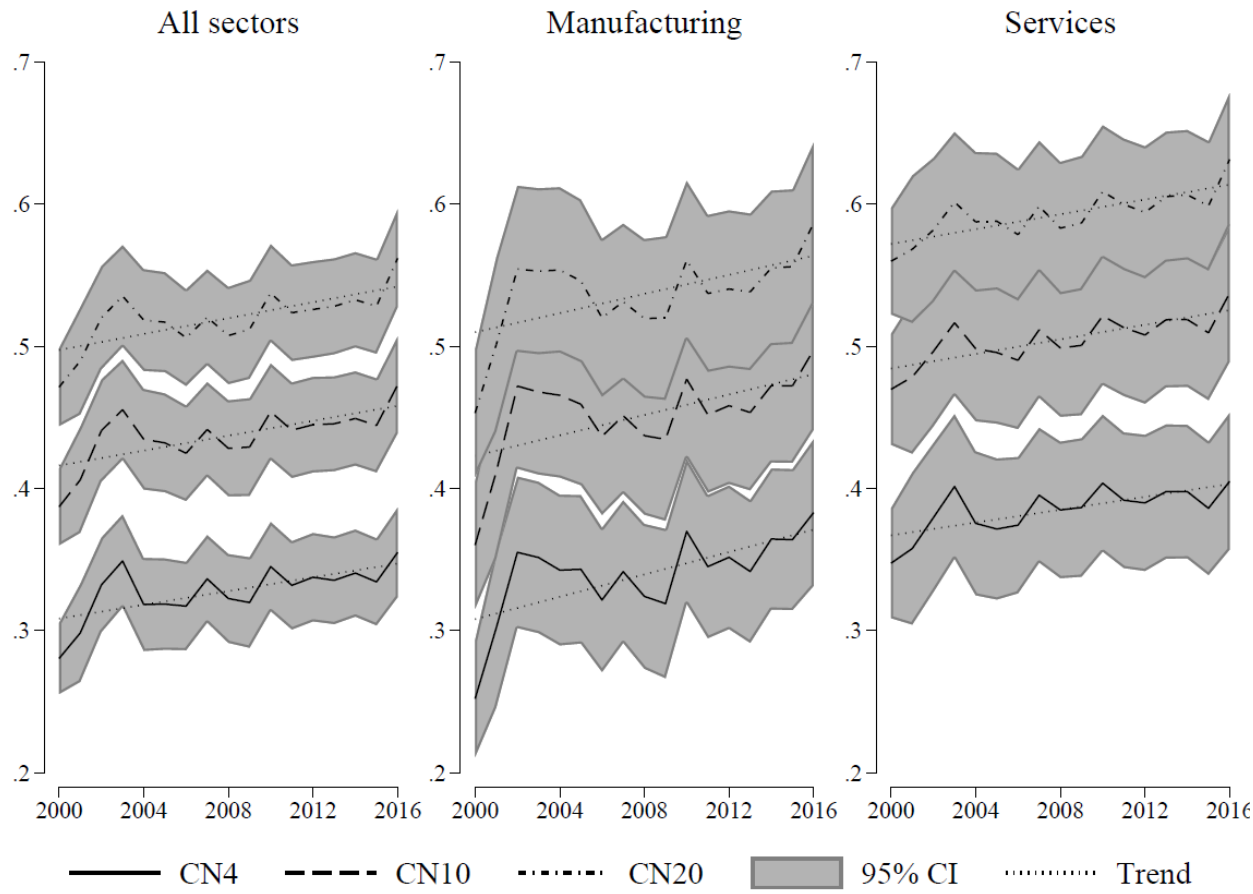
We find that market concentration is rising in Europe, irrespective of the number of firms considered. For example, *CN*4 increased from 28% in 2000 to 35.5% in 2016; the four largest firms' market share grew by 7.5 percentage points (pp) on average. The evolution of *CN*10 and *CN*20 exhibits the same pattern, indicating that the four largest firms are driving the overall evolution of the measures. In particular, *CN*10 increased from 38.7% in 2000 to 47.3% in 2016. Since the four largest firms increased their market share by 7.5 pp, the remaining 'top six' increased their market share by 1.1 pp only. Similarly, *CN*20 rose from 47.1% in 2000 to 56.2% in 2016. Thus, the additional 'top 10' capture only 0.5 pp. Overall, we find that a small handful of firms dominate the economy, which is in line with the recent literature on superstar firms and increasing market concentration in the product market (Autor et al., 2020).[29]

Two main findings emerge at the sectoral level. First, comparing the middle and right panel shows that market concentration rises twice as fast in Manufacturing versus Services.[30] Second, market concentration levels in Manufacturing remain below those in Services in 2016, even after the

[29] This point is further supported by (Appendix) Figures 2.9 and 2.10, where we see that on average, since 2000, both the productivity and wages of superstar firms have increased at a faster pace than the rest of firms.
[30] It increases by 13.1 pp (*CN*4), 13.7 pp (*CN*10) and 13.4 pp (*CN*20) in Manufacturing versus 5.8 pp (*CN*4), 6.7 pp (*CN*10) and 7.1 pp (*CN*20) in Services.

accelerated growth in the most recent years.[31] Market concentration has thus converged to approximately the same magnitude in these two sectors.

Figure 2.3 Evolution of market concentration (CN)



Source: Authors' estimations using Orbis Global database.
Notes: The lines connect the estimated coefficients from regressing the market concentration measures (*CN*4, *CN*10, *CN*20) on a set of year dummies. All regressions are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. The shaded area represents the clustered at the country-industry (*ci*) level 95% confidence interval. Left, middle and right column panels use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively.

2.4.4 The mediating role of superstar firms

We estimate equation (8) to unpack how the rise of superstar firms impacts the link between productivity and wage dispersion. Table 2.3 presents the results, where our main variables of interest are the direct effect of superstar firms—proxied by market concentration—on wage dispersion and the mediating effect of superstar firms on the link between productivity and wage dispersion. The latter is captured by the interaction between productivity dispersion and market concentration. Column (1) shows the estimates for the entire distribution while columns (2) and (3) repeat the analysis for the top and bottom parts, respectively. Sectoral results are presented in columns (4)-(9).

[31] In particular, market concentration equals 38.3% (*CN*4), 49.7% (*CN*10) and 58.7% (*CN*20) in Manufacturing versus 40.5% (*CN*4), 53.7% (*CN*10) and 63.1% (*CN*20) in Services in 2016.

Table 2.3 Superstar firms and the link between productivity and wage dispersion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All sectors			Manufacturing			Services		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.52***			0.50***			0.56***		
	(0.04)			(0.06)			(0.06)		
$PD_{cit}^{90/50}$		0.31***			0.29***			0.36***	
		(0.04)			(0.05)			(0.06)	
$PD_{cit}^{50/10}$			0.79***			0.53***			0.93***
			(0.08)			(0.07)			(0.12)
$CN4_{cit}$	0.36***	0.06	0.33***	0.39**	0.10	0.12	0.53***	0.11	0.55**
	(0.09)	(0.04)	(0.09)	(0.13)	(0.06)	(0.09)	(0.14)	(0.07)	(0.17)
$PD_{cit}^{90/10} * CN4_{cit}$	-0.20***			-0.21*			-0.26***		
	(0.05)			(0.09)			(0.07)		
$PD_{cit}^{90/50} * CN4_{cit}$		-0.08*			-0.10			-0.11*	
		(0.04)			(0.08)			(0.05)	
$PD_{cit}^{50/10} * CN4_{cit}$			-0.39**			-0.08			-0.60**
			(0.12)			(0.13)			(0.19)
R^2	0.893	0.882	0.853	0.912	0.869	0.891	0.882	0.876	0.844
Observations	10,268	10,268	10,268	3,757	3,757	3,757	4,727	4,727	4,727

Notes: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration ($CN4_{cit}$), and their interaction (PD_{cit}*$CN4_{cit}$), i.e. β, γ and δ parameters in equation (8), respectively. The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distribution. $CN4_{cit}$ captures the market shares of the 4 largest firms in each country-industry-year (*cit*) group. All regressions include country-industry (*ci*), country-year (*ct*), and industry-year (*it*) fixed effects, and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. Standard errors are clustered at the country-industry (*ci*) level and reported in parentheses below point estimates. Columns (1)-(3), (4)-(6), and (7)-(9) use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively.

Two key findings emerge from column (1). First, the positive and significant point estimate on our market concentration proxy (*CN*4) suggests that industries with a larger dominance of superstar firms exhibit higher wage dispersion, on average. This is consistent with various models, such as fair-wage models (Egger and Kreickemeier, 2012). As superstar firms become more dominant in terms of market share and profitability workers demand fair wages which are proportional to profits. Similarly, results are also in line with the literature on rent sharing (Card et al. 2013, 2014). As top firms accumulate rents because of increasing market shares they are also able to partially transfer those gains to their employees in the form of increased wages. Both explanations support a positive link between market concentration and wage dispersion. An alternative explanation could be that top firms screen and search for additional and better workers more intensively to meet increased production needs. This, in turn, could lead to an increase in employment and wages relative to firms at the bottom of the distribution which have limited production and profits (Cortes and Tschopp, 2020). Therefore, we conclude that between-firm wage inequality increases with concentration of production within industries.

Next, we find a statistically significant negative effect from the interaction between market concentration and productivity dispersion. This result suggests a mediating effect of superstar firms on the link between productivity and wage dispersion. Specifically, industries with high market concentration, i.e. which are likely dominated by superstar firms, are associated with a weaker link between productivity and wage dispersion. Overall, superstar firms appear to induce a larger disconnect between productivity and wages, hence, a more incomplete pass-through, on average. This

finding is in line with firms in more concentrated industries having larger markdowns due to higher labour market power and thus charging relatively lower wages, while the opposite happens to firms in less concentrated industries (Berger et al., 2019).[32]

When considering different parts of the firm-level wage distribution in columns (2) and (3), results suggest that the rise of market concentration is associated with a statistically significant increase of wage dispersion at the bottom of the distribution only. A possible explanation could be an increased threat of offshoring and relocation, which becomes credible as firms grow and become more international, thus putting downward pressure on wages at the lower part of the distribution (Autor et al., 2013).

In addition, results suggest that superstar firms weaken the link between productivity and wages both at the top and bottom parts of the distribution. However, various different mechanisms might be at play in different parts of the distribution. For example, firms at the top part of the productivity distribution compete at a global level but might be shielded from wage competition which occurs primarily at the local level. Thus, there is no motive to pass-through a larger part of their productivity advantage to wages, since these firms already pay the highest wages in the domestic labour market (Gouin-Bonenfant, 2018). At the bottom part of the distribution, the emergence of superstar firms reduces the overall competitive pressure in the labour market which allows even the least productive firms to have some monopsony power, i.e. large markdowns, and thus keep wages low (Azkarate-Askasua and Zerecero, 2019; Berger et al., 2019).

Turning to results for the entire distribution at the sectoral level, columns (4) and (7) suggest that highly concentrated industries are associated with high wage dispersion while market concentration weakens the link between productivity and wage dispersion in both Manufacturing and Services. When we consider the top and bottom parts of the distribution separately (columns 5, 6, 8 and 9) we find that the mediating effect on the link between productivity and wages remains significant only in the top and bottom parts for Services, while results become insignificant for the top and bottom parts for Manufacturing. This sectoral heterogeneity is likely driven from underlying structural differences in the output and labour markets between Manufacturing and Services, however, further research is needed to fully understand this differential impact.

[32] In (Appendix) Figure 2.8 we repeat the analysis in column (1) for each county separately and plot the estimated coefficients. Except Italy (direct effect) and Austria (indirect effect), results remain across all 14 EU countries.

2.5 Robustness

We conduct nine exercises to test the robustness of our findings. The first robustness test considers alternative market concentration measures. Second, we construct measures of wage and productivity dispersion by looking more closely at the tails of the distributions. Third, we compute a measure of total factor productivity instead of labour productivity. Fourth, we focus on a balanced sample of country-industry combinations present in all years to account for the effect of entry and exit of country-industry combinations. Fifth, we use a sample excluding country-industry groups with irregular changes in the number of firms reported between years to account for issues related to the time-varying coverage of our sample. Sixth, we implement the suggestions in Bajgar et al. (2020) to further improve the representativeness of Orbis Global. Seventh, we control for additional unobserved heterogeneity by including a richer set of fixed effects. Eight, we fix the ranking of the wage distribution based on the productivity distribution and finally, we demean the interaction terms in the regressions. Main results hold under all robustness checks. For conciseness, we relegate a presentation of all Tables and Figures to the Tables appendix (2.7.3).

Alternate market concentration measures.—We start with two sets of alternative market concentration measures to test the robustness of our main results. First, we repeat the analysis in Table 3 but now consider a more broadly defined concentration index by using *CN*10 and *CN*20 as proxies for superstar firms, respectively. On the other hand, in order to examine top firms more closely, we restrict the concentration index to the top-two firms *CN*2. Results from this exercise, presented in (Appendix) Tables 2.11, 2.12 and 2.13 support our main findings. We thus conclude that irrespective of the measure used, market concentration appears to have a mediating role on the link between productivity and wage dispersion.

Continuing, we employ an alternate measure of market concentration, the Herfindahl-Hirschman Index (*HHI*). This index sums the squared market share of all firms within a country-industry-year combination. High values indicate a high degree of market concentration, i.e. there might be an oligopoly or monopoly position, whereas low values indicate less market concentration, i.e. closer to perfect competition.[33] As above, we repeat the analysis from Table 2.3 now using *HHI*, and present results in (Appendix) Table 2.14. This exercise supports the main conclusions found when using the *CN* measures to proxy market concentration.[34]

[33] The average and median value for *HHI* are 900 and 452, respectively. The standard deviation equals 1,322. Markets with an *HHI* between 1,500 and 2,500 are considered to be moderately concentrated while markets with a *HHI* above 2,500 are highly concentrated (US Department of Justice, 2020).

[34] For the regressions, we divide *HHI* by 10,000 such that it lies in the interval [0,1] and the order of magnitude of the estimated coefficient is easier to interpret.

Wider dispersion measures.—We construct alternative measures of productivity and wage dispersion by looking more closely at the tails of the distribution. Specifically, for each country-industry-year group of firms (*cit*) we use the ratio of the 95th to 5th percentile of the firm-level distribution, which tells us how many times more productive the firm at the 95th percentile is relative to that at the 5th percentile of the distribution. With these dispersion measures we repeat the analysis in Table 3. Results presented in (Appendix) Table 2.15 confirm the robustness of our baseline findings.

Total factor productivity.—We now compute the Hicks-neutral total factor productivity (TFP) term from a gross-output production function with capital, labour and material inputs. To identify the production function, we follow the non-parametric estimation strategy of Gandhi et al. (2020).[35] We then construct the measures of productivity dispersion at the country-industry-year and: a) plot their evolution over time (see Appendix Figure 2.11); and b) repeat the analysis in Table 2.3 (see Appendix Table 2.16). In both cases, the main results remain robust to this alternative measure of firm performance which accounts for the contributions from factors of production other than labour.

Balanced sample.—In this robustness test, we ensure a balanced panel by keeping country-industry combinations which are present throughout our entire sample period. When doing this, the number of observed country-industry-year combinations decreases from 10,280 to 7,480. (Appendix) Figures 2.12, 2.13 and 2.14 show the evolution of productivity dispersion, wage dispersion and market concentration, respectively, for the balanced sample. To ease comparison we also present the baseline trends from Figures 2.1, 2.2 and 2.3. We find that productivity and wage dispersion for the balanced and unbalanced samples display practically the same pattern. In level terms, market concentration is slightly lower for the balanced sample, but closely follows the trends in the baseline sample. Using the balanced sample, we next repeat our baseline analysis and present results in (Appendix) Table 2.17. We confirm our baseline findings, and thus demonstrate that our results are not driven by varying coverage due to the entry and exit of country-industry combinations.

In both the baseline and balanced sample, we observe a relatively large change in the evolution of productivity dispersion, wage dispersion and market concentration in the year 2002. This change might be driven by the increasing sample coverage of Orbis, especially in the early years of the sample. To ensure the robustness of our results, we repeat the baseline analysis in Table 2.3, but restrict the sample period to 2002-2016. Results presented in (Appendix) Table 2.18 are similar to the baseline.

[35] Note that the additional information on production inputs needed for the estimation are not reported by all firms. This results in reducing the sample from 20,210,495 to 15,268,943 firm-year observations and from 10,280 to 7,723 country-industry-year groups. This translates to a 22% reduction in the number of firm-year observations, encompassing dropping all observations for Denmark, Ireland and the United Kingdom.

Varying sample coverage.—In line with the previous exercise, the sample now includes country-industry groups which satisfy the following conditions throughout the entire period 2000-2016: (1) the number of firms do not double or halve between two consecutive years; or (2) the difference in the number of firms between two consecutive years is smaller than 25. These sample restrictions allow us to exclude country-industry groups where irregular changes in firm coverage over time could arise due to changes in reporting standards. With this sample, we repeat the baseline analysis in Table 2.3 and present results in (Appendix) Table 2.19. We confirm our baseline findings, which support that our results are not driven by the varying coverage of country-industry combinations.

Enhancing representativeness.—Orbis represents a rich source of cross-country firm-level data, but this comes at the cost of some coverage and representativeness issues. Bajgar et al. (2020) document the coverage and representativeness of Orbis, and compare it with industry-level data OECD STAN as well as micro-aggregated data from the OECD MultiProd and DynEmp projects. Firms in Orbis are disproportionately larger, older, and more productive, even within a given size class. This explains why reweighting does not improve the representativeness beyond the mechanical effect on the firm size distribution. Bajgar et al. (2020) further show that focusing on country-industries that contain at least 5,000 firms (which report value added), imputing value added,[36] and considering firms with at least ten employees improves the representativeness considerably. Moreover, despite its somewhat incomplete coverage, Bajgar et al. (2020) point out that other commercial datasets still underperform Orbis, thus making it the best option at hand. We restrict our sample by following these three guidelines and present estimation results in (Appendix) Table 2.20. The main findings hold.

Fixed effects.—As a next robustness check, we extend the set of fixed effects in equation (8) to account for country-industry linear time trends. Adding these to our regression specification controls for various factors such as technical progress or more granular business cycle effects. (Appendix) Table 2.21 shows these estimation results. While we lose some statistical significance due to conditioning on a very restrictive set of fixed effects, the estimated magnitudes are in line with the baseline. Overall, this exercise seemingly confirms our main finding that superstar firms weaken the link between productivity and wage dispersion.

Fixed distributions.—An alternative way to implicitly control for the monotonic relationship between productivity and wages implied by equation (6) is to fix the wage distribution against that of productivity when constructing the dispersion measures. Specifically, we first rank firms by their productivities within each country-sector-year combination and use the 90th, 50th and 10th percentiles

[36] This includes proxying value added as the sum of ebitda (earnings before interest, taxes, depreciation and amortization) and costs of employees.

to calculate the relevant productivity dispersion measures. In turn, instead of ranking firms based on wages, we compute the wage dispersion measures by fixing the wage distribution against the ranking of the productivity distribution. To do so, we use the wages of the respective firms at the 90th, 50th and 10th percentiles of the productivity distribution as the 90th, 50th and 10th wage percentiles. Results in (Appendix) Table 2.22 confirm the negative coefficient on the interaction term. Magnitudes are in the same ballpark as the baseline results, but with weaker statistical significance due to larger variation introduced from fixing the wage distribution.

Demeaned variables in interaction term.—Giesselmann and Schmidt-Catran (2020) show that estimates from a standard fixed effects estimator with interaction terms may be subject to bias if both interacted variables vary within units. Intuitively, the fixed effects estimator might contain unobserved unit-specific effect heterogeneity of both variables. Thus, following their suggestions, we first demean each of the variables in the interaction term before running the fixed effects regression. Results presented in (Appendix) Table 2.23 show that our main findings remain robust. Any discrepancies in standard errors arise from the fact that this estimator is less efficient compared to standard FE (Giesselmann and Schmidt-Catran, 2020).

2.6 Conclusion

This chapter examines links between evolutions in productivity dispersion, wage dispersion, and superstar firms. Using a rich sample of firms in 14 EU countries over the period 2000-2016, we confirm previous findings in the literature of increases in all three variables—albeit with a moderating effect for wage and productivity dispersion in recent years. The positive correlation between productivity and wage dispersion that we document points to an incomplete pass-through of productivity gains to wages.

We present novel cross-country empirical evidence that the rise of superstar firms has a mediating effect on this correlation and is observed both at the top and bottom parts of the productivity and wage distributions. At the top, the findings might underscore that highly productive firms enjoy increased profit margins from access to globalisation while being shielded from local wage competition through increased labour market power. At the bottom, such effects might point to underlying structural changes in the labour market from the dominance of superstar firms. Moreover, we find stronger effects for services (versus manufacturing) sectors, highlighting differences between the nature of the two.

Our findings suggest that firms in industries with limited product market competition pass on fewer productivity gains to wages compared to more competitive industries. From a policy standpoint, this

raises interesting questions related to the optimal degree of regulation of both product and labour markets needed to reduce wage inequality.[37] In its entirety, our analysis lays important groundwork in understanding the role of superstar firms in mediating the transfer of productivity gains to wages. Based on our novel empirical findings, we see rich potential for additional research to structurally identify and test the mechanisms at play.

2.7 Appendix

2.7.1 Data appendix

Our empirical analysis relies on unconsolidated firm-level accounts between 2000-2016 for 14 EU countries: Austria; Belgium; Denmark; Finland; France; Germany; Ireland; Italy; Luxembourg; the Netherlands; Portugal; Spain; Sweden; and United Kingdom.[38] We include all firms which report employment, costs of employees, value added and their NACE Rev. 2 industry codes.[39] In what follows, we document our data cleaning procedure and subsequently provide detailed summary statistics on the firm-level variables and their representativeness relative to country statistics.

Data cleaning procedure.—We take various steps to ensure a sample of high quality underlying variables. First, we keep only firms which report a strictly positive value for employment, costs of employees and value added. Second, to account for outliers which could suffer from mismeasurement issues (e.g. values in thousands instead of millions), for firms with value added above one million euros, we drop those with value added or cost of employees which is 1,000 times larger or smaller from the previous year. Finally, we drop country-industry-year combinations with less than 20 firms to ensure that our *CN* measures do not capture the full market.

[37] A back-of-the-envelope calculation, based on Table 2.3, shows that a more aggressive competition policy which reduces the average market concentration C4 by 0.10, might lead to an increase in the pass-through from productivity dispersion into wage dispersion by 0.02. Besides this indirect effect, the direct effect of the decrease in the market concentration would decrease the wage dispersion by 0.036.

[38] Unconsolidated accounts do not incorporate statements of controlled subsidiaries or branches of the firm. Focusing on these accounts comes with three main advantages for our analysis. First, it allows us to capture more granular variation, i.e. we observe information on all individual firms within a corporate group instead of one large consolidated firm. Second, they allow us to closely link firms to the location and sector of economic activity. For example, consolidated accounts could mask the fact that a company consists of various firms which are active in several countries and/or industries, thereby attributing part of the economic activity to the 'wrong' country and/or sector. Finally, it also helps to avoid double counting the statements of firms within the same corporate group.

[39] NACE is the industry standard classification system used in the European Union. Eurostat (2020b) provides a detailed description of the NACE Rev.2 2-digit industries included in our sample. Our dataset covers 11 broad sectors of the economy: manufacturing (10-33); electricity, gas and water supply, sewerage, waste management and remediation activities (35-39); construction (41-43); wholesale and retail (45-46); transportation and storage (49-53); accommodation and food service activities (55-56); information and communication (58-63); financial and insurance activities (64-66); real estate activities (68); professional, scientific and technical activities (69-75); and administrative and support service activities (77-82).

Next, we correct for broken book years that could affect our three variables of interest at the annual level. More specifically, the reported book year should match the corresponding calendar year, i.e. 1 January - 31 December. When this is not the case, we proportionally allocate the reported values of our variables of interest based on the number of months covering the respective calendar year.[40]

Table 2.4 Number of firm-year observations

Year	Observations	Share %
2000	784,874	3.88
2001	864,205	4.28
2002	995,055	4.92
2003	1,023,400	5.06
2004	957,939	4.74
2005	984,121	4.87
2006	1,283,135	6.35
2007	1,271,686	6.29
2008	1,408,581	6.97
2009	1,355,538	6.71
2010	1,225,115	6.06
2011	1,407,991	6.97
2012	1,410,202	6.98
2013	1,396,756	6.91
2014	1,318,824	6.53
2015	1,345,071	6.66
2016	1,178,002	5.83
Total	20,210,495	100.00

Notes: Unbalanced panel of 3,601,418 firms over the period 2000-2016.

Summary statistics and representativeness.—Finally, (Appendix) Table 2.4 shows the number of observations for each time period, which increase from 784,874 in year 2000 to 1,345,071 in 2015. We note that the number of observations in 2016 is slightly lower, 1,178,002. This likely indicates that some firm-year observations have yet to be included in Orbis Global. (Appendix) Table 2.5 shows the number of observations by country. Spain, Italy, France, Portugal, and Sweden are most reported in the data, while Germany, on the other hand, seems to be underrepresented.

[40] For example, assume that a firm produces €100 during a book year which spans 1 April 2004 – 31 March 2005. To align this with the calendar year, we thus assign €75 (9 out of 12 months) to year 2004 and €25 (3 out of 12 months) to year 2005. Now, if in the subsequent book year (1 April 2005 – 31 March 2006) the firm produces €200, we assign €150 to year 2005 and €50 in year 2006. Summing the information within the same year results in a value of €175 for 2005. Note that we only do this if there is information available for a full 12 month period. If not the case, we extrapolate the monthly values within the calendar year. Note that this procedure results in some cases with data in 1999, which we drop.

Table 2.5 Number of firm-year observations by country

Country	Observations	Share %
AT	34,084	0.17
BE	179,59	0.89
DE	468,685	2.32
DK	174,631	0.86
ES	7,567,313	37.44
FI	488,455	2.42
FR	3,071,521	15.20
IE	19,506	0.10
IT	4,548,408	22.51
LU	4,344	0.02
NL	3,326	0.02
PT	1,582,086	7.83
SE	1,614,338	7.99
UK	454,208	2.25
Total	20,210,495	100.00

Notes: Unbalanced panel of 3,601,418 firms over the period 2000-2016.

Moving to our variables of interest, (Appendix) Table 2.6 compares total number of employees for each country in year 2015 based on data from Orbis with official aggregate data from Eurostat. Our dataset covers approximately the entire private labour force in Italy, Spain, Ireland, and Portugal. On the other hand, countries like Germany are only partly covered. This represents on average 67% of total private employment across the 14 EU countries considered (see Appendix Table 2.6). Next, (Appendix) Table 2.8 shows the number of firms by country-year. Key information is lacking for the Netherlands and Luxembourg in certain years, leading to a small sample for these countries. To account for this, we check the robustness of our results using a balanced sample of country-sectors. Table (Appendix) Table 2.9 shows the number of industries at the country-year level. Lastly, (Appendix) Table 2.10 shows the number of sectors which are present in all years at the country-year level, i.e. for the balanced sample. Overall, the firm-level dataset includes an unbalanced panel of 3,601,418 firms between 2000 to 2016.

Table 2.6 Representativeness of private sector employment in Orbis Global vs. Eurostat

(1)	(2)	(3)	(4)	(5)	(6)
Country	Total Employment		Employment Share %	Self-employed Eurostat	Employment Share % excl. (5)
	Orbis	Eurostat			
AT	961,630	2,471,300	0.39	261,500	0.44
BE	1,163,283	2,307,400	0.50	468,900	0.63
DE	7,211,553	24,170,700	0.30	2,614,700	0.33
DK	736,287	1,421,800	0.52	143,000	0.58
ES	6,805,309	9,369,200	0.73	2,287,300	0.96
FI	652,583	1,243,900	0.52	183,600	0.62
FR	6,167,852	13,684,600	0.45	1,750,700	0.52
IE	941,396	1,122,700	0.84	176,100	0.99
IT	7,817,975	10,994,000	0.71	3,741,100	1.08
LU	49,481	117,100	0.42	2,700	0.43
PT	1,916,934	2,326,900	0.82	409,900	1.00
SE	1,209,570	2,466,100	0.49	304,100	0.56
UK	6,656,555	15,977,700	0.42	2,974,400	0.51
Mean	3,253,108	6,744,108	0.55	1,178,308	0.67

Notes: Column (2) shows the total number of employees based on our sample from the Orbis Global database. Column (3) shows the total number of employees based on Eurostat (2020a) statistics. Both columns cover NACE Rev.2 2-digit industry categories 10-82. Column (4) is defined as the ratio of column (2) over column (3). Column (5) displays the number of self-employed workers reported in Eurostat which in most countries are not included in the Orbis annual accounts. Column (6) is the ratio of (2) over the difference between (3) and (5).

Table 2.7 Summary statistics of firm level variables

	Observations	Mean	St.Dev.	Min	Percentiles			Max
					25th	50th	75th	
VA_{jcit}	20,210,495	2,256,200	54,110,778	0.00012	75,602	207,494	635,051	4.10e+10
L_{jcit}	20,210,495	31	578	0.06667	2	5	13	427130
W_{jcit}	20,210,495	33,359	666,739	0.02032	17,152	26,987	39,404	2.03e+09
P_{jcit}	20,210,495	83,414	5,213,056	0.00003	22,091	36,941	59,182	1.59e+10

Notes: This table presents summary statistics of firm-level value added (*VA*), number of employees (*L*), average wage (*W*), and labour productivity (*P*) for the unbalanced panel of 3,601,418 firms covering the period 2000-2016.

Table 2.8 Number of firm-year observations by country-year groups

	AT	BE	DE	DK	ES	FI	FR	IE	IT	LU	NL	PT	SE	UK	Total
2000	28	11,303	1,416	17,134	256,571	26,570	216,191	0	120,807	0	928	756	95,515	37,655	784,874
2001	36	10,748	1,949	17,746	317,444	29,200	214,183	0	133,245	0	1,255	607	99,807	37,985	864,205
2002	182	7,685	3,932	19,099	386,482	34,304	203,803	0	198,421	0	185	543	103,799	36,620	995,055
2003	237	8,379	5,433	17,557	435,252	36,800	227,134	0	155,191	0	131	165	103,014	34,107	1,023,400
2004	669	8,497	7,394	267	451,154	33,024	233,975	0	91,095	0	167	219	101,807	29,671	957,939
2005	298	8,560	16,053	0	482,047	30,542	228,721	162	96,474	0	239	68	92,172	28,785	984,121
2006	369	9,984	31,389	0	515,057	30,259	191,499	1,631	196,527	0	217	195,640	81,938	28,625	1,283,135
2007	241	10,354	34,012	0	485,829	30,462	180,157	2,336	225,106	29	172	189,737	85,123	28,128	1,271,686
2008	238	10,291	34,874	0	520,476	25,599	167,447	2,221	321,838	130	32	189,178	109,965	26,292	1,408,581
2009	670	10,305	35,614	0	519,493	24,806	176,552	1,988	263,842	380	0	185,840	112,280	23,768	1,355,538
2010	2,630	10,682	37,455	0	494,005	24,738	192,110	1,800	205,000	545	0	140,297	93,880	21,973	1,225,115
2011	4,739	11,051	43,963	2,554	482,023	28,064	177,926	1,604	414,491	589	0	132,153	87,786	21,048	1,407,991
2012	4,910	11,973	65,250	13,955	464,589	29,203	154,401	1,419	432,782	609	0	123,263	87,551	20,297	1,410,202
2013	5,152	12,662	68,825	13,436	456,145	29,431	154,276	1,505	428,377	606	0	118,235	88,118	19,988	1,396,756
2014	5,408	12,862	38,409	13,490	461,301	29,215	145,619	1,742	440,068	608	0	59,263	90,500	20,339	1,318,824
2015	5,320	12,953	32,896	16,272	446,987	26,533	123,417	1,820	442,275	560	0	122,725	92,649	20,664	1,345,071
2016	2,957	11,301	9,821	43,121	392,458	19,705	84,110	1,278	382,869	288	0	123,397	88,434	18,263	1,178,002
Total	34,084	179,590	468,685	174,631	7,567,313	488,455	3,071,521	19,506	4,548,408	4,344	3,326	1,582,086	1,614,338	454,208	20,210,495

Notes: Unbalanced panel of 3,601,418 firms observations over the period 2000-2016.

Table 2.9 Number of industries by country-year groups for country-industry-year pairs with more than 20 firm-year observations

	AT	BE	DE	DK	ES	FI	FR	IE	IT	LU	NL	PT	SE	UK	Total
2000	1	51	25	50	64	59	65	0	63	0	16	12	61	62	529
2001	1	51	29	51	64	60	65	0	63	0	19	12	60	63	538
2002	5	48	42	53	65	60	64	0	63	0	4	12	61	63	540
2003	7	50	49	52	65	60	65	0	63	0	2	4	61	62	540
2004	12	52	52	5	65	60	65	0	63	0	3	5	60	62	504
2005	7	50	58	0	65	58	65	5	63	0	6	2	60	62	501
2006	10	52	61	0	65	59	65	26	64	0	5	62	60	63	592
2007	5	52	63	0	65	59	65	32	65	1	4	62	60	62	595
2008	5	52	63	0	65	57	65	32	65	4	1	62	60	63	594
2009	15	52	63	0	65	57	64	32	65	10	0	62	60	63	608
2010	36	53	63	0	65	57	65	29	65	11	0	62	60	63	629
2011	46	52	63	25	64	59	63	28	65	11	0	62	60	63	661
2012	47	52	64	57	64	59	64	26	65	11	0	62	61	61	693
2013	47	53	64	57	64	59	64	25	65	11	0	62	61	61	693
2014	47	53	63	58	64	59	64	28	65	11	0	61	61	62	696
2015	47	53	63	58	64	59	64	27	65	11	0	62	61	62	696
2016	37	53	56	61	64	58	63	22	65	8	0	62	61	61	671
Total	375	879	941	527	1,097	999	1,095	312	1,092	89	60	728	1,028	1,058	10,280

Notes: Unbalanced panel of 10,280 country-industry-year groups over the period 2000-2016.

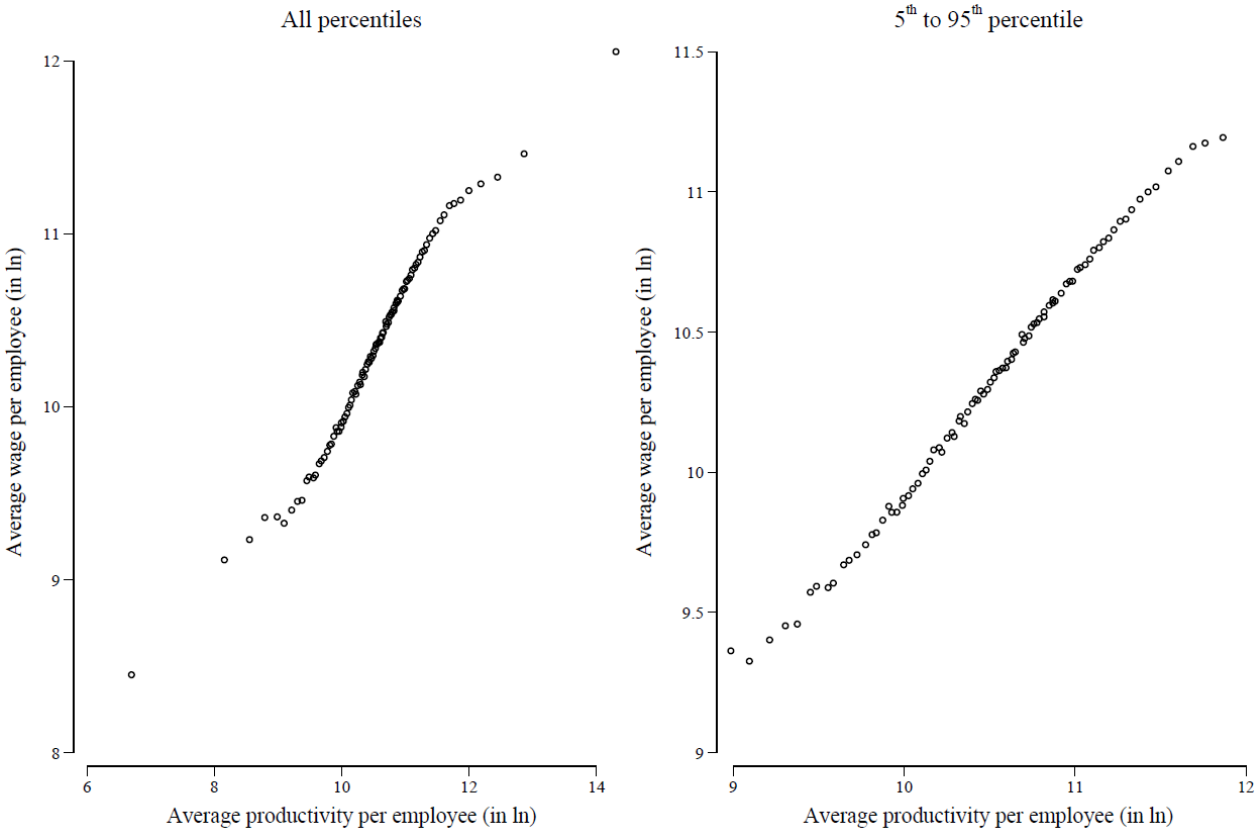
Table 2.10 Number of industries by country-year groups for country-industry-year pairs with more than 20 firm-year observations for all years in the sample (balanced sample)

	AT	BE	DE	ES	FI	FR	IT	PT	SE	UK	Total
2000	1	48	24	64	56	63	63	2	60	59	440
2001	1	48	24	64	56	63	63	2	60	59	440
2002	1	48	24	64	56	63	63	2	60	59	440
2003	1	48	24	64	56	63	63	2	60	59	440
2004	1	48	24	64	56	63	63	2	60	59	440
2005	1	48	24	64	56	63	63	2	60	59	440
2006	1	48	24	64	56	63	63	2	60	59	440
2007	1	48	24	64	56	63	63	2	60	59	440
2008	1	48	24	64	56	63	63	2	60	59	440
2009	1	48	24	64	56	63	63	2	60	59	440
2010	1	48	24	64	56	63	63	2	60	59	440
2011	1	48	24	64	56	63	63	2	60	59	440
2012	1	48	24	64	56	63	63	2	60	59	440
2013	1	48	24	64	56	63	63	2	60	59	440
2014	1	48	24	64	56	63	63	2	60	59	440
2015	1	48	24	64	56	63	63	2	60	59	440
2016	1	48	24	64	56	63	63	2	60	59	440
Total	17	816	408	1,088	952	1,071	1,071	34	1,020	1,003	7,480

Notes: Balanced panel of 7,480 country-industry-year groups over the period 2000-2016.

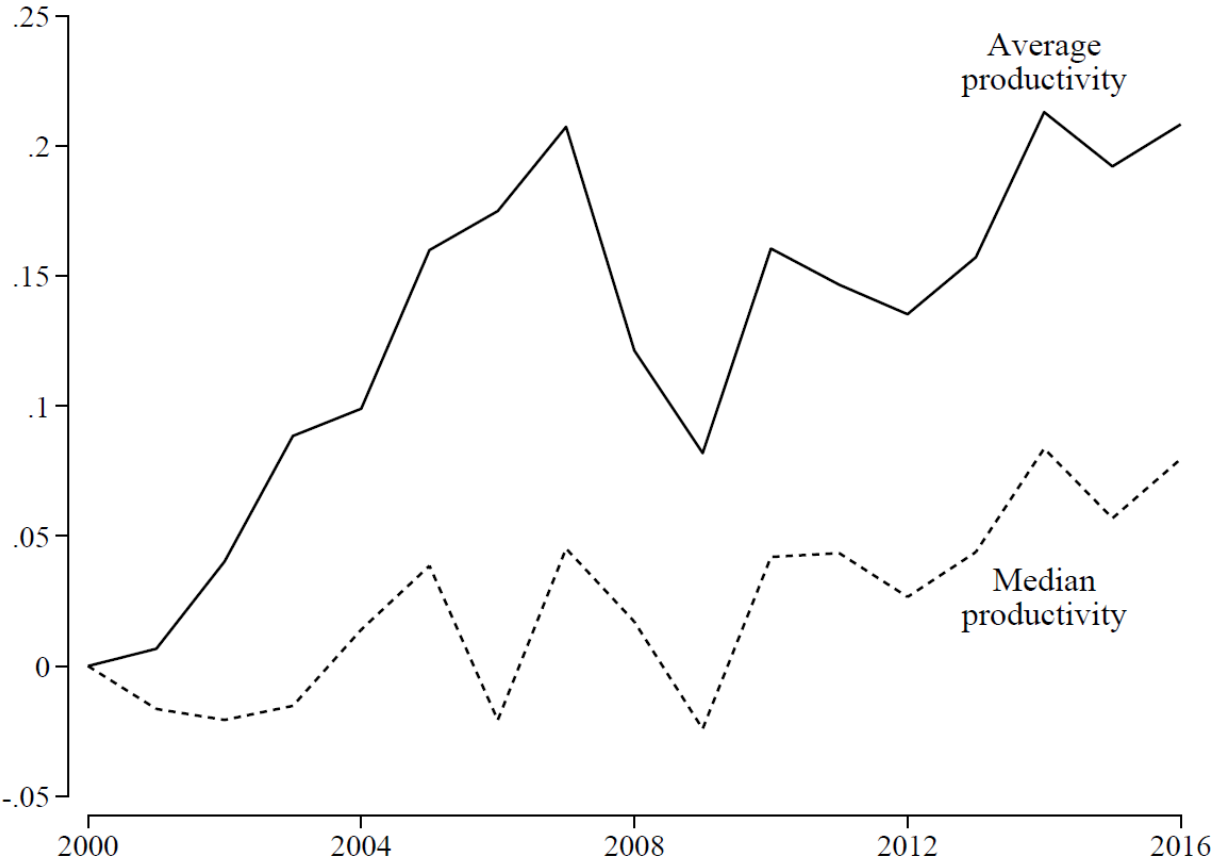
2.7.2 Figures appendix

Figure 2.4 Monotonic relationship between productivity and wages



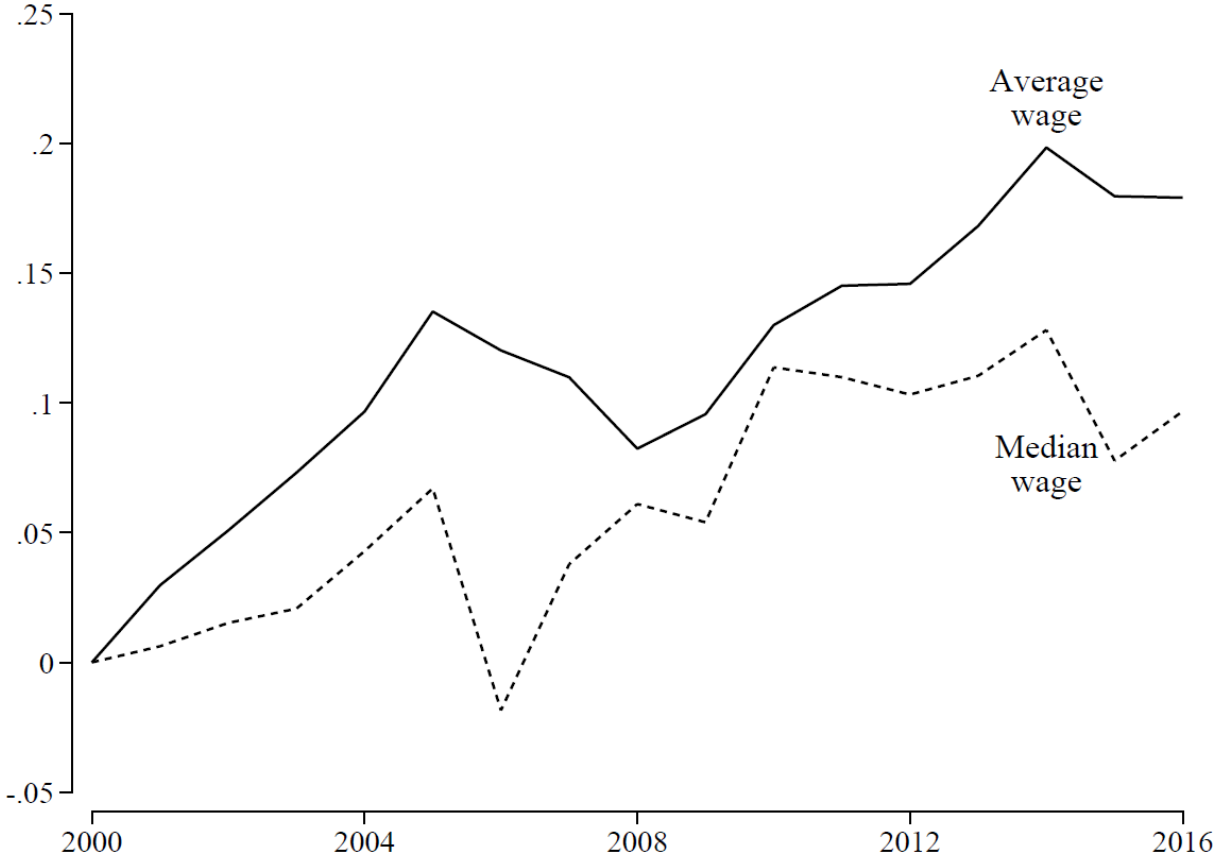
Source: Authors' calculations using Orbis Global database.
Notes: Both panels plot the logarithm of the average labour productivity for each percentile of the productivity distribution (x-axis) against the corresponding percentile of the logarithm of the average wage distribution (y-axis). The left panel presents results for all percentiles while the right panel presents results between the 5th and 95th percentiles.

Figure 2.5 Evolution of average and median productivity relative to 2000



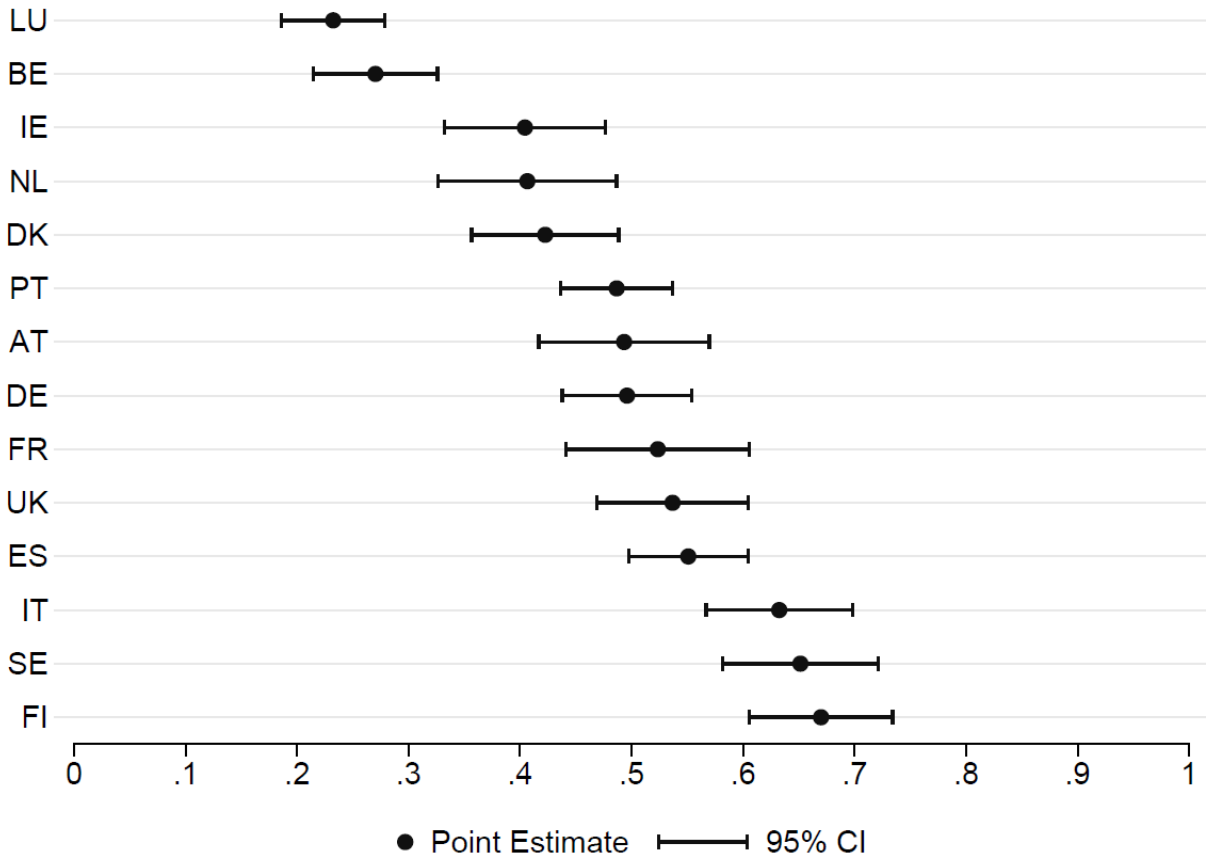
Source: Authors' calculations using Orbis Global database.
Notes: This figure shows the evolution of the average (solid line) and median (dashed line) productivity relative to the base year. The y-axis reflects logarithmic changes.

Figure 2.6 Evolution of average and median wage relative to 2000



Source: Authors' calculations using Orbis Global database.
Notes: This figure shows the evolution of the average (solid line) and median (dashed line) wage relative to the base year. The y-axis reflects logarithmic changes.

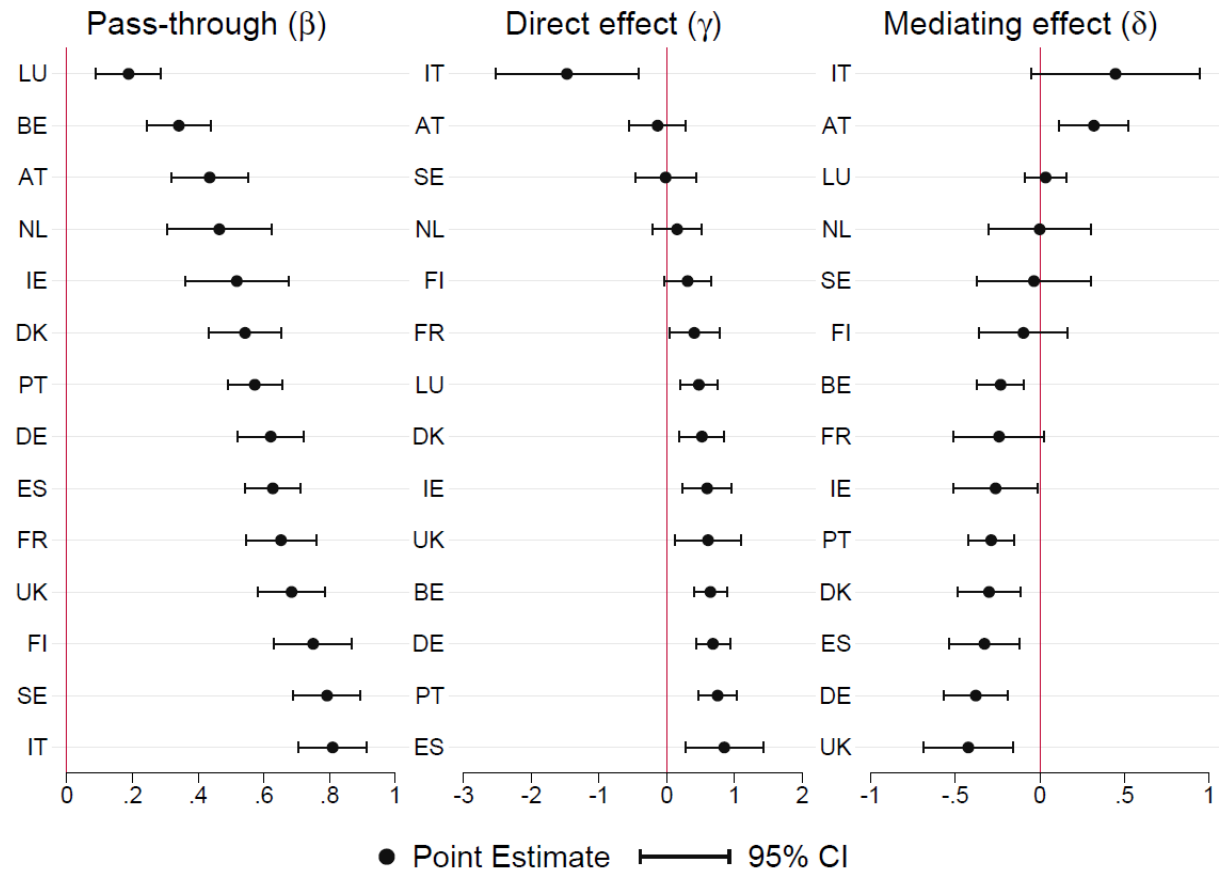
Figure 2.7 The link between wage and productivity dispersion by country



Source: Authors' estimations using Orbis Global database.

Notes: Each dot presents the point estimate from regressing wage dispersion ($WD_{cit}^{90/10}$) on productivity dispersion ($PD_{cit}^{90/10}$), i.e. β parameter in equation (7), for each country separately. All regressions include industry (*i*) and year (*t*) fixed effects, and are weighted by the logarithm of total value added at the industry-year (*it*) level. The tick-marks around the point estimates represent the clustered at the industry (*i*) level 95% confidence intervals.

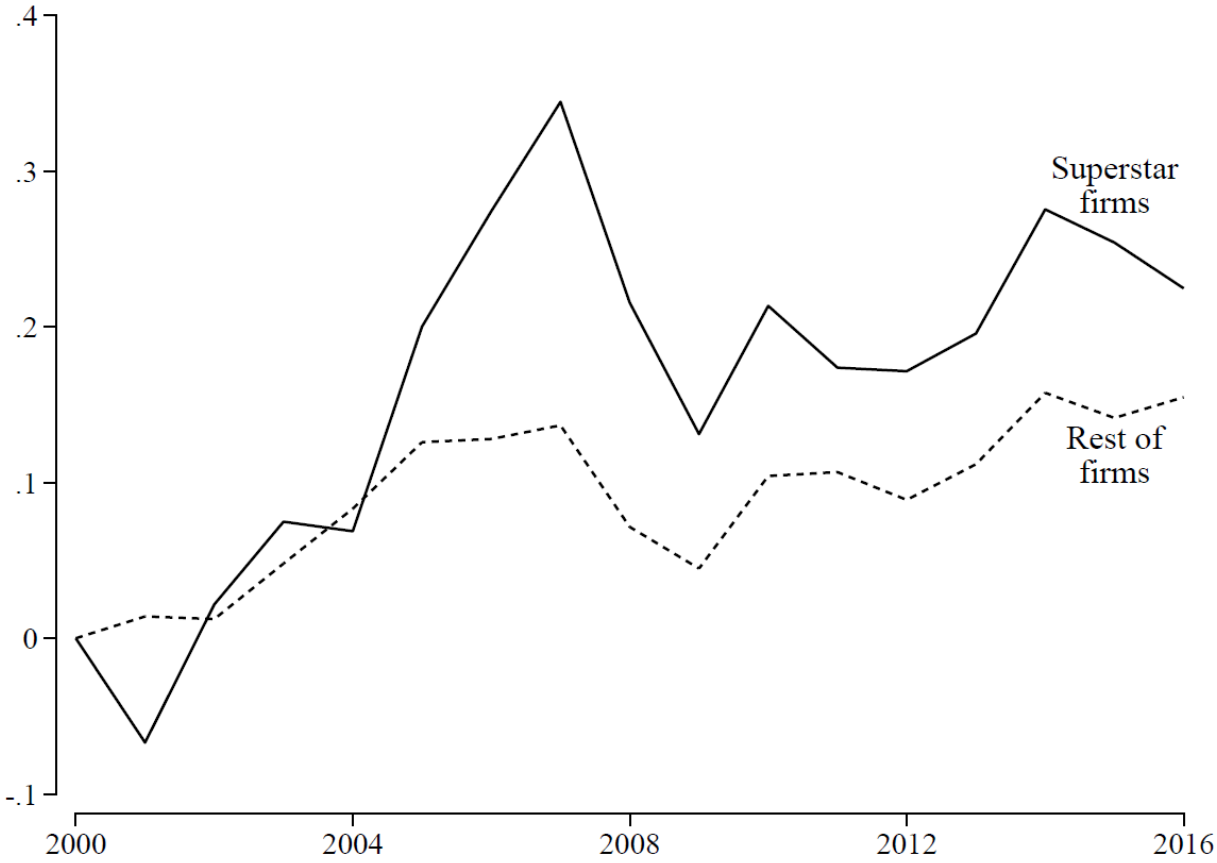
Figure 2.8 Superstar firms and the link between productivity and wage dispersion by country



Source: Authors' estimations using Orbis Global database.

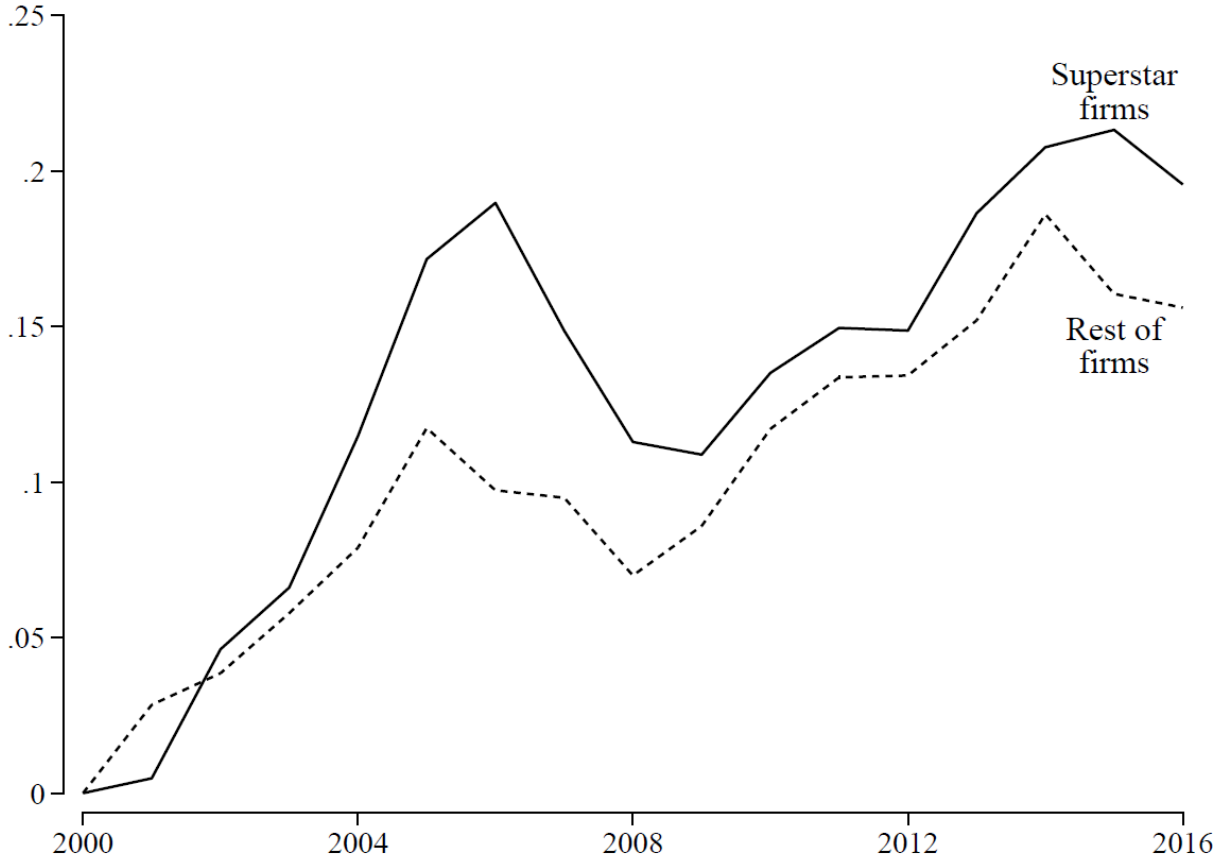
Notes: The dots present point estimates from regressing wage dispersion ($WD_{cit}^{90/10}$) on productivity dispersion ($PD_{cit}^{90/10}$), market concentration ($CN4_{cit}$), and their interaction ($PD_{cit}^{90/10} * CN4_{cit}$), i.e. β, γ, and δ parameters in equation (8), respectively. All regressions include industry (*i*) and year (*t*) fixed effects, and are weighted by the logarithm of total value added at the industry-year (*it*) level. The tick-marks around the point estimates represent the clustered at the industry (*i*) level 95% confidence intervals.

Figure 2.9 Productivity evolution of superstar firms versus rest of firms



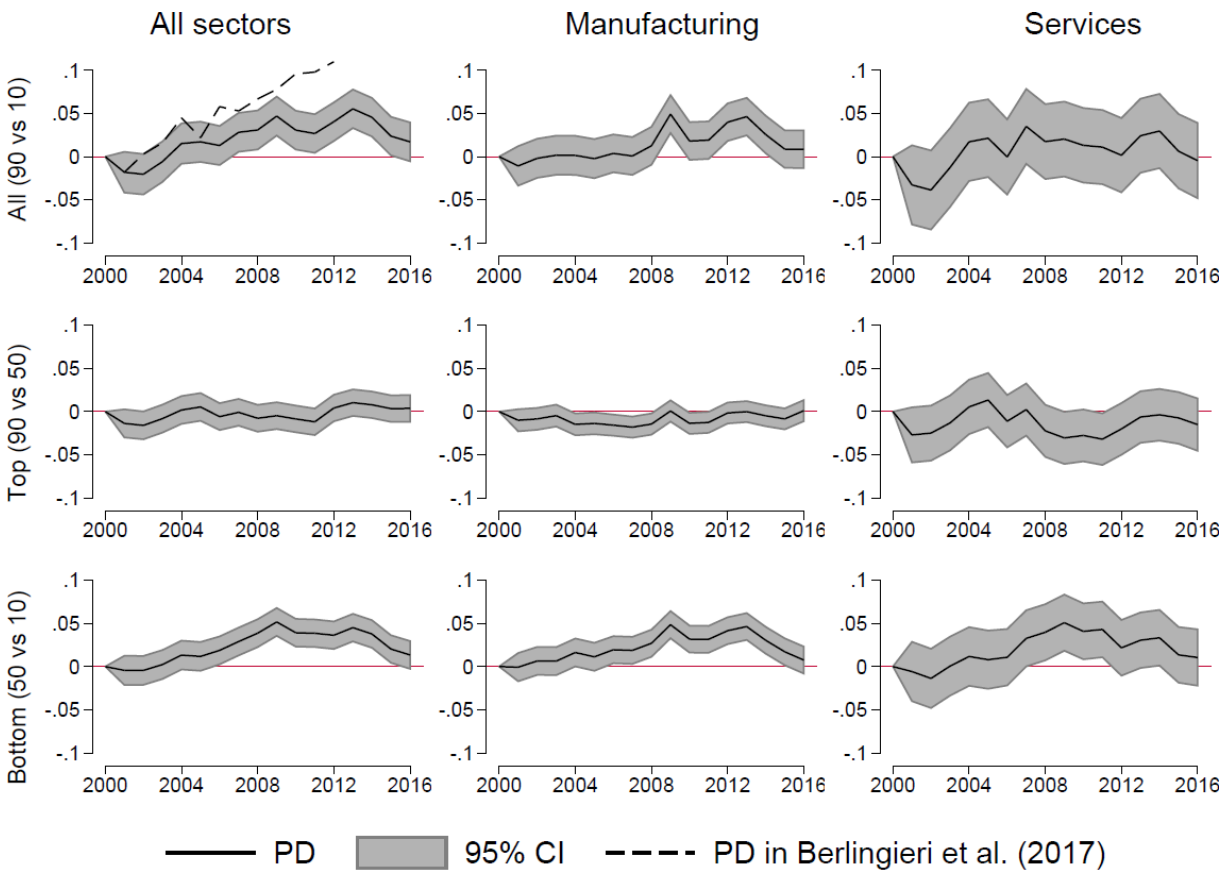
Source: Authors' calculations using Orbis Global database.
Notes: This figure shows the evolution of average productivity for superstar firms (solid line) and the rest of firms (dashed line) relative to the base year. The y-axis reflects logarithmic changes. The set of superstar firms includes the top-four firms in terms of market shares within each country-industry-year pair. Rest of firms is the set of firms other than superstars.

Figure 2.10 Wage evolution of superstar firms versus rest of firms



Source: Authors' calculations using Orbis Global database.
Notes: This figure shows the evolution of average wage for superstar firms (solid line) and the rest of firms (dashed line) relative to the base year. The y-axis reflects logarithmic changes. The set of superstar firms includes the top-four firms in terms of market shares within each country-industry-year pair. Rest of firms is the set of firms other than superstars.

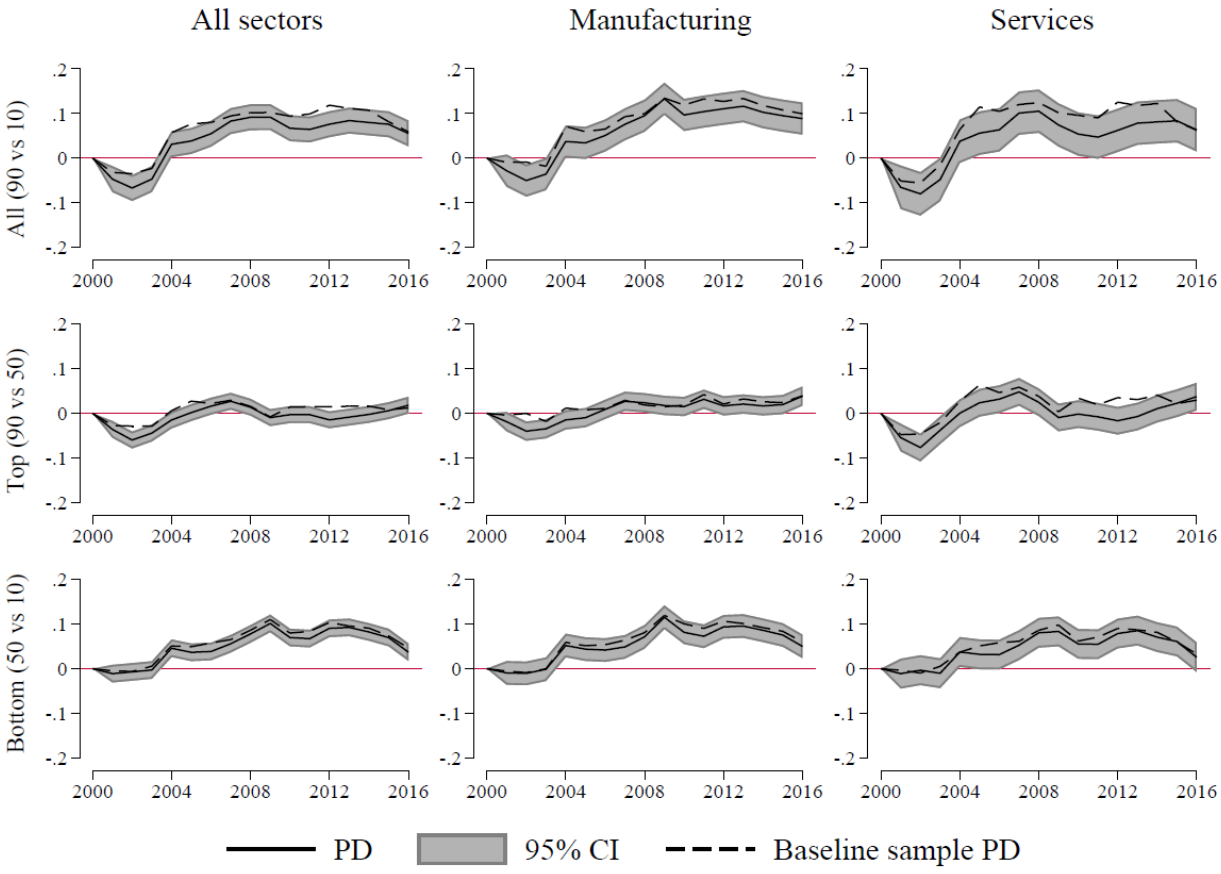
Figure 2.11 Evolution of productivity dispersion (PD) using TFP estimates



Source: Authors' estimations using Orbis Global database.

Notes: The solid line connects the estimated coefficients from regressing productivity dispersion (PD_{cit}) on a set of year dummies, i.e. parameter set β_t in equation (3). The chosen base year is 2000. All regressions include country-industry (*ci*) fixed effects and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. The dispersion measures considered in the top, middle and bottom row panels capture the entire All (90 vs 10), upper 'Top (90 vs 50)' and bottom 'Bottom (50 vs 10)' parts of the distributions, respectively. The shaded area represents the clustered at the country-industry (*ci*) level 95% confidence interval. Left, middle and right column respectively. The PD_{cit} measures are computed using firm-level TFP estimated from a gross-output production function with capital, labour and material inputs following the non-parametric identification strategy of (Gandhi et al. 2020). The dashed line in the top-left panel corresponds to PD_{cit} of TFP found in Berlingieri et al. (2017).

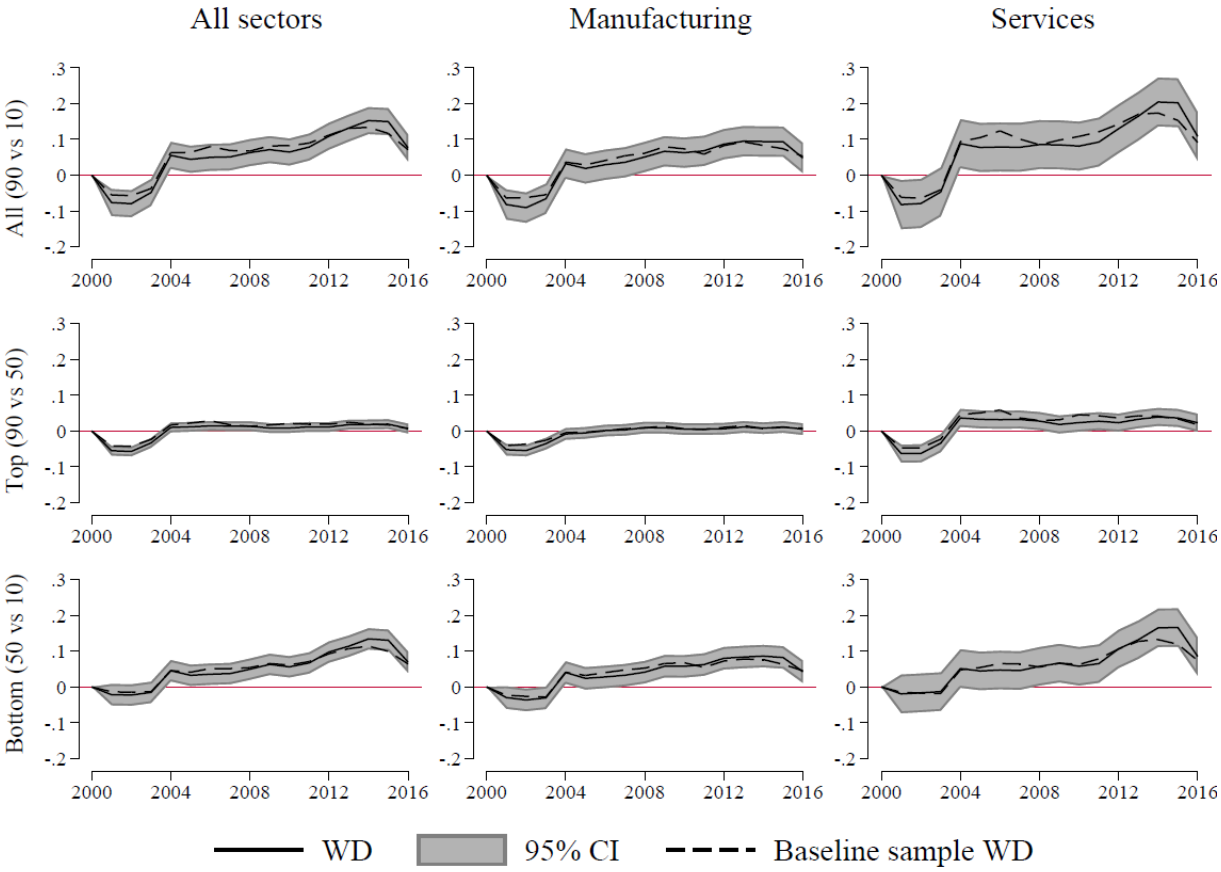
Figure 2.12 Evolution of productivity dispersion (PD) for balanced sample



Source: Authors' estimations using Orbis Global database.

Notes: The solid line connects the estimated coefficients from regressing productivity dispersion (PD_{cit}) on a set of year dummies, i.e. parameter set β_t in equation (3). The chosen base year is 2000. All regressions include country-industry (*ci*) fixed effects and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. The dispersion measures considered in the top, middle and bottom row panels capture the entire 'All (90 vs 10)', upper 'Top (90 vs 50)' and bottom 'Bottom (50 vs 10)' parts of the distributions, respectively. The shaded area represents the clustered at the country-industry (*ci*) level 95% confidence interval. Left, middle and right column panels use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The dashed line in the top-left panel corresponds to PD_{cit} found in Berlingieri et al. (2017). The sample is balanced and only includes country-industry groups present in all years between 2000-2016.

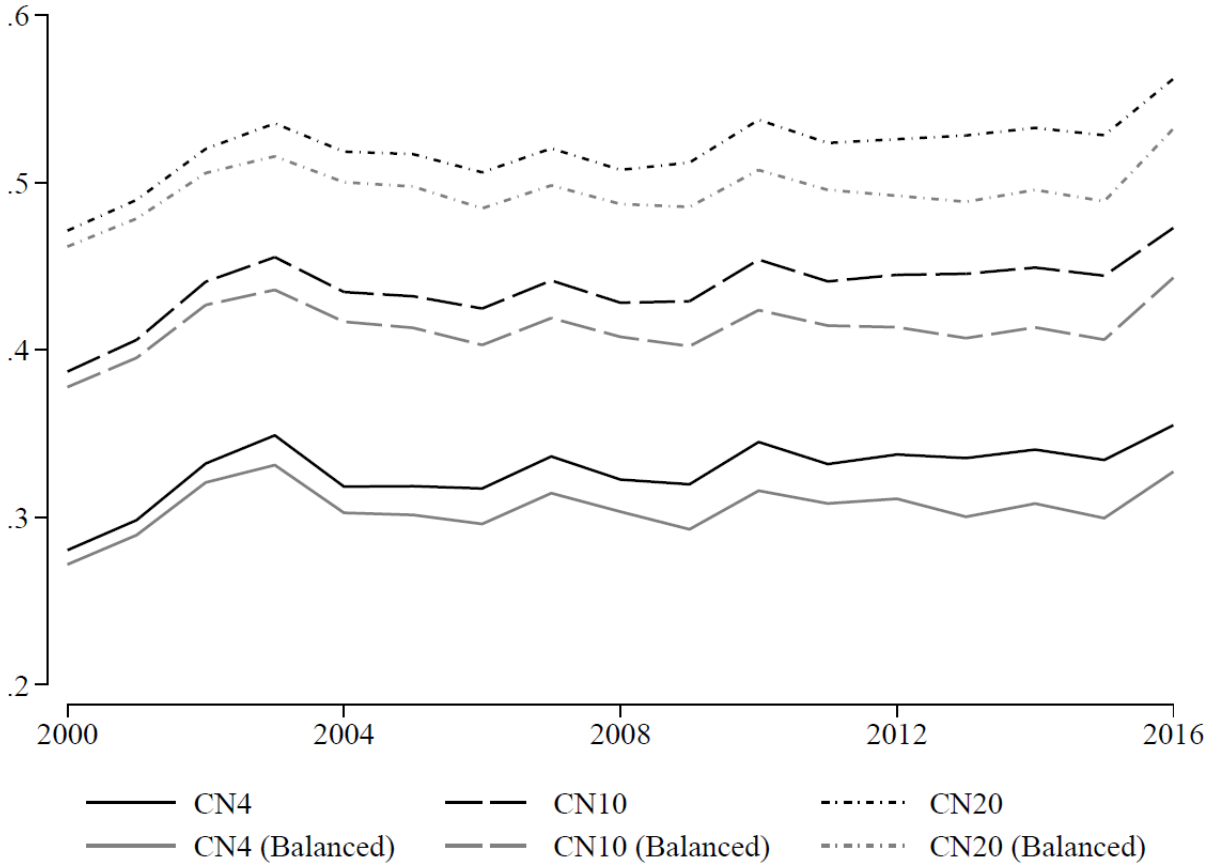
Figure 2.13 Evolution of wage dispersion (WD) for balanced sample



Source: Authors' estimations using Orbis Global database.

Notes: The solid line connects the estimated coefficients from regressing wage dispersion (WD_{cit}) on a set of year dummies, i.e. parameter set β_t in equation (4). The chosen base year is 2000. All regressions include countryindustry (*ci*) fixed effects and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. The dispersion measures considered in the top, middle and bottom row panels capture the entire 'All (90 vs 10)', upper 'Top (90 vs 50)' and bottom 'Bottom (50 vs 10)' parts of the distributions, respectively. The shaded area represents the clustered at the country-industry (*ci*) level 95% confidence interval. Left, middle and right column panels use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The dashed line in the top-left panel corresponds to WD_{cit} in Berlingieri et al. (2017). The sample is balanced and only includes country-industry groups present in all years between 2000-2016.

Figure 2.14 Evolution of market concentration (CN) for balanced sample



Source: Authors' estimations using Orbis Global database.
Notes: The lines connect the estimated coefficients from regressing the market concentration measures (*CN*4, *CN*10, *CN*20) on a set of year dummies. All regressions are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. The shaded lines repeat the analysis for the balanced sample, i.e. only includes country-industry groups present in all years between 2000-2016.

2.7.3 Tables appendix

Table 2.11 Superstar firms and the link between productivity and wage dispersion with CN10 concentration measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All sectors			Manufacturing			Services		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.61***			0.57***			0.68***		
	(0.06)			(0.07)			(0.08)		
$PD_{cit}^{90/50}$		0.35***			0.34***			0.42***	
		(0.05)			(0.08)			(0.07)	
$PD_{cit}^{50/10}$			0.91***			0.54***			1.10***
			(0.11)			(0.08)			(0.18)
$CN10_{cit}$	0.45***	0.08	0.37***	0.47***	0.12	0.13	0.69***	0.13	0.62**
	(0.12)	(0.04)	(0.11)	(0.14)	(0.08)	(0.10)	(0.19)	(0.07)	(0.20)
$PD_{cit}^{90/10} * CN10_{cit}$	-0.27***			-0.27**			-0.36***		
	(0.07)			(0.10)			(0.10)		
$PD_{cit}^{90/50} * CN10_{cit}$		-0.11*			-0.13			-0.16*	
		(0.05)			(0.10)			(0.06)	
$PD_{cit}^{50/10} * CN10_{cit}$			-0.45**			-0.08			-0.70**
			(0.14)			(0.14)			(0.24)
R^2	0.894	0.882	0.853	0.912	0.869	0.891	0.883	0.876	0.845
Observations	10,268	10,268	10,268	3,757	3,757	3,757	4,727	4,727	4,727

Notes: $*p<0.05$, $**p<0.01$, $***p<0.001$. This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration ($CN10_{cit}$), and their interaction (PD_{cit}*$CN10_{cit}$), i.e. β, γ and δ parameters in equation (8), respectively. The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distribution. $CN10_{cit}$ captures the market shares of the 10 largest firms in each country-industry-year (*cit*) group. All regressions include country-industry (*ci*), country-year (*ct*), and industry-year (*it*) fixed effects, and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. Standard errors are clustered at the country-industry (*ci*) level and reported in parentheses below point estimates. Columns (1)-(3), (4)-(6), and (7)-(9) use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively.

Table 2.12 Superstar firms and the link between productivity and wage dispersion with CN20 concentration measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All sectors			Manufacturing			Services		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.69***			0.64***			0.79***		
	(0.08)			(0.08)			(0.11)		
$PD_{cit}^{90/50}$		0.37***			0.38***			0.43***	
		(0.06)			(0.10)			(0.09)	
$PD_{cit}^{50/10}$			1.00***			0.57***			1.26***
			(0.15)			(0.09)			(0.24)
$CN20_{cit}$	0.53***	0.08	0.38**	0.57***	0.15	0.17	0.81***	0.15	0.68**
	(0.14)	(0.05)	(0.12)	(0.14)	(0.09)	(0.10)	(0.24)	(0.09)	(0.24)
$PD_{cit}^{90/10} * C20_{cit}$	-0.33***			-0.32**			-0.44**		
	(0.09)			(0.10)			(0.14)		
$PD_{cit}^{90/50} * C20_{cit}$		-0.12			-0.17			-0.16	
		(0.06)			(0.11)			(0.09)	
$PD_{cit}^{50/10} * C20_{cit}$			-0.51**			-0.11			-0.80**
			(0.17)			(0.14)			(0.28)
R^2	0.894	0.882	0.854	0.913	0.870	0.891	0.883	0.876	0.845
Observations	10,268	10,268	10,268	3,757	3,757	3,757	4,727	4,727	4,727

Notes: $*p<0.05$, $**p<0.01$, $***p<0.001$ This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration ($CN20_{cit}$), and their interaction (PD_{cit}*$CN20_{cit}$), i.e. β, γ and δ parameters in equation (8), respectively. The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distribution. $CN20_{cit}$ captures the market shares of the 20 largest firms in each country-industry-year (*cit*) group. All regressions include country-industry (*ci*), country-year (*ct*), and industry-year (*it*) fixed effects, and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. Standard errors are clustered at the country-industry (*ci*) level and reported in parentheses below point estimates. Columns (1)-(3), (4)-(6), and (7)-(9) use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively.

Table 2.13 Superstar firms and the link between productivity and wage dispersion with CN2 concentration measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All sectors			Manufacturing			Services		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.47***			0.45***			0.49***		
	(0.04)			(0.05)			(0.05)		
$PD_{cit}^{90/50}$		0.30***			0.27***			0.34***	
		(0.04)			(0.04)			(0.05)	
$PD_{cit}^{50/10}$			0.69***			0.52***			0.78***
			(0.06)			(0.06)			(0.09)
$CN2_{cit}$	0.28**	0.06	0.27**	0.34**	0.09	0.12	0.42**	0.09	0.45**
	(0.09)	(0.04)	(0.09)	(0.13)	(0.06)	(0.09)	(0.15)	(0.06)	(0.17)
$PD_{cit}^{90/10} * CN2_{cit}$	-0.14**			-0.17*			-0.19**		
	(0.05)			(0.09)			(0.06)		
$PD_{cit}^{90/50} * CN2_{cit}$		-0.07*			-0.08			-0.10*	
		(0.03)			(0.07)			(0.05)	
$PD_{cit}^{50/10} * CN2_{cit}$			-0.28*			-0.07			-0.45*
			(0.12)			(0.13)			(0.19)
R^2	0.893	0.882	0.852	0.912	0.869	0.891	0.881	0.876	0.842
Observations	10,268	10,268	10,268	3,757	3,757	3,757	4,727	4,727	4,727

Notes: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration ($CN2_{cit}$), and their interaction (PD_{cit}*$CN2_{cit}$), i.e. β, γ and δ parameters in equation (8), respectively. The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distribution. $CN2_{cit}$ captures the market shares of the 2 largest firms in each country-industry-year (*cit*) group. All regressions include country-industry (*ci*), country-year (*ct*), and industry-year (*it*) fixed effects, and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. Standard errors are clustered at the country-industry (*ci*) level and reported in parentheses below point estimates. Columns (1)-(3), (4)-(6), and (7)-(9) use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively.

Table 2.14 Superstar firms and the link between productivity and wage dispersion with HHI concentration measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All sectors			Manufacturing			Services		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.42***			0.41***			0.43***		
	(0.03)			(0.04)			(0.05)		
$PD_{cit}^{90/50}$		0.28***			0.25***			0.31***	
		(0.03)			(0.03)			(0.04)	
$PD_{cit}^{50/10}$			0.63***			0.51***			0.67***
			(0.05)			(0.06)			(0.06)
HHI_{cit}	0.29*	0.07	0.32**	0.38*	0.12*	0.14	0.37*	0.09	0.45*
	(0.12)	(0.06)	(0.12)	(0.15)	(0.06)	(0.13)	(0.19)	(0.09)	(0.18)
$PD_{cit}^{90/10} * HHI_{cit}$	-0.13*			-0.20*			-0.15		
	(0.06)			(0.09)			(0.08)		
$PD_{cit}^{90/50} * HHI_{cit}$		-0.09			-0.11			-0.10	
		(0.06)			(0.07)			(0.07)	
$PD_{cit}^{50/10} * HHI_{cit}$			-0.33*			-0.11			-0.44*
			(0.15)			(0.19)			(0.20)
R^2	0.892	0.881	0.852	0.911	0.869	0.891	0.881	0.875	0.841
Observations	10,268	10,268	10,268	3,757	3,757	3,757	4,727	4,727	4,727

Notes: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration (HHI_{cit}), and their interaction (PD_{cit}*HHI_{cit}), i.e. β, γ and δ parameters in equation (8), respectively. The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distribution. HHI_{cit} is the Herfindahl-Hirschman Index for each country-industry-year (*cit*) group. All regressions include country-industry (*ci*), country-year (*ct*), and industry-year (*it*) fixed effects, and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. Standard errors are clustered at the country-industry (*ci*) level and reported in parentheses below point estimates. Columns (1)-(3), (4)-(6), and (7)-(9) use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively.

Table 2.15 Superstar firms and the link between productivity and wage dispersion with wider dispersion measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All sectors			Manufacturing			Services		
	$WD_{cit}^{95/5}$	$WD_{cit}^{95/50}$	$WD_{cit}^{50/5}$	$WD_{cit}^{95/5}$	$WD_{cit}^{95/50}$	$WD_{cit}^{50/5}$	$WD_{cit}^{95/5}$	$WD_{cit}^{95/50}$	$WD_{cit}^{50/5}$
$PD_{cit}^{95/5}$	0.53***			0.44***			0.57***		
	(0.04)			(0.09)			(0.06)		
$PD_{cit}^{95/50}$		0.38***			0.42**			0.38***	
		(0.04)			(0.13)			(0.06)	
$PD_{cit}^{50/5}$			0.81***			0.54***			0.93***
			(0.07)			(0.07)			(0.09)
$CN4_{cit}$	0.57***	0.17*	0.50***	0.21	0.10	0.18	0.82***	0.23*	0.75***
	(0.16)	(0.08)	(0.11)	(0.37)	(0.25)	(0.12)	(0.24)	(0.12)	(0.19)
$PD_{cit}^{95/5} * CN4_{cit}$	-0.21***			-0.10			-0.26**		
	(0.06)			(0.17)			(0.08)		
$PD_{cit}^{95/50} * CN4_{cit}$		-0.14*			-0.08			-0.17*	
		(0.06)			(0.22)			(0.07)	
$PD_{cit}^{50/5} * CN4_{cit}$			-0.39***			-0.20			-0.51***
			(0.11)			(0.10)			(0.15)
R^2	0.870	0.846	0.840	0.838	0.762	0.833	0.871	0.862	0.845
Observations	10,268	10,268	10,268	3,757	3,757	3,757	4,727	4,727	4,727

Notes: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration ($CN4_{cit}$), and their interaction (PD_{cit}*$CN4_{cit}$), i.e. β, γ and δ parameters in equation (8), respectively. The dispersion measures considered capture the entire (95/5), upper (95/50) and bottom (50/5) parts of the respective distribution. $CN4_{cit}$ captures the market shares of the 4 largest firms in each country-industry-year (*cit*) group. All regressions include country-industry (*ci*), country-year (*ct*), and industry-year (*it*) fixed effects, and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. Standard errors are clustered at the country-industry (*ci*) level and reported in parentheses below point estimates. Columns (1)-(3), (4)-(6), and (7)-(9) use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively.

Table 2.16 Superstar firms and the link between productivity (using TFP estimates) and wage dispersion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All sectors			Manufacturing			Services		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.33***			0.62***			0.22**		
	(0.05)			(0.07)			(0.08)		
$PD_{cit}^{90/50}$		0.18***			0.48***			0.15*	
		(0.04)			(0.08)			(0.06)	
$PD_{cit}^{50/10}$			0.40***			0.55***			0.24*
			(0.08)			(0.08)			(0.11)
$CN4_{cit}$	0.21**	0.09**	0.17*	0.13	0.12*	0.03	0.03	0.09	0.08
	(0.08)	(0.03)	(0.07)	(0.12)	(0.05)	(0.08)	(0.16)	(0.07)	(0.13)
$PD_{cit}^{90/10} * CN4_{cit}$	-0.14*			-0.06			-0.01		
	(0.06)			(0.17)			(0.10)		
$PD_{cit}^{90/50} * CN4_{cit}$		-0.11*			-0.26*			-0.09	
		(0.05)			(0.12)			(0.07)	
$PD_{cit}^{50/10} * CN4_{cit}$			-0.24*			0.09			-0.09
			(0.12)			(0.23)			(0.17)
R^2	0.884	0.866	0.850	0.928	0.895	0.902	0.864	0.850	0.834
Observations	7,696	7,696	7,696	2,977	2,977	2,977	3,364	3,364	3,364

Notes: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration ($CN4_{cit}$), and their interaction (PD_{cit}*$CN4_{cit}$), i.e. β, γ and δ parameters in equation (8), respectively. The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distribution. $CN4_{cit}$ captures the market shares of the 4 largest firms in each country-industry-year (*cit*) group. All regressions include country-industry (*ci*), country-year (*ct*), and industry-year (*it*) fixed effects, and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. Standard errors are clustered at the country-industry (*ci*) level and reported in parentheses below point estimates. Columns (1)-(3), (4)-(6), and (7)-(9) use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The PD_{cit} measures are computed using firm-level TFP estimated from a gross-output production function with capital, labour and material inputs following the non-parametric identification strategy of (Gandhi et al. 2020).

Table 2.17 Superstar firms and the link between productivity and wage dispersion with balanced sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All sectors			Manufacturing			Services		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.64***			0.57***			0.65***		
	(0.06)			(0.06)			(0.09)		
$PD_{cit}^{90/50}$		0.30***			0.37***			0.30***	
		(0.05)			(0.07)			(0.07)	
$PD_{cit}^{50/10}$			0.95***			0.65***			1.06***
			(0.12)			(0.07)			(0.17)
$CN4_{cit}$	0.49***	0.02	0.50***	0.48***	0.16*	0.29**	0.47	-0.09	0.72**
	(0.13)	(0.04)	(0.13)	(0.13)	(0.08)	(0.09)	(0.26)	(0.06)	(0.23)
$PD_{cit}^{90/10} * CN4_{cit}$	-0.30***			-0.27**			-0.27		
	(0.08)			(0.09)			(0.14)		
$PD_{cit}^{90/50} * CN4_{cit}$		-0.05			-0.20*			0.05	
		(0.04)			(0.10)			(0.05)	
$PD_{cit}^{50/10} * CN4_{cit}$			-0.64***			-0.30*			-0.85**
			(0.18)			(0.14)			(0.28)
R^2	0.917	0.925	0.884	0.941	0.885	0.931	0.909	0.927	0.879
Observations	7,446	7,446	7,446	2,788	2,788	2,788	3,366	3,366	3,366

Notes: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration ($CN4_{cit}$), and their interaction (PD_{cit}*$CN4_{cit}$), i.e. β, γ and δ parameters in equation (8), respectively. The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distribution. $CN4_{cit}$ captures the market shares of the 4 largest firms in each country-industry-year (*cit*) group. All regressions include country-industry (*ci*), country-year (*ct*), and industry-year (*it*) fixed effects, and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. Standard errors are clustered at the country-industry (*ci*) level and reported in parentheses below point estimates. Columns (1)-(3), (4)-(6), and (7)-(9) use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The sample is balanced and only includes country-industry groups present in all years between 2000-2016.

Table 2.18 Superstar firms and the link between productivity and wage dispersion with sample starting from 2002

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All sectors			Manufacturing			Services		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.50***			0.45***			0.55***		
	(0.04)			(0.05)			(0.06)		
$PD_{cit}^{90/50}$		0.30***			0.24***			0.36***	
		(0.04)			(0.05)			(0.06)	
$PD_{cit}^{50/10}$			0.77***			0.51***			0.90***
			(0.08)			(0.07)			(0.13)
$CN4_{cit}$	0.33***	0.07	0.29**	0.30*	0.06	0.10	0.51**	0.14	0.47*
	(0.10)	(0.04)	(0.10)	(0.13)	(0.06)	(0.09)	(0.16)	(0.07)	(0.19)
$PD_{cit}^{90/10} * CN4_{cit}$	-0.18***			-0.15			-0.24***		
	(0.05)			(0.08)			(0.07)		
$PD_{cit}^{90/50} * CN4_{cit}$		-0.08*			-0.04			-0.12*	
		(0.04)			(0.07)			(0.05)	
$PD_{cit}^{50/10} * CN4_{cit}$			-0.35**			-0.05			-0.53*
			(0.13)			(0.14)			(0.21)
R^2	0.896	0.886	0.854	0.911	0.870	0.890	0.884	0.881	0.845
Observations	9,203	9,203	9,203	3,353	3,353	3,353	4,255	4,255	4,255

Notes: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration ($CN4_{cit}$), and their interaction (PD_{cit}*$CN4_{cit}$), i.e. β, γ and δ parameters in equation (8), respectively. The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distribution. $CN4_{cit}$ captures the market shares of the 4 largest firms in each country-industry-year (*cit*) group. All regressions include country-industry (*ci*), country-year (*ct*), and industry-year (*it*) fixed effects, and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. Standard errors are clustered at the country-industry (*ci*) level and reported in parentheses below point estimates. Columns (1)-(3), (4)-(6), and (7)-(9) use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The sample includes country-industry groups present in all years between 2002-2016.

Table 2.19 Superstar firms and the link between productivity and wage dispersion excluding country-industry groups with irregular changes in firm coverage over time

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All sectors			Manufacturing			Services		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.54***			0.57***			0.53***		
	(0.05)			(0.07)			(0.07)		
$PD_{cit}^{90/50}$		0.29***			0.37***			0.30***	
		(0.06)			(0.08)			(0.08)	
$PD_{cit}^{50/10}$			0.69***			0.65***			0.79***
			(0.07)			(0.07)			(0.09)
$CN4_{cit}$	0.23*	0.01	0.24**	0.45**	0.20*	0.25*	0.07	-0.12	0.39**
	(0.10)	(0.04)	(0.08)	(0.16)	(0.08)	(0.10)	(0.18)	(0.06)	(0.13)
$PD_{cit}^{90/10} * CN4_{cit}$	-0.13*			-0.26*			-0.05		
	(0.06)			(0.11)			(0.09)		
$PD_{cit}^{90/50} * CN4_{cit}$		-0.03			-0.26*			0.08	
		(0.04)			(0.10)			(0.06)	
$PD_{cit}^{50/10} * CN4_{cit}$			-0.29**			-0.27			-0.44**
			(0.10)			(0.15)			(0.14)
R^2	0.932	0.933	0.899	0.941	0.889	0.931	0.930	0.936	0.903
Observations	6,341	6,341	6,341	2,550	2,550	2,550	2,720	2,720	2,720

Notes: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration ($CN4_{cit}$), and their interaction (PD_{cit}*$CN4_{cit}$), i.e. β, γ and δ parameters in equation (8), respectively. The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distribution. $CN4_{cit}$ captures the market shares of the 4 largest firms in each country-industry-year (*cit*) group. All regressions include country-industry (*ci*), country-year (*ct*), and industry-year (*it*) fixed effects, and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. Standard errors are clustered at the country-industry (*ci*) level and reported in parentheses below point estimates. Columns (1)-(3), (4)-(6), and (7)-(9) use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The sample only includes country-industry groups which satisfy the following conditions throughout the entire period 2000-2016: (1) the number of firms do not double or halve between two consecutive years; or (2) the difference in the number of firms between two consecutive years is smaller than 25.

Table 2.20 Superstar firms and the link between productivity and wage dispersion with enhanced data representativeness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All sectors			Manufacturing			Services		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.59***			0.64***			0.60***		
	(0.06)			(0.14)			(0.08)		
$PD_{cit}^{90/50}$		0.29***			0.26***			0.32**	
		(0.09)			(0.05)			(0.11)	
$PD_{cit}^{50/10}$			0.71***			0.66***			0.77***
			(0.06)			(0.14)			(0.07)
$CN4_{cit}$	0.40***	0.06	0.24***	0.21	0.06	0.06	0.53**	0.05	0.36***
	(0.11)	(0.08)	(0.07)	(0.15)	(0.05)	(0.12)	(0.18)	(0.12)	(0.09)
$PD_{cit}^{90/10} * CN4_{cit}$	-0.26***			-0.20			-0.28**		
	(0.08)			(0.11)			(0.10)		
$PD_{cit}^{90/50} * CN4_{cit}$		-0.10			-0.12			-0.09	
		(0.10)			(0.07)			(0.14)	
$PD_{cit}^{50/10} * CN4_{cit}$			-0.27**			-0.13			-0.35**
			(0.09)			(0.16)			(0.11)
R^2	0.91	0.88	0.87	0.91	0.90	0.85	0.90	0.86	0.88
Observations	9987	9987	9987	3695	3695	3695	4654	4654	4654

Notes: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration ($CN4_{cit}$), and their interaction (PD_{cit}*$CN4_{cit}$), i.e. β, γ and δ parameters in equation (8), respectively. The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distribution. $CN4_{cit}$ captures the market shares of the 4 largest firms in each country-industry-year (*cit*) group. All regressions include country-industry (*ci*), country-year (*ct*), and industry-year (*it*) fixed effects, and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. Standard errors are clustered at the country-industry (*ci*) level and reported in parentheses below point estimates. Columns (1)-(3), (4)-(6), and (7)-(9) use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The sample used follows the suggestions in Bajgar et al. (2020) to further improve the representativeness of Orbis Global (see Section 2.5).

Table 2.21 Superstar firms and the link between productivity and wage dispersion with additional FE & trends

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All sectors			Manufacturing			Services		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.43***			0.36***			0.47***		
	(0.04)			(0.06)			(0.06)		
$PD_{cit}^{90/50}$		0.29***			0.21***			0.34***	
		(0.04)			(0.04)			(0.06)	
$PD_{cit}^{50/10}$			0.65***			0.44***			0.70***
			(0.06)			(0.07)			(0.08)
$CN4_{cit}$	0.26**	0.04	0.25**	0.18	0.02	0.06	0.30*	0.07	0.26
	(0.09)	(0.05)	(0.09)	(0.15)	(0.06)	(0.11)	(0.13)	(0.07)	(0.14)
$PD_{cit}^{90/10} * CN4_{cit}$	-0.13**			-0.08			-0.16**		
	(0.05)			(0.10)			(0.06)		
$PD_{cit}^{90/50} * CN4_{cit}$		-0.07			0.00			-0.11	
		(0.05)			(0.07)			(0.06)	
$PD_{cit}^{50/10} * CN4_{cit}$			-0.25*			-0.01			-0.27
			(0.11)			(0.15)			(0.15)
R^2	0.927	0.913	0.900	0.934	0.905	0.917	0.916	0.906	0.891
Observations	10,268	10,268	10,268	3,757	3,757	3,757	4,727	4,727	4,727

Notes: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration ($CN4_{cit}$), and their interaction (PD_{cit}*$CN4_{cit}$), i.e. β, γ and δ parameters in equation (8), respectively. The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distribution. $CN4_{cit}$ captures the market shares of the 4 largest firms in each country-industry-year (*cit*) group. All regressions include country-industry (*ci*), country-year (*ct*), and industry-year (*it*) fixed effects, country-industry linear time trends, and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. Standard errors are clustered at the country-industry (*ci*) level and reported in parentheses below point estimates. Columns (1)-(3), (4)-(6), and (7)-(9) use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The number of observations differs slightly compared to Table 3 due to dropping more singleton groups from the presence of the additional trends (Correia 2015).

Table 2.22 Superstar firms and the link between productivity and wage dispersion under fixed distributions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All sectors			Manufacturing			Services		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.77***			0.68***			0.86***		
	(0.07)			(0.13)			(0.10)		
$PD_{cit}^{90/50}$		0.82***			0.66***			0.90***	
		(0.10)			(0.18)			(0.15)	
$PD_{cit}^{50/10}$			0.64***			0.83***			0.75***
			(0.09)			(0.16)			(0.12)
$CN4_{cit}$	-0.13	-0.11	-0.01	-0.05	-0.02	-0.21	-0.28	-0.09	-0.15
	(0.19)	(0.12)	(0.13)	(0.32)	(0.20)	(0.21)	(0.29)	(0.21)	(0.20)
$PD_{cit}^{90/10} * CN4_{cit}$	-0.09			-0.14			-0.13		
	(0.12)			(0.21)			(0.16)		
$PD_{cit}^{90/50} * CN4_{cit}$		-0.20			-0.13			-0.20	
		(0.16)			(0.32)			(0.23)	
$PD_{cit}^{50/10} * CN4_{cit}$			0.01			-0.38			-0.02
			(0.14)			(0.24)			(0.18)
R^2	0.526	0.397	0.424	0.415	0.334	0.329	0.557	0.415	0.492
Observations	9,361	9,361	9,361	3,672	3,672	3,672	4,059	4,059	4,059

Notes: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration ($CN4_{cit}$), and their interaction (PD_{cit}*$CN4_{cit}$), i.e. β, γ and δ parameters in equation (8), respectively. The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distribution. Instead of constructing the productivity and wage dispersion measures from each distribution separately, we fix the wage distribution using the ranking of the productivity distribution. Specifically, we find the firms in the relevant productivity percentiles used to construct the productivity dispersion measures and use their corresponding wages to construct the wage dispersion measures. $CN4_{cit}$ captures the market shares of the 4 largest firms in each country-industry-year (*cit*) group. All regressions include country-industry (*ci*), country-year (*ct*), and industry-year (*it*) fixed effects, country-industry linear time trends, and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. Standard errors are clustered at the country-industry (*ci*) level and reported in parentheses below point estimates. Columns (1)-(3), (4)-(6), and (7)-(9) use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The number of observations differs slightly compared to Table 3 due to dropping more singleton groups from the presence of the additional trends (Correia 2015).

Table 2.23 Superstar firms and the link between productivity and wage dispersion with demeaned variables of the interaction term

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All sectors			Manufacturing			Services		
	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$	$WD_{cit}^{90/10}$	$WD_{cit}^{90/50}$	$WD_{cit}^{50/10}$
$PD_{cit}^{90/10}$	0.44***			0.42***			0.46***		
	(0.03)			(0.04)			(0.04)		
$PD_{cit}^{90/50}$		0.28***			0.26***			0.32***	
		(0.03)			(0.03)			(0.04)	
$PD_{cit}^{50/10}$			0.65***			0.50***			0.70***
			(0.05)			(0.05)			(0.07)
$CN4_{cit}$	0.02	-0.02	0.03	0.02	0.01	0.06	0.08	-0.00	0.08
	(0.04)	(0.02)	(0.03)	(0.05)	(0.02)	(0.03)	(0.06)	(0.03)	(0.05)
$PD_{cit}^{90/10} * CN4_{cit}$	-0.20***			-0.21*			-0.26***		
	(0.05)			(0.09)			(0.07)		
$PD_{cit}^{90/50} * CN4_{cit}$		-0.08*			-0.10			-0.11*	
		(0.04)			(0.08)			(0.05)	
$PD_{cit}^{50/10} * CN4_{cit}$			-0.39**			-0.08			-0.60**
			(0.12)			(0.13)			(0.19)
R^2	0.893	0.882	0.853	0.912	0.869	0.891	0.882	0.876	0.844
Observations	10,268	10,268	10,268	3,757	3,757	3,757	4,727	4,727	4,727

Notes: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. This table presents point estimates from regressing wage dispersion (WD_{cit}) on productivity dispersion (PD_{cit}), market concentration ($CN4_{cit}$), and their interaction (PD_{cit}*$CN4_{cit}$), i.e. β, γ and δ parameters in equation (8), respectively. The dispersion measures considered capture the entire (90/10), upper (90/50) and bottom (50/10) parts of the respective distribution. Following Giesselmann and Schmidt-Catran (2020), the interaction term is calculated after demeaning each of the interacted variables. $CN4_{cit}$ captures the market shares of the 4 largest firms in each country-industry-year (*cit*) group. All regressions include country-industry (*ci*), country-year (*ct*), and industry-year (*it*) fixed effects, country-industry linear time trends, and are weighted by the logarithm of total value added at the country-industry-year (*cit*) level. Standard errors are clustered at the country-industry (*ci*) level and reported in parentheses below point estimates. Columns (1)-(3), (4)-(6), and (7)-(9) use data for all sectors (NACE 10-82), manufacturing (NACE 10-33), and services (NACE 49-82), respectively. The number of observations differs slightly compared to Table 3 due to dropping more singleton groups from the presence of the additional trends (Correia 2015).

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Chapter 3

Price-cost margins and fixed costs

3.1 Introduction

The economic implications of institutional change, trade liberalization and anti-trust policy on market power have been widely conjectured and researched. The long-term trend of the global rise in markups (De Loecker, Eeckhout & Unger, 2020; Diez, Leigh & Duval, 2018; Hall, 2018) has stirred concerns not only about the efficiency of competition policy, but also about the potential macroeconomic effects of market power. The documented rise in global markups has been accompanied by a fall in investment rates (Gutierrez & Philippon, 2017), declining business dynamism (Decker, Haltiwanger, Jarmin & Miranda 2016; Bijnens & Konings, 2018) and the fall in the labor share (Autor, Dorn, Katz, Patterson & Van Reenen, 2020). This suggests that increased market power may have detrimental effects going beyond a single industry, affecting the overall economy (Syverson, 2019).

A key aspect in this debate is the measurement of market power, which is typically proxied by the markup, i.e. the ratio of price over marginal cost. In the absence of fixed costs, rising markups may reflect increasing market power as they are a good proxy for profitability. But in the presence of fixed costs, the rise in markups may just reflect a rise in fixed costs associated with production, such as overhead costs (e.g. rents, advertising, administration workers). Just as marginal costs are hard to observe, fixed costs in production are also not easily observed. Most of the literature estimating markups tends to ignore the role of fixed costs and assumes that one or all inputs are entirely variable. Yet, changes in the environment in which firms operate do not only affect price-cost margins, but also the scale of operations and hence the share of fixed costs in production. For instance, De Loecker et al. (2020) show that the rise in U.S. markups has been accompanied by an increase in fixed costs, proxied by a rise in the Selling, General & Administrative costs (SGA).[1] But since markups have

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[1] U.S. firms report costs of production in two main categories: costs of goods sold (COGS) and selling, general & administrative costs (SGA). They are often interpreted as a proxy for variable and fixed costs, respectively. De Loecker et al. (2020) document a rise of SG&A in total costs from 15% (1980) to 21% (2014). Unlike U.S. firms, European firms do not report their costs of production in these two categories. Instead, they report their costs by input without making a distinction between variable and fixed costs.

increased even faster, they argue that the rise in markups also reflects a rise in profitability and market power.

In this chapter, we develop and illustrate a new method, which simultaneously estimates price-cost margins and fixed costs in production, using standard production data on expenditures of inputs and revenues at the firm level. We start from the framework introduced by Hall (1988), and further extended by Roeger (1995), exploiting properties of the primal and the dual Solow residual for estimating price-cost margins using the observed variation in input and output values.

The main advantage of our approach is that it allows not only for the flexible treatment of capital (either fixed, variable or a combination of both) but also for the flexible treatment of other input factors, such as labor and intermediate inputs. We do not have to classify costs as quasi-variable or quasi-fixed[2], nor do we have to assume that one or all inputs are entirely variable.[3] Instead, the model estimates the share of fixity for each input factor based on variation in the underlying firm level data. Further, unlike most other approaches, we do not need to rely on unobserved product price data for deflating firm level sales or deflating input factors such as material costs. Our method makes use of nominal values rather than price deflators and real values. Another advantage of our approach is that it deals with the endogeneity problems caused by unobservable productivity shocks (Roeger, 1995). Finally, the method allows to directly estimate a weighted aggregate price-cost margin. To this end, we assume constant returns to scale in the *variable* input factors of production, the share of variable input factors adjusts freely within the time period, and perfectly competitive *input* markets.

We illustrate our method using longitudinal firm level data for Belgium for the period 1985-2014. We study both the level and the evolution of the price-cost margins over time. The rich time dimension of the data set enables us to distinguish cyclical variation from a secular trend.

Our main findings can be summarized as follows. First, accounting for the distinction between fixed and variable costs has a profound impact on the estimation of price-cost margins. Ignoring fixed costs typically underestimates price-cost margins and overestimates excess profitability. Second, the largest part of price-cost margins is needed to cover the fixed costs while only a smaller part remains left as excess profits ratio. In particular, as a fraction of sales, the price-cost margins, the fixed cost ratio and the excess profit margin are estimated at 25.9%, 23.4% and 2.5% respectively over the sample period.

[2] U.S. firms classify costs into costs of goods sold (COGS) or selling, general & administrative (SG&A). Classifying costs into the appropriate category is not always straightforward. Sometimes, costs are classified as COGS in one industry while being classified as SG&A in another industry, and vice versa.

[3] De Loecker and Warzynski (2012) develop a widely used method to estimate markups using production data. The assumption that at least one input is completely variable is key in this method. Often, capital and labor are thought of as at least partially fixed. Therefore, applications often assume that intermediate inputs are entirely variable. However, it is very unlikely that each and every category within intermediate inputs is completely variable. In section 3.4.3, we compare the estimates from their and our method.

Third, Belgian price-cost margins decline by 4.6 percentage points between 1985 and 2014. Our method allows to decompose the change of the price-cost margin into a change in the fixed costs ratio on the one hand and a change in the excess profits margin on the other hand. These components decrease respectively by 3.7 and 0.9 percentage points, thereby reinforcing each other. Finally, we show that heterogeneity is present at the sectoral level, both in level and in trend.

The remainder of the chapter is structured as follows. In the next section 3.2, we introduce our model which allows us to simultaneously estimate the price-cost margin and the share of fixity for each input. In section 3.3, we describe our data set, while section 3.4 discusses the estimation results and compares our estimation results to other methods which are currently used in the literature. Section 3.5 provides various robustness tests after which we conclude.

3.2 Methodology

We start by introducing the Hall (1988) framework, further extended by Roeger (1995), which estimates price-cost margins under imperfect competition in the output market. It assumes that all inputs (i.e. capital, labor and intermediate inputs) are entirely variable. Afterwards, we relax this assumption and allow inputs to be variable, fixed or a combination of both.

Our methodology builds on the concept of the Solow residual, which is a measure of total factor productivity (TFP) growth. The Solow residual can differ in two main dimensions. First, Solow residuals might use shares of inputs in operating revenue or total costs. Second, Solow residuals can be derived from the production function (primal) or the cost function (dual). Contrasting these four different Solow residuals enables us to estimate price-cost margins in the presence of fixed costs.

The intuition of the method builds on two principles. First, linking changes in output (i.e. quantity in the primal; prices in the dual) to weighted changes in inputs informs us about price-cost margins, i.e. how much prices differ from costs. Second, if one would like to increase output, then one can only raise the amount of variable inputs as fixed inputs are, by definition, fixed in the short-run. This gives information about the fixity of each input. Finally, we can decompose the price-cost margin into a part needed to cover the fixed costs after which another part remains left as excess profitability.

3.2.1 The Hall (1988) and Roeger (1995) approach[4]

We start from a production function $\mathrm{Q}_{it} = \mathrm{F}(\mathrm{K}_{it}, \mathrm{L}_{it}, \mathrm{M}_{it})\Theta_{it}$ for firm *i* at time *t*, where Q, K, L and M are quantities of output, capital, labor and intermediate inputs, respectively. Θ is an index of Hicks-

[4] Note that we follow the derivation and notation used in Konings, Roeger and Zhao (2011).

neutral technological progress.[5] Assuming perfect competition and constant returns to scale, the Solow residual $SRQ^R \equiv \Delta q - \frac{WL}{PQ}\Delta l - \frac{P^M M}{PQ}\Delta m - (1 - \frac{WL}{PQ} - \frac{P^M M}{PQ})\Delta k$ is an estimate of $\Delta\theta$ or the growth rate of total factor productivity (Solow, 1957). Define Δq , Δl, Δm and Δk as the growth rates of output, labor, intermediate inputs and capital, respectively. $\frac{\mathrm{WL}}{\mathrm{PQ}}$ and $\frac{\mathrm{P^M M}}{\mathrm{PQ}}$ are the shares of labor cost and intermediate input cost in operating revenue, respectively. W and $\mathrm{P^M}$ are the wage rate and the price of intermediate inputs. Assume for example that the product quantity increases by 5% (Δq) while the inputs (Δl, Δk and Δm) increase by 3%, then the firm becomes 2% more productive (SRQ^R) as it is able to produce proportionally more output.

Allowing the price to deviate from marginal costs, the Hall (1988) shows that the primal quantity-based Solow residual can be rewritten as a combination of a markup and a productivity component:

$$\mathrm{SRQ^R} \equiv \mathrm{B}(\Delta \mathrm{q} - \Delta \mathrm{k}) + (1 - \mathrm{B})\Delta\theta \quad (1)$$

with price-cost margin $\mathrm{B} \equiv \frac{\mathrm{P-MC}}{\mathrm{P}}$, which is linked to markups via $\mu = \frac{1}{1-B}$. Price-cost margins are typically within the interval [0, 1] whereas markups are in the interval [0, +∞).

This approach has been used to obtain an average estimate of the price-cost margin. An estimate of B larger than 0 rejects the model of perfect competition. This approach has been used in many papers using industry level or firm level data (e.g. Amit, Domowitz & Fershtmann, 1988; Waldmann, 1991; Morrison, 1992; Levinsohn, 1993; Norrbin, 1993; Harrison, 1994; Basu and Fernald, 1993; Klette, 1999; Konings, Van Cayseele & Warzynski, 2001; Hall, 2018). An important issue, however, in estimating equation (1) is that unobserved productivity shocks may be positively correlated with output (or input) growth. One possibility to address this is the use of instrumental variables but it has often turned out to be difficult to find good instruments, especially when firm level data are used. In addition, when the impact of policy changes is analyzed, not only price-cost margins may be affected, but also productivity and productivity growth (Harrison, 1994), which can bias the estimated change in price-cost margins. Finally, in equation (1) deflated sales are used to proxy for physical output, but with firm heterogeneity and multiple-product firms, this can introduce a bias (see Klette & Griliches, 1996; De Loecker, 2011; De Loecker & Warzynski, 2012).

One way to deal with these problems is the extension suggested by Roeger (1995). He derives the dual price-based Solow residual by solving the cost minimization problem. Following Roeger (1995), similar to the production function, we define the total cost function as $C(W, R, P^M, Q, \theta) = \frac{G(W,R,P^M)}{\theta} * Q$. G(.)

[5] To simplify notation, we omit firm and time subscripts. The empirical analysis is at the firm-year level. F(.) is a linear homogenous production function. We add the subscripts again in the final regression equations.

is the marginal cost function which is homogeneous of degree one. The dual price-based Solow residual is:

$$SRP^R \equiv \frac{WL}{PQ}\Delta w + \frac{P^M M}{PQ}\Delta p^M + \left(1 - \frac{WL}{PQ} - \frac{P^M M}{PQ}\right)\Delta r - \Delta p = -B(\Delta p - \Delta r) + (1 - B)\Delta\theta \qquad (2)$$

where Δp, Δw, Δp^M and Δr are the growth rates of product price, wage per employee, intermediate input price and the rental price of capital, respectively. Assume for example that the product price increases by 2% while all input prices increase by 1%, then SRP^R will equal -1% indicating that a firms' output price increases faster than its input prices.

By subtracting the dual from the primal Solow residual, unobserved productivity shocks cancel out and the aggregate price-cost margin B can be estimated consistently using equation (3), in which we add an i.i.d. error term[6], ϵ, as well as the corresponding subscripts for firm *i* and year *t*:

$$SRQ_{it}^R - SRP_{it}^R = B[(\Delta p + \Delta q)_{it} - (\Delta k + \Delta r)_{it}] + \epsilon_{it} \qquad (3)$$

An important advantage of equation (3) is the fact that all variables are expressed in nominal terms, hence, price deflators are not required for estimating B consistently. In particular, we can use the growth rate of operating revenue ($\Delta p + \Delta q$) which combines the growth rate of the product price (Δp) and the product quantity (Δq).

At this point, all factors of production are fully flexible and adjust to the equilibrium values in equation (3), which is not realistic. Typically, there are substantial overhead costs which are fixed and not directly attributable to the short run variations in output. We extend our framework and introduce fixed factors of production such that we can estimate price-cost margins as well as the shares of unobserved fixed input factors in a consistent way.

3.2.2 Solow residuals in the presence of fixed factors of production

We proceed by using the primal and dual *revenue-based* Solow residuals as well as the primal and dual *cost-based* Solow residuals. Contrasting these four Solow residuals allows to estimate price-cost margins in the presence of fixed costs. The roadmap of the derivations as well as the notation of this section builds on Konings, Roeger and Zhao (2011). They estimate price-cost margins in the presence of fixed capital and fixed labor, however, they do not allow for the existence of fixed intermediate

[6] At this stage, we assume that there is no measurement error, nor any specification error. We come back to these issues in this section (3.2.2.3) and in the robustness tests (3.5.1 and 3.5.3).

inputs, which is the most dominant input factor.[7] A key insight of our approach is that all production factors can be fixed, variable or a combination of both rather than only capital and/or labor.

3.2.2.1 Primal and dual Solow residuals with revenue-based shares

We use a standard short run[8] production function with constant returns to scale in the variable input factors for firm *i* at period *t*:[9]

$$Q = F(K^v, L^v, M^v)\Theta \qquad (4)$$

with physical output Q, variable capital input $K^v \equiv K - K^f$, variable labor input $L^v \equiv L - L^f$ and variable intermediate inputs $M^v = \mathrm{M} - \mathrm{M}^f$. Fixed inputs do not directly enter into the short run production function.[10] We implicitly assume that firms are price-takers in their input markets.[11] Θ is defined as before. $K^v(L^v\ ;\ M^v)$ is the part of total capital (labor; intermediates) which adjusts within a time period to current demand and cost changes without friction. On the other hand, $K^f(L^f\ ;\ M^f)$ is the part of total capital (labor; intermediates) which does not adjust within a period to current demand and cost changes. Examples of fixed capital, labor and intermediate inputs might consist out of rent for buildings, administration workers or the insurance for buildings, respectively (Stigler, 1939). On the other hand, examples of variable capital, labor and intermediate inputs might be a printer, a production worker or electricity, respectively. In a typical firm level dataset, there is information on the total amount of an input, but no clear distinction can be made between the variable and fixed component of that input.

Define sv^k, sv^l and sv^m as the share of variable capital $\frac{K^v}{K^v+K^f}$, the share of variable labor input $\frac{L^v}{L^v+L^f}$ and the share of variable intermediate inputs $\frac{M^v}{M^v+M^f}$, respectively. These terms contain the production technology that firms use but are not observable to the econometrician.

[7] Not allowing for fixed intermediate inputs might cause a large bias in the estimated coefficients due to the fact that intermediate inputs are the most dominant input factor.

[8] In the short run, one would expect that capital displays the highest level of fixity while intermediate inputs and labor are more variable. Our empirical findings will support this idea. Further, moving from the short run to the middle and long run, we would expect that the level of fixity decreases for each input, and especially so for capital. Robustness section 3.5.5 looks into the issue of short and long(er) time horizons, and empirically confirms this claim.

[9] The production function F(.) is homogeneous of degree one in the variable inputs.

[10] A firm uses both fixed and variable inputs in its production process. Every period, the firm has to pay, or allocate, a certain level of fixed factor inputs in order to be able to produce. These fixed inputs are necessary but, by definition, do not produce any output. For this, the firm needs variable input. At the margin, the firm can only vary its variable input whereas it cannot change its fixed input anymore within that time period.

[11] Crépon, Desplatz and Mairesse (2005) extend Hall's (1988) approach by relaxing the condition that the labor market is perfectly competitive. For applications of this approach, see Dobbelaere (2004) and Dobbelaere and Mairesse (2009). See section 3.5.7 for a discussion on how monopsony power in the labor and intermediate inputs market might affect our coefficients.

Deriving the primal revenue-based Solow residual: SRQ^R

The primal Solow residual is defined as in Hall (1988) and equals:

$$SRQ^R \equiv \Delta q - \frac{WL}{PQ}\Delta l - \frac{P^M M}{PQ}\Delta m - (1 - \frac{WL}{PQ} - \frac{P^M M}{PQ})\Delta k \qquad (5)$$

Assuming imperfect competition, the output growth is determined by a weighted sum of the variable input growth and the growth rate of productivity. The corresponding input weights are calculated as the ratio of the variable input costs over revenues, and then adjusted by the markup such that,

$$\Delta \mathrm{q} = \frac{\mathrm{P}}{\mathrm{MC}}\left(\frac{\mathrm{sv^k RK}}{\mathrm{PQ}}\Delta \mathrm{k^v} + \frac{\mathrm{sv^l WL}}{\mathrm{PQ}}\Delta \mathrm{l^v} + \frac{\mathrm{sv^{m} P^M M}}{\mathrm{PQ}}\Delta \mathrm{m^v}\right) + \Delta\theta \qquad (6)$$

where $\frac{\mathrm{sv^k RK}}{\mathrm{PQ}}$, $\frac{\mathrm{sv^l WL}}{\mathrm{PQ}}$ and $\frac{\mathrm{sv^{m} P^M M}}{\mathrm{PQ}}$ are shares of variable capital cost, variable labor cost and variable intermediate input cost in revenue, respectively. We assume constant returns to scale on variable inputs, hence, the total variable cost is $\mathrm{C^v} = \mathrm{MC} \cdot \mathrm{Q} = \mathrm{sv^k RK} + \mathrm{sv^l WL} + \mathrm{sv^m P^M M}$. Marginal costs are defined as $MC = \frac{G(W,R,P^M)}{\theta}$. More details on the derivation of Δq can be found in the Methodology appendix (3.7.4).

Inserting equation (6) into (5), we get the primal Solow residual with revenue-based shares.

$$SRQ^R = B(\Delta q - \Delta k) + \frac{(1-\mathrm{sv^l})WL}{PQ}(\Delta k - \Delta l) + \frac{(1-\mathrm{sv^m})P^M M}{PQ}(\Delta k - \Delta m) + \frac{\mathrm{sv^k} RK}{PQ}(\Delta \mathrm{k^v} - \Delta k) +$$
$$\frac{\mathrm{sv^l} WL}{PQ}(\Delta l^{\mathrm{v}} - \Delta l) + \frac{\mathrm{sv^m} P^M M}{PQ}(\Delta \mathrm{m^v} - \Delta m) + (1 - B)\Delta\theta \qquad (7)$$

Equation (7) shows that the presence of fixed factors introduces additional wedges between SRQ^R and Δθ , which are proportional to the share of fixed factors of production. The bias linked to the second and third component of equation (7) arises if labour and intermediate inputs are not entirely variable, i.e., sv^l or sv^m are smaller than one. In this case, the shares of labor and intermediate inputs in revenues overestimate the share of variable labor and variable intermediate inputs in revenues. This leads to a positive term which we multiply by $(\Delta k - \Delta l)$ and $(\Delta k - \Delta m)$ in respectively the second and third component. Considering the second component, assume for example that $sv^l = 0$, $\Delta k > \Delta l$ and $\Delta l > 0$. This implies that SRQ^R underestimates the true efficiency improvement Δθ. It assumes that part of Δq is due to Δl^{v}, but l^{v} is zero. The bias in the fourth, fifth and sixth component appears as soon as fixed inputs grow at a different rate than the total input. Looking at the fifth component, assume for example that $0 < sv^l < 1$, $\Delta l^{\mathrm{v}} > 0$, $\Delta l^f = 0$, such that $\Delta l^{\mathrm{v}} > \Delta \mathrm{l}$. This implies that the growth rate of labor underestimates the true increase of variable labor and therefore attributes part of Δq to an increase in efficiency. In the extreme case that all inputs are fixed (e.g. $sv^l = 0$), this bias disappears again.

Deriving the dual revenue-based Solow residual: SRP^R

Similar to the approach adopted by Roeger (1995), we consider alternative representations of the Solow residual to eliminate the unobservable components. First, we make use of the dual Solow residual to eliminate the growth rate of productivity in equation (7). The dual Solow residual is defined by equation (8) as,

$$SRP^R \equiv \frac{WL}{PQ}\Delta w + \frac{P^M M}{PQ}\Delta p^M + \left(1 - \frac{WL}{PQ} - \frac{P^M M}{PQ}\right)\Delta r - \Delta p \qquad (8)$$

Logarithmic differentiation of marginal costs and Shepard's lemma gives:

$$\Delta p = \frac{P}{MC}\left(\frac{\mathrm{sv^k RK}}{\mathrm{PQ}}\Delta r + \frac{\mathrm{sv^l WL}}{\mathrm{PQ}}\Delta w + \frac{\mathrm{sv}^m P^M M}{\mathrm{PQ}}\Delta p^M\right) - \Delta\theta \qquad (9)$$

Substituting equation (9) into equation (8), we obtain equation (10):

$$SRP^R = -B(\Delta p - \Delta r) + \frac{(1-\mathrm{sv^l})WL}{PQ}(\Delta w - \Delta r) + \frac{(1-\mathrm{sv^m})P^M M}{PQ}(\Delta p^M - \Delta r) + (1-B)\Delta\theta \qquad (10)$$

As with the primal Solow residual, the total revenue shares of labour and materials overstate the revenue shares of variable labour and variable materials.

Combining the primal and dual revenue-based Solow residual

By subtracting equation (10) from (7), we can eliminate the unobservable component $(1-B)\Delta\theta$:

$$SRQ^R - SRP^R = B[(\Delta p + \Delta q) - (\Delta k + \Delta r)] + \frac{(1-\mathrm{sv^l})WL}{PQ}(\Delta k + \Delta r) + \frac{(1-\mathrm{sv^m})P^M M}{PQ}(\Delta k + \Delta r) +$$
$$\frac{(\mathrm{sv^l}-1)WL}{PQ}(\Delta w + \Delta l) + \frac{(\mathrm{sv^m}-1)P^M M}{PQ}(\Delta p^M + \Delta m) + \frac{\mathrm{sv^k RK}}{\mathrm{PQ}}(\Delta \mathrm{k^v} - \Delta \mathrm{k}) + \frac{\mathrm{sv^l WL}}{\mathrm{PQ}}(\Delta \mathrm{l^v} - \Delta \mathrm{l}) +$$
$$\frac{\mathrm{sv^m}P^M M}{\mathrm{PQ}}(\Delta m^v - \Delta \mathrm{m}) \qquad (11)$$

Equation (11) shows that the difference of the primal Solow residual and the price-based dual Solow residual can be explained by input fixity and imperfect competition.[12] In contrast to equation (3), seven additional terms appear in equation (11) which make the prediction of the direction of the estimation bias of the Roeger (1995) approach impossible. The omission of the second, third and fourth component leads to a downward bias. The omission of the fifth, sixth and seventh component leads to an upward bias. Hence, equation (11) cannot be used to estimate B. The average share of fixed capital $sf^k \equiv 1 - sv^k$, the average share of fixed labor input $sf^l \equiv 1 - sv^l$ and the average share of fixed

[12] Shapiro (1987) focuses on capital fixity to explain why the primal Solow residual might be poorly correlated to the dual Solow residual. Roeger (1995) stresses imperfect competition in explaining the difference between the primal Solow residual and dual Solow residual. Konings, Roeger and Zhao (2011) consider fixed capital and fixed labor to explain the difference between the primal and dual Solow residual.

intermediate inputs $sf^m \equiv 1 - sv^m$ and the growth rates of variable inputs Δk^v, Δl^v and Δm^v are unobservable in the firm level data. The components Δk^v, Δl^v and Δm^v are likely to be positively correlated with the growth rate of output, which may lead to an upward bias in the estimate of the price-cost margins using equation (11).

In the next section we show that the unobservable terms, containing variations in variable factor inputs also appear in Solow residuals with cost based shares. This opens the possibility of eliminating these unobservable components by appropriately combining revenue and cost based Solow residuals.[13]

3.2.2.2 Primal and dual Solow residuals with cost-based shares

Hall (1990) proposes a cost-weighted measure as a way of avoiding the bias caused by imperfect competition. However, in the presence of fixed inputs, the cost-weighted Solow residual captures not only productivity growth but also the fixity of inputs. In this section, we derive cost-weighted primal and dual Solow residuals in the presence of fixed inputs.

Deriving the primal cost-based Solow residual: SRQ^C

The primal Solow residual with cost-based shares $\mathrm{SRQ^C}$ is defined as follows:

$$SRQ^C \equiv \Delta q - \frac{WL}{C}\Delta l - \frac{P^M M}{C}\Delta m - \frac{RK}{C}\Delta k \qquad (12)$$

Similarly, the growth rate of output can be written as a cost-weighted average of the growth rate of variable inputs plus the growth rate of productivity. Using $MC * Q = C^v$, equation (6) can be rewritten with weights equal to the respective share of the variable factor in total variable cost.

$$\Delta \mathrm{q} = \frac{\mathrm{sv^k RK}}{\mathrm{C^v}}\Delta \mathrm{k^v} + \frac{\mathrm{sv^l WL}}{\mathrm{C^v}}\Delta \mathrm{l^v} + \frac{sv^m \mathrm{P^M M}}{\mathrm{C^v}}\Delta \mathrm{m}^v + \Delta\theta \qquad (13)$$

Substituting equation (13) into (12), we get:

$$\mathrm{SRQ^C} = \left(1 - \mathrm{sv^k}\right)\frac{\mathrm{RK}}{\mathrm{C}}(\Delta \mathrm{q} - \Delta \mathrm{k}) + \left(1 - \mathrm{sv^l}\right)\frac{\mathrm{WL}}{\mathrm{C}}(\Delta \mathrm{q} - \Delta \mathrm{l}) + (1 - \mathrm{sv^m})\frac{P^M M}{\mathrm{C}}(\Delta \mathrm{q} - \Delta \mathrm{m}) +$$
$$\mathrm{sv^k}\frac{\mathrm{RK}}{\mathrm{C}}(\Delta \mathrm{k^v} - \Delta \mathrm{k}) + \mathrm{sv^l}\frac{\mathrm{WL}}{\mathrm{C}}(\Delta \mathrm{l^v} - \Delta \mathrm{l}) + \mathrm{sv^m}\frac{P^M M}{\mathrm{C}}(\Delta \mathrm{m^v} - \Delta \mathrm{m}) + \frac{\mathrm{C^v}}{\mathrm{C}}\Delta\theta \qquad (14)$$

While $\mathrm{SRQ^C}$ is a correct measure of $\Delta\theta$ irrespective of the level of the price-cost margin, it is nevertheless sensitive to fixed factors of production. In the presence of fixed factors, $\mathrm{SRQ^C}$ underestimates $\Delta\theta$ by the factor $\frac{\mathrm{C^v}}{\mathrm{C}}$ and is otherwise subject to the same types of bias as $\mathrm{SRQ^R}$.

[13] Roeger and Warzynski (2004) derive a similar estimation equation. However, they assume that the unobservable growth rate of variable capital in equation (11) can be proxied by the growth rate in labor productivity. Further, they do not allow for quasi-fixed labor, nor for quasi-fixed intermediate inputs.

Deriving the dual cost-based Solow residual: SRP^C

The dual cost minimization problem implies that the growth rate of price can be written as a (variable) cost-weighted average of the growth rate of inputs' prices minus the growth rate of productivity.

$$\Delta p = \frac{\mathrm{sv^k RK}}{\mathrm{C^v}}\Delta r + \frac{\mathrm{sv^l WL}}{\mathrm{C^v}}\Delta w + \frac{sv^m \mathrm{P^M M}}{\mathrm{C^v}}\Delta p^M - \Delta\theta \qquad (15)$$

The dual Solow residual with cost-based shares is then

$$SRP^C \equiv \frac{RK}{C}\Delta r + \frac{WL}{C}\Delta w + \frac{P^M M}{C}\Delta p^M - \Delta p = -\left(1-\mathrm{sv^k}\right)\frac{RK}{C}(\Delta p - \Delta r) - (1-\mathrm{sv^l})\frac{WL}{C}(\Delta p - \Delta w) - (1-\mathrm{sv}^m)\frac{P^M M}{C}(\Delta p - \Delta p^M) + \frac{\mathrm{C^v}}{\mathrm{C}}\Delta\theta \qquad (16)$$

Combining the primal and dual cost-based Solow residual

By subtracting equation (16) from equation (14), the growth rate of productivity $\frac{\mathrm{C^v}}{\mathrm{C}}\Delta\theta$ is eliminated. The difference of the primal and dual Solow residual with cost-based shares is,

$$SRQ^C - SRP^C = \left(1-\mathrm{sv}^k\right)\frac{RK}{C}[(\Delta p + \Delta q) - (\Delta k + \Delta r)] + \left(1-\mathrm{sv^l}\right)\frac{WL}{C}[(\Delta p + \Delta q) - (\Delta w + \Delta l)] + (1-\mathrm{sv^m})\frac{P^M M}{C}[(\Delta p + \Delta q) - (\Delta m + \Delta p^M)] + \frac{\mathrm{sv}^k RK}{C}(\Delta k^v - \Delta k) + \frac{\mathrm{sv}^l WL}{C}(\Delta l^v - \Delta l) + \frac{\mathrm{sv}^m P^M M}{C}(\Delta m^v - \Delta m) \qquad (17)$$

3.2.2.3 Difference-in-differences Approach

We find that in equation (11) and (17) the unobservable parts are similar except for the denominator. Multiplying both sides of equation (11) by firm-specific PQ and multiplying both sides of equation (17) by firm-specific C gives:

$$(SRQ^R - SRP^R)PQ = B \cdot PQ[(\Delta p + \Delta q) - (\Delta k + \Delta r)] + \left(1-\mathrm{sv^l}\right)WL(\Delta k + \Delta r) + \left(\mathrm{sv^l} - 1\right)WL(\Delta w + \Delta l) + (1-\mathrm{sv^m})P^M M(\Delta k + \Delta r) + (\mathrm{sv}^m - 1)P^M M(\Delta p^M + \Delta m) + \mathrm{sv}^k RK(\Delta k^v - \Delta k) + \mathrm{sv}^l WL(\Delta l^v - \Delta l) + \mathrm{sv}^m P^M M(\Delta m^v - \Delta m) \qquad (18)$$

$$(SRQ^C - SRP^C)C = \left(1-\mathrm{sv}^k\right)RK[(\Delta p + \Delta q) - (\Delta k + \Delta r)] + \left(1-\mathrm{sv^l}\right)WL[(\Delta p + \Delta q) - (\Delta w + \Delta l)] + (1-\mathrm{sv}^m)P^M M[(\Delta p + \Delta q) - (\Delta m + \Delta p^M)] + \mathrm{sv}^k RK(\Delta k^v - \Delta k) + \mathrm{sv}^l WL(\Delta l^v - \Delta l) + \mathrm{sv}^m P^M M(\Delta m^v - \Delta m) \qquad (19)$$

We allow for firm-specific heterogeneity and assume that B_i, sf_i^k, sf_i^l and sf_i^m are i.i.d. with unconditional mean $B, sf^k, sf^l \; and \; sf^m$ and stochastic terms $\epsilon_i^B, \epsilon_i^k, \epsilon_i^l, \epsilon_i^m$ with a mean of zero and variance $\sigma_i^B, \sigma_i^k, \sigma_i^l, \sigma_i^m$ respectively, in each year *t*. We regard firm-specific heterogeneity as the main

source of the error term, and assume that any other errors are captured by the pure measurement error term ϵ_{it}.

By subtracting equation (18) from equation (19), the unobserved parts $\mathrm{sv}^k RK(\Delta k^v - \Delta k)$, $\mathrm{sv}^l WL(\Delta l^v - \Delta l)$ and $\mathrm{sv}^m P^M M(\Delta m^v - \Delta m)$ cancel out. This yields the static correlated random coefficient model:

$$\left(SRQ_{it}^C - SRP_{it}^C\right)C_{it} - \left(SRQ_{it}^R - SRP_{it}^R\right)PQ_{it} = -(B_t + \epsilon_{it}^B)PQ_{it}[(\Delta p + \Delta q)_{it} - (\Delta k + \Delta r)_{it}] + (sf_t^k + \epsilon_{it}^k)RK_{it}[(\Delta p + \Delta q)_{it} - (\Delta k + \Delta r)_{it}] + (sf_t^l + \epsilon_{it}^l)WL_{it}[(\Delta p + \Delta q)_{it} - (\Delta k + \Delta r)_{it}] + (sf_t^m + \epsilon_{it}^m)P^M M_{it}[(\Delta p + \Delta q)_{it} - (\Delta k + \Delta r)_{it}] + \epsilon_{it} \qquad (20).$$

All variables in equation (20) are observable except for B, $\mathrm{s}f^k$, $\mathrm{s}f^l$ and $\mathrm{s}f^m$, so equation (20) can be estimated with firm-level data to obtain the coefficients: price-cost margin B, the share of fixed capital $\mathrm{s}f^k$, the share of fixed labor $\mathrm{s}f^l$ and the share of fixed intermediate input $\mathrm{s}f^m$. Since the left-hand side of equation (20) is the difference of the difference of the primal and dual Solow residual with cost-based shares and the difference of the primal and dual Solow residual with revenue-based shares, we call it a "difference-in-differences" (DID) approach.[14, 15]

As shown by Hsiao et al. (2019) the unconditional mean of the price-cost margin and the shares of fixed costs can be estimated consistently with a fixed effects estimator, even if the error terms are correlated with the regressors, provided regressors and error terms are distributed symmetrically.

Notice that the right hand sides of equation (18) and (19) have some common components capturing fixed inputs, which implies a positive correlation between $(SRQ^R - SRP^R)PQ$ and $(SRQ^C - SRP^C)C$.[16] If a firm's price-cost margin can exactly cover fixed cost, i.e., $B \cdot PQ = sf^K RK + sf^L WL + sf^m P^M M$, the right hand side of equation (20) is equal to 0 and thus $(SRQ^C - SRP^C)C = (SRQ^R - SRP^R)PQ$. In particular, the correlation between the difference of the primal and dual Solow residuals with revenue-based shares and that of the primal and dual Solow residuals with cost-based shares is stronger if price-cost margins go in the same direction as fixed costs.

3.2.2.4 Price-cost margins = Fixed costs ratio + Excess profits ratio

Price-cost margins can be decomposed into two components: the fixed costs ratio and the excess profits ratio. The former is needed to cover fixed costs whereas the latter represents the remaining

[14] The left-hand side consists of the components defined in equation (5), (8), (12) and (15).
[15] Our method assumes that inputs cannot influence demand (for a discussion on this, see Syversson (2011)). Furthermore, we have to assume that prices are uncorrelated with input choices at the firm-level. This assumption is likely to be less problematic in manufacturing than outside this sector.
[16] In the absence of fixed costs, the primal and dual cost-based Solow residual are equal.

profitability.[17] In absence of fixed costs, price-cost margins $\hat{B}$ are equal to the average firms' profitability. However, the existence of fixed costs introduces a wedge. We calculate the aggregate fixed costs ratio as $\widehat{FCR} \equiv (\widehat{sf}^{k} RK^{agg} + \widehat{sf}^{l} WL^{agg} + \widehat{sf}^{m} P^{M} M^{agg}) \,/\, PQ^{agg}$, where the superscript '*agg*' refers to the total amount of capital costs, labor costs, intermediate input costs and operating revenue at the aggregate level. The difference between the price-cost margins and the fixed costs ratio leads to the excess profits ratio $\widehat{EPR}$. This decomposition looks as follows:

$$\hat{B} = \widehat{FCR} + \widehat{EPR}. \tag{21}$$

Equation (21) shows that price-cost margins are no longer equal to profitability in the presence of fixed costs. Firms generate a margin to cover their fixed costs and to obtain excess profits. The evolution of price-cost margins depends on the combination of the evolution of the fixed costs ratio and the excess profits ratio. These components might reinforce, or offset each other.

3.2.2.5 Challenges and limitations

The main advantages of our approach are that (i) we do not have to classify inputs as quasi-variable or quasi-fixed[18], (ii) we do not need to rely on price deflators, (iii) the endogeneity problem between productivity shocks and growth in output or input factors is resolved and (iv) we obtain an aggregate price-cost margin estimate which can be decomposed into a fixed costs ratio and an excess profits ratio.[19, 20]

In comparison with Roeger (1995), we relax the assumption of constant returns to scale on all inputs to constant returns to scale on the variable inputs. Returns to scale might thus range from constant, i.e. if all costs are entirely variable, to increasing, i.e. if at least a part of the costs are fixed.[21] Further, we assume that all inputs are non-dynamic such that we rule out, for example, adjustment costs.[22]

[17] The excess profits ratio might be negative for some firms. This might happen if a firm generates a price-cost margin which is not large enough to cover its fixed costs.
[18] See section 3.4.3 for a discussion on the assumption of quasi-variable and quasi-fixed inputs.
[19] Much of the current debate is about the evolution of the aggregate price-cost margin. De Loecker et al. (2020) show that the aggregate markup rises from 21% above marginal costs in 1980 to 61% in recent years in the United States.
[20] Our method links changes in inputs to changes in output, and identifies the aggregate price-cost margin which suits the data best. Firms are not assumed to have the same markup, rather, we are only able to estimate an aggregate price-cost margin. Recent papers (e.g. De Loecker et al., 2020) have shown that markups might differ substantially at the firm-year level. Our approach is able to estimate price-cost margins and the shares of fixity as soon as we are able to aggregate up one level. We discuss this in more detail in section 3.5.8.
[21] When external information on the returns to scale is unavailable, the assumption of constant returns to scale on *all* inputs is commonly used in applied production papers as well as in applied work with firm-level data as aid to identification (Flynn, Gandhi and Traina, 2019). See section 3.5.7 for a discussion on how to interpret our results in the presence of non-constant returns to scale.
[22] Ackerberg, Benkard, Berry and Pakes (2007) or Asker, Collard-Wexler and De Loecker (2014) focus on the issue of dynamic inputs. An input is static if its current choice has no impact on future profits whereas an input is dynamic if it does. Intermediate inputs, and regularly labor as well, are considered to be non-dynamic or static inputs while capital can be thought of as dynamic due to, for example, adjustment costs.

Another concern might be measurement error in input factors. Since our model is estimated in first differences, it may exacerbate measurement errors, which leads to a downward bias of the estimates as suggested by Griliches and Hausman (1986) and Griliches and Mairesse (1995). However, this conclusion rests on the classical errors in variables in models under strict exogeneity. So whether the bias in first differences is larger than that in OLS, or vice versa, is unknown (Wooldridge, 2002). Our method allows that variables are measured in nominal values, rather that deflated input or output quantities. This limits the scope of mismeasurement profoundly, especially so for revenues, labor and intermediate input costs. Unfortunately, the nominal cost of capital is not observed and estimating this variable remains challenging. Therefore, we provide various robustness tests in robustness section 3.5.1. Reassuringly, our results are robust to alternative definitions of the cost of capital.

Finally, we might worry about a specification error. Following Roeger (1995), we allow the price-cost margin B and the various shares of fixed factor inputs sf^l, sf^k and sf^m to vary systematically with firm size. We provide a discussion about these concerns in robustness section 3.5.3.

3.3 Data

We illustrate our method by applying it to Belgian unconsolidated firm level data, obtained from the National Bank of Belgium.[23] This dataset covers all for-profit firms from 1985 until 2014. We use the following balance sheet variables in our analysis: operating revenue[24], wage costs, intermediate input costs, tangible fixed assets and depreciation. In order to compute the cost of capital, we extend the definition used by Hall and Jorgenson (1967). We refer to the data appendix in section 3.7.1 for more detailed information about the data.

Table 3.1 provides summary statistics. A Belgian firm generates on average an operating revenue of 34.05 million EUR. It pays 4.44 million EUR in wage costs and 26.63 million EUR in intermediate input costs. Belgian firms increase their nominal operating revenue on average by 7.1% while they face a 4.8% increase for their labor costs and a 7.3% for their intermediate input costs.[25] Tangible fixed assets increase by 1.7%. Further, we observe that the intermediate input share (77.9%) is the most dominant input factor, followed by the labor share (12.6%) and the capital share (9.6%).

[23] We provide a robustness test in which we exploit a proxy for consolidated accounts in section 3.5.6.

[24] Operating revenue captures the value of output produced in one period. We link this to the value of inputs used in the same period. On the other hand, sales capture the value of output sold and is not directly linked to the value of inputs. Taken to the extreme, a firm which does not produce anything (and thus uses no inputs) might still be able to sell some of its inventory. In this case, the operating revenue will be zero whereas sales will be positive. Note that we use operating revenue rather than revenue.

[25] We calculate the growth rate in year t as the increase (decrease) between year t-1 and year t relative to the average of the values in year t-1 and year t. This ensures that growth rates are part of the interval [-2.00, 2.00].

Table 3.1 Summary Statistics

Variable	Mean	SD	P25	P50	P75	N
PQ	34.05	282.16	2.90	7.67	18.79	358,143
WL	4.44	29.81	0.39	1.07	2.59	358,143
$P^M M$	26.63	258.09	1.57	5.19	13.96	358,143
TFA	6.92	81.84	0.11	0.57	2.05	358,143
Depreciation	1.30	13.86	0.04	0.16	0.53	253,451
ΔPQ	7.1%	24.4%	-2.5%	4.7%	13.9%	316,232
ΔWL	4.8%	21.8%	2.0%	3.7%	10.1%	316,232
$\Delta P^M M$	7.3%	26.3%	-3.1%	5.0%	15.5%	316,232
ΔTFA	1.7%	34.2%	-11.4%	-1.5%	1.04%	316,232
LS	0.126	0.137	0.022	0.085	0.170	358,143
MS	0.779	0.199	0.687	0.838	0.940	358,143
CS	0.096	0.119	0.029	0.052	0.115	358,143

Notes: : *The mean, standard deviation, P25, P50 and P75 are shown in nominal million EUR for operating revenue, wage costs, intermediate input costs, tangible fixed assets and depreciation. The number of observations are shown in units. The summary statistics for the growth rates and the input shares have been weighted by firm-year operating revenue. The labor (intermediates) share is calculated as total labor (intermediate input) cost divided by operating revenue.*

3.4 Results

Our results section consists out of three main parts. First of all, we present pooled estimation results over the period 1985-2014. We start by considering price-cost margins in the absence of fixed factors of production after which we relax this assumption and allow each input factor to have a variable and a fixed component. We compare both estimation results, and show that ignoring fixed input factors overestimates the excess profits ratio while it underestimates price-cost margins. The second section repeats this procedure at the yearly level such that we can look into potential secular trends. The third and final part compares the results based on our methodology to the price-cost margin estimation methods which are currently dominant in the literature.

3.4.1 Pooled estimation results: with and without fixed costs

Following Roeger (1995), we use equation (3) in order to estimate price-cost margins, and pool over the period 1985-2014. Hereby, we assume that capital, labor and intermediate inputs are fully flexible and adjust immediately to their equilibrium values without any adjustment costs. We weigh this regression by firm-year operating revenue to obtain a weighted aggregate price-cost margin for Belgium. We include a broad set of fixed effects: year, industry[26] and/or year-industry fixed effects.[27]

Next, we extend our framework and allow each input factor to have a variable and a fixed part. We make use of equation (20) to jointly estimate price-cost margins and the share of fixity for each input,

[26] An industry is defined as a NACE (rev. 2) two digits category.

[27] Note that the yearly estimates include only industry fixed effects while the industry estimates (see section 3.5.8) include only year fixed effects.

and pool over the entire sample period. Columns (1)-(6) and column 7 in Table 3.2 show the estimation results for the case without and with fixed costs, respectively.

As long as inputs are fully variable, price-cost margins are equal to the excess profits ratio since there are no fixed costs to cover. Introducing fixed input factors leads to a decomposition of price-cost margins into two components: one part is needed to cover fixed costs while the remaining part represents firms' profitability. We include the fixed costs ratio and the excess profits ratio as additional rows in Table 3.2.

Considering first the scenario without fixed costs in columns (1)-(6), we find that a price-cost margin of 8.0% maps one-to-one into an excess profits ratio of 8.0% due to the fact that the fixed costs ratio equals 0.0%. Column (7) shows the estimation results once we allow for fixed costs. Price-cost margins rise to a value of 25.9%, however, this does not mean that firms generate the same level for the excess profits ratio. Instead, the largest part (23.4%) is needed to cover fixed costs as a percentage of operating revenue while only a smaller part remains left as excess profits ratio (2.5%).[28, 29]

Table 3.2 Price-cost margins

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Price-cost Margins	0.079***	0.079***	0.080***	0.079***	0.080***	0.080***	0.259***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)	(0.012)	(0.016)
Share of Fixed Capital							0.679***
							(0.036)
Share of Fixed Labor							0.169***
							(0.028)
Share of Fixed Intermediates							0.236***
							(0.017)
Fixed Costs Ratio	-	-	-	-	-	-	*.234****
	-	-	-	-	-	-	*(0.016)*
Excess Profits Ratio	*0.079****	*0.079****	*0.080****	*0.079****	*0.080****	*0.080****	*.025****
	(0.010)	*(0.010)*	*(0.010)*	*(0.010)*	*(0.012)*	*(0.012)*	*(0.002)*
Year FE	No	Yes	No	Yes	No	No	No
Industry FE	No	No	Yes	Yes	No	No	No
Year-Industry FE	No	No	No	No	Yes	Yes	Yes
N	280,252	280,252	280,252	280,252	280,252	280,252	280,252
r2	0.272	0.276	0.274	0.278	0.349	0.349	0.510

Notes: *Columns (1)-(6) show results from equation (3). Column (7) shows results from equation (20). Regressions are weighted by operating revenue at the firm-year level. Standard errors in parentheses (+ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001). Standard errors are clustered by NACE 2 digits.*

[28] Note that total costs do not increase once we account for fixed costs. Rather, we are able to estimate which share of total costs is variable and which share is fixed.

[29] Traina (2018) defines the share of fixed costs in total costs as SG&A / (SG&A + COGS). Considering U.S. firms in 2016, it approximately equals 22% which is in the same order of magnitude as our Belgian fixed costs ratio.

If there would be truly no fixed costs, then we would estimate three insignificant coefficients for the shares of fixed inputs. In that case, equation (20) would collapse to equation (3). However, the estimated shares of fixed input factors show that this is clearly not the case as they are all (highly) significant. The highest share of fixed costs is found for capital (67.9%), followed by intermediate inputs (23.6%) and labor (16.9%).[30]

We are now able to define the price-cost margin 'bias' as the difference between the price-cost margins in the absence of fixed costs (column 6) and price-cost margins in the presence of fixed costs (column 7). Likewise, we can define the excess profits ratio 'bias' as the difference between the excess profits ratio in the absence of fixed costs (i.e. this equals the price-cost margins in the absence of fixed costs) and the excess profits ratio in the presence of fixed costs. The PCM bias and the EPR bias are respectively equal to 17.9% and 5.5%. The sum of these two types of bias is equal to the fixed costs ratio of 23.4%. Ignoring the existence of fixed costs would thus underestimate the price-cost margin and overestimate the excess profitability.

3.4.2 Yearly estimation results: with and without fixed costs

Until here, we estimated pooled price-cost margins thereby implicitly assuming that the price-cost margins and shares of fixed input factors remain constant over time. This may well be an unrealistic setting. Firms are likely to vary their price-cost margins as well as their mix of variable and fixed input factors in response to changing economic circumstances over time. In fact, a large strand of the price-cost margin literature deals with the question whether the secular trend of the price-cost margin has increased or not, and whether this change is due to a rise of market power or due to changes in the production process (De Loecker et al., 2020). In this section, we estimate equation (20) at the yearly level such that we obtain a yearly price-cost margin estimate and yearly estimates for the shares of fixed input factors.

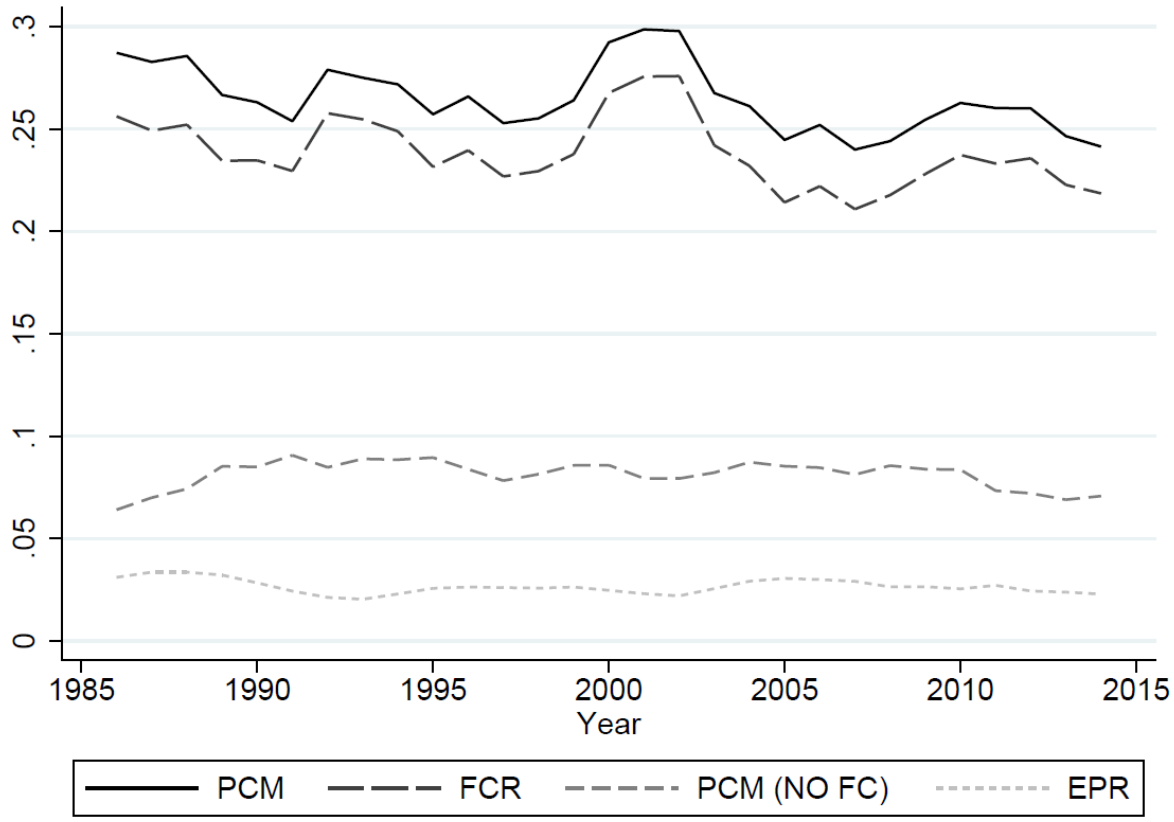
Figure 3.1 shows the evolution of Belgian price-cost margins, the fixed costs ratio and the excess profits ratio in the presence of fixed costs.[31] As a comparison, we add the evolution of price-cost margins in the absence of fixed costs, based on equation (3). Note that we lose the year 1985 due to the fact that we use growth rates in our regressions.[32]

[30] This does not mean that fixed capital will also be the largest component in terms of absolute fixed costs. In particular, the intermediate input share is 8.1 time as large as the capital share but the estimated share of fixed capital is 'only' 2.9 times as large as the estimated share of fixed intermediate inputs. Ignoring the presence of fixed intermediate inputs in the estimation of price-cost margins might induce a substantial bias.

[31] (Appendix) Table 3.8 displays the corresponding actual values for the price-cost margin, fixed-cost ratio and excess profits ratio. Figures display smoothed values. We also include standard errors and significance stars. Note that figures and numbers in the text refer to smoothed values.

[32] We omit confidence intervals in the figures in order to simplify it. All yearly coefficients are always significant in Figure 3.1.

Figure 3.1 Evolution of price-cost margins



Notes: *This figure shows the evolution of price-cost margins (equation 3), and the evolution of the price-cost margins, fixed cost ratio and the excess profits ratio (equation 20) at the yearly level. The evolution of variables has been smoothed. Each observation is the simple average of its current observations and one observation before and after its current observation.*

This figure reveals various interesting patterns. Overall, the Belgian price-cost margin displays a moderately decreasing trend and goes from 28.7% in 1986 to 24.1% in 2014.[33] This evolution seems to be driven by the fixed costs ratio which drops from 25.6% in 1986 to 21.9% in 2014. Both components experience quite some fluctuations from one year to the other.[34] Further, the excess profits ratio has been rather stable, especially during the past two decades. It falls from 3.1% in 1986 to 2.0% in 1993 after which it increases again until 3.0% in 2006. From 2007 onwards, the Belgian economy is hit by respectively the financial and European debt crisis such that the excess profits ratio falls again to a value of 2.2% in 2014.

Looking at price-cost margins in the absence of fixed costs, we find that they increase and decrease moderately at respectively the beginning and the end of the sample period while they barely move between 1990 and 2009. These dynamics differ clearly from the evolution of the price-cost margins

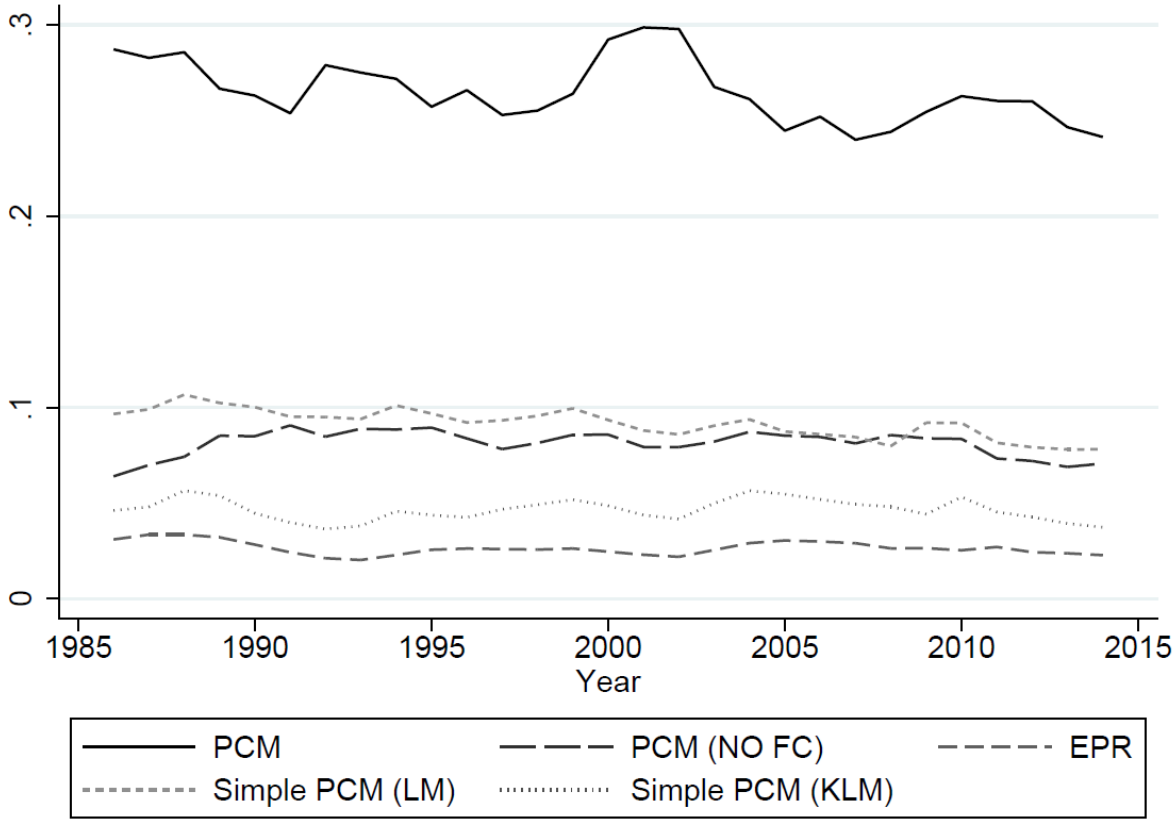
[33] De Loecker, Fuss and Van Biesebroeck (2018) find that Belgian price-cost margins are falling in recent decades.
[34] Moreover, part of the variation in the price-cost margin and the fixed costs ratio seems to be linked to the business cycle. The price-cost margins and the fixed costs ratio reach a peak around the early '90s, the early '00s and the end of the '00s, which corresponds to years with an economic slowdown or recession in Belgium. See Bormans, Konings and Muraközy (2020) for a paper which looks at the cyclicality of the price-cost margin and its components.

and the excess profits ratio in the presence of fixed costs. The next section compares our estimation results in more detail to methods which are currently dominantly used in the literature.

3.4.3 Comparison with other price-cost margin estimation methods

We compare our estimation results to two other methods. First of all, we look at price-cost margins based on the accounting approach. Second, we compare our estimates to the De Loecker and Warzynski (2012) framework.

Figure 3.2 Evolution of price-cost margins and simple price-cost margins



Notes: *This figure shows the evolution of the price-cost margin, excess profits ratio (equation 20), price-cost margins (equation 3) and the two simple price-cost margins at the yearly level. The evolution of variables has been smoothed. Each observation is the simple average of its current observations and one observation before and after its current observation.*

Our baseline price-cost margin estimates originate from a so-called production function approach. Another well-known approach is the accounting approach. For example, Cavallerri et al. (2019) explore the evolution of the markup in the euro area. Their 'simple markup' is defined as the ratio of operating revenue over the sum of wage costs and intermediate input costs at the country-year level. We calculate this markup and convert it into a price-cost margin. Additionally, we calculate a second simple markup as the ratio of operating revenue over the sum of wage costs, intermediate input costs and capital costs.

Figure 3.2 shows the price-cost margins, with and without fixed costs, the excess profits ratio and the two 'simple' price-cost margins (LM refers to labor and intermediate inputs; KLM refers to capital, labor and intermediate costs). We observe that the evolution of the price-cost margin in the absence of fixed cost and the two simple price-cost margins are reasonably similar in terms of level and trend over time. None of these measures are able to distinguish between variable and fixed costs as they rely on the concept of total costs. Therefore, the simple price-cost margin might be a good proxy for price-cost margins in the absence of fixed costs. However, these measures do not match the dynamics of our baseline estimation results.

Next, we compare our estimation results to the markups obtained by the De Loecker and Warzynski (2012) framework. Their markup can be obtained as follows:

$$\mu_{it} = \theta_{it}^{V} * (\alpha_{it}^{V})^{-1}$$

with μ_{it}, θ_{it}^{V} and $(\alpha_{it}^{V})^{-1}$ denoting respectively the markup, the output elasticity of the variable input and the inverse of the corresponding revenue share at the firm-year level. Firm-specific markups are then aggregated into an aggregate markup, taking firm size weights into account. This looks as follows:

$$\mu_t = \sum_i m_{it}\mu_{it}$$

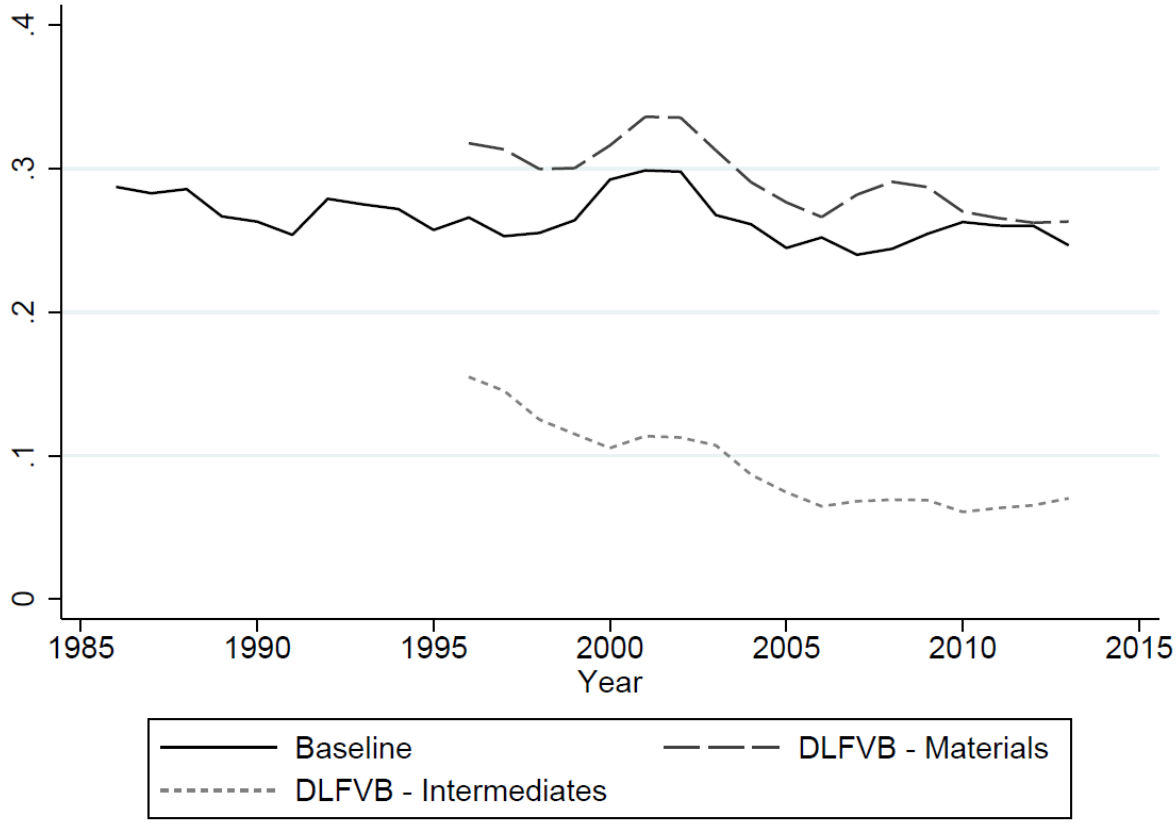
with m_{it} denoting the market share for firm *i* in a specific market in year t.

The method requires one input which is entirely variable, and often intermediate inputs are used for this. However, De Loecker et al. (2018) claim that intermediate inputs might still contain various quasi-fixed categories. They exploit a unique feature of the Belgian firm level data: since 1996, firms have to break down their intermediate inputs into materials and services inputs.[35] De Loecker, Fuss & Van Biesebroeck (2018)[36] claim that service inputs are quasi-fixed whereas materials are quasi-variable. If this is true, then markups based on material inputs on the one hand and markups based on services inputs on the other hand would lead to different estimated markups. The former markup should be accurate while the latter one would be biased. We follow the estimation procedure used in De Loecker et al. (2018)[37] and estimate markups, once based on material inputs and once based on intermediate inputs. We convert these aggregate markups in aggregate price-cost margins. Figure 3.3 shows the evolution of these estimates as well as the evolution of our baseline results.

[35] Intermediate inputs, material inputs and services inputs are respectively classified as category 60/61, 60 and 61 in the financial statement. The sum of material and services inputs is equal to intermediate inputs.
[36] We use the abbreviation DLFVB to refer to the estimation procedure used in their paper.
[37] We follow De Loecker et al. (2018) and compute a normalized aggregate markup in which we normalize the output elasticity such that the median firm markup equals 1.1 over the sample.

We observe that the DLFVB price-cost margins based on materials fall from 31.8% in 1996 to 26.3% in 2014 while our baseline price-cost margins fall from 26.6% in 1996 to 24.1% in 2014. The DLFVB price-cost margins based on intermediate inputs fall from 15.5% in 1996 to 7.0% in 2014. This means that our baseline price-cost margins correspond reasonably well to the DLFVB price-cost margins based on *materials*, in level as well as in (secular and cyclical) trend.

Figure 3.3 Evolution of price-cost margins: Baseline and DLFVB estimates



Notes: *This figure shows the evolution of our baseline price-cost margins, and the price-cost margins based on DLFVB estimates (once based on materials as variable input and once based on intermediate inputs as variable input) at the yearly level. The evolution of variables has been smoothed. Each observation is the simple average of its current observations and one observation before and after its current observation. DLFVB refers to the estimation procedure applied by De Loecker et al. (2018).*

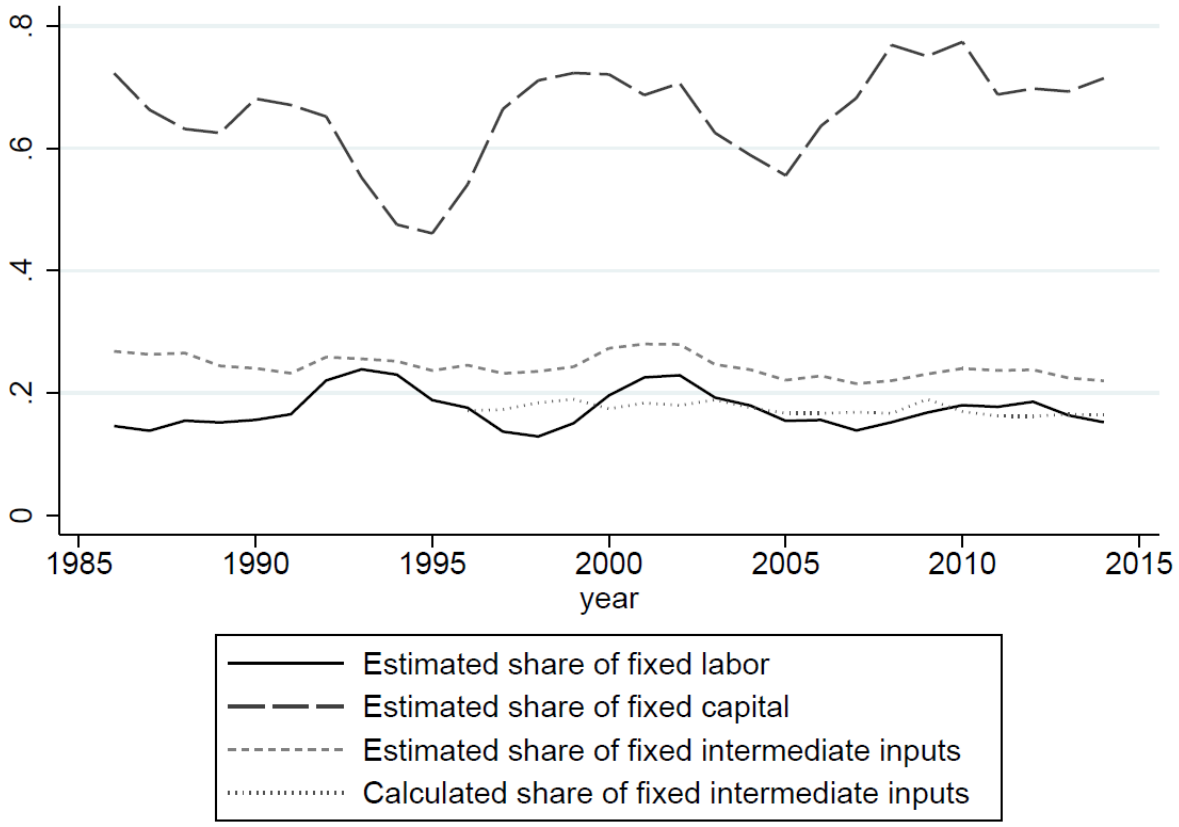
On the other hand, our baseline results clearly differ from the DLFVB price-cost margins based on *intermediate inputs*. This suggests that one should estimate price-cost margins based on material inputs rather than intermediate inputs, as intermediate inputs might contain a substantial part of quasi-fixed categories. However, this distinction between material inputs and services inputs is typically not available in European firm-level datasets. This implies that one should provide strong arguments on why an input would be entirely variable if one is about to implement the De Loecker et al. (2018) framework, an issue often overlooked in the literature.

If one assumes that material inputs and services inputs are quasi-variable and quasi-fixed, respectively, then we should find that our estimated share of fixed intermediate inputs $\widehat{sfm}$ is reasonably similar to

a proxy for this: the calculated share of fixed intermediate inputs. The calculated share of fixed intermediate inputs is defined as service inputs over intermediate inputs (i.e. the sum of material and services inputs).

Figure 3.4 shows the evolution of the estimated share of fixed inputs and the calculated share of fixed intermediate inputs.[38] Both trends appear to evolve in parallel over time.[39] The calculated share is in the same order of magnitude, but is lower than the estimated share of fixed intermediate inputs.

Figure 3.4 Estimated and calculated share of fixed intermediate inputs



Notes: *This figure shows the evolution of the estimated share of fixed intermediate inputs (equation 20) and the calculated share of fixed intermediate inputs for the Belgian economy.*

Note that the calculated share of fixed intermediate inputs assumes that materials and services are respectively entirely variable and fixed. This might hold for the vast majority of these categories, however, one can argue that some of the underlying components are respectively fixed and variable. This is likely to shift the level of the calculated share of fixed intermediate inputs.[40] Our estimated

[38] Note that the Belgian dataset allows to construct a proxy for the share of fixed intermediate inputs, however, this level of disaggregation is not needed for the main analysis.

[39] The estimated share of fixed intermediate inputs equals 24.5% in 1996 and moves to 22.0% in 2014, whereas the calculated share of fixed intermediate components equals 17.1% in 1996 and 16.4% in 2014.

[40] It is likely that this will increase the calculated share of fixed intermediate inputs as this measure assumes that materials, by far the largest component of intermediate inputs, are entirely variable. Even if a small fraction of materials is quasi-fixed, then, this might dominate the possibility that a fraction of services is quasi-variable. However, the data does not allow us to verify this claim. The correlation between the estimated and calculated share of fixed intermediate inputs is 0.45.

share of fixed intermediate inputs does not require us to specify ex-ante whether a specific input is fixed or variable.

3.5 Robustness tests

This part provides various robustness tests. First, we delve deeper into the error term. In particular, we discuss measurement error, and especially so for the cost of capital. The second part considers weighted and unweighted aggregate price-cost margins after which we look into specification issues. The fourth part presents sectoral estimates. Next, we consider five-year and ten-year differences in the fifth part after which we use a proxy for consolidated accounts in the sixth section. The seventh part explores how non-constant returns to scale and how monopsony power affect our coefficients. Finally, we elaborate on how our approach can be used to obtain estimates at a more disaggregated level.

3.5.1 Measurement error: cost of capital

Pinning down the cost of capital remains challenging as there might be measurement error in the nominal cost of capital. We provide three alternative definitions: the first one considers the firms' loan rate instead of the Belgian government long-term interest rate. The second one uses an adjusted formula for the capital allowance by including a capital allowance for patents as well. The third adjustment considers a risk premium for the Belgian market.

3.5.1.1 Loan rate

First, we replace the Belgian long-term interest rate by the cost of borrowing for firms, which we call the loan rate. This loan rate is closer related to the real borrowing cost for corporations than the Belgian long-term interest rate, however, data are only available from 2003 onwards. The loan rate is made available by the Statistical Data Warehouse of the European Central Bank. (Appendix) table 3.7 displays the values for the nominal interest rate and the loan rate. During the Financial crisis, the loan rate is above the Belgian long-term interest rate. During the European debt crisis, the loan rate is lower than the Belgian long-term interest rate.

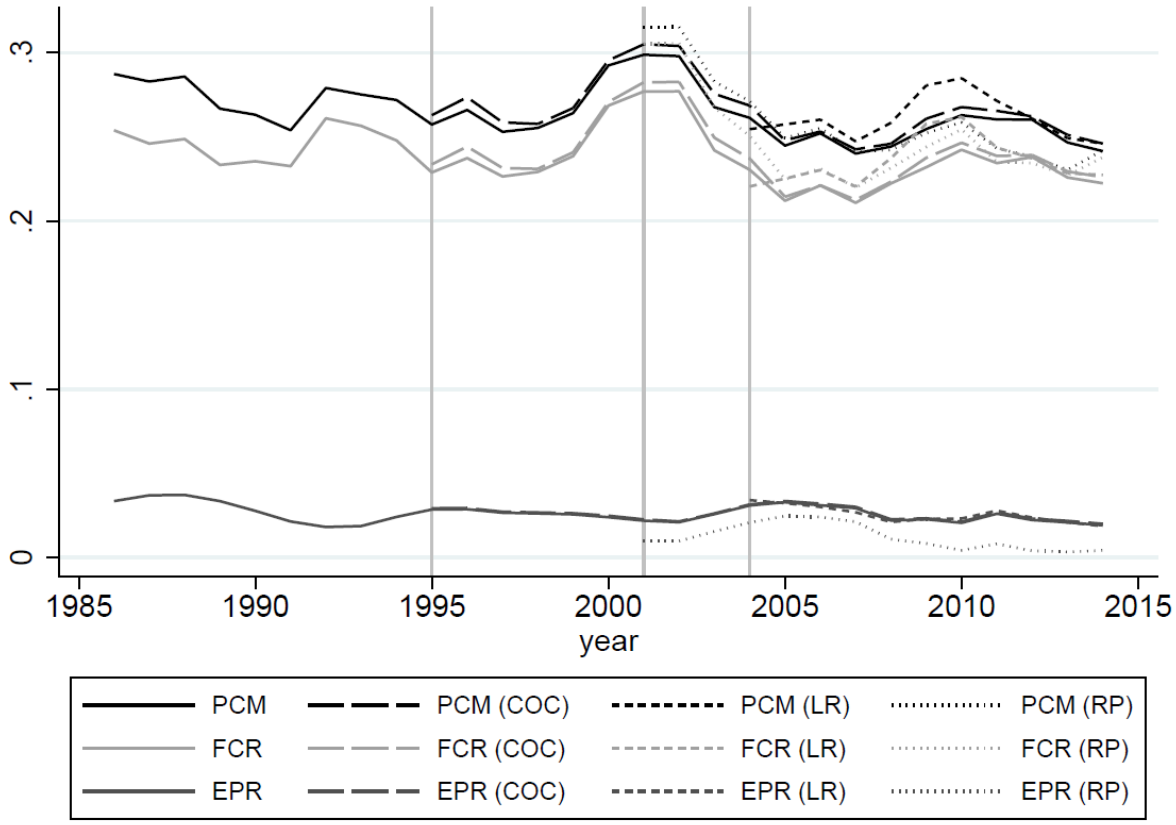
We compare our new results with our baseline results in Figure 3.5.[41] The new results are consistent with our main findings: the excess profits ratio remains basically unchanged while the fixed costs ratio and the price-cost margins are close to the baseline results, i.e. they are slightly higher, especially during the Financial Crisis.

[41] (Appendix) Table 3.12 displays the corresponding actual (not smoothed) values for the price-cost margin, fixed-cost ratio and excess profits ratio. We also include standard errors and significance stars.

3.5.1.2 Capital allowances

The second robustness test considers an adjustment of the cost of capital. Our baseline cost of capital measure considers capital allowances for machines and buildings. Additionally, we also take patents into account, made available by the OECD (2021). Note that these data are only available from 1994 onwards. We add these values to (appendix) table 3.7 as well.

Figure 3.5 Evolution of excess profits ratio: cost of capital & loan rate



Notes: *This figure shows the evolution the excess profits ratio (equation 20) under various robustness tests for the Belgian economy. The evolution of Belgian variables has been smoothed. Each observation is the simple average of its current observations and one observation before and after its current observation.*

We show the results in Figure 3.5 and demonstrate that our main findings still hold.[42] The price-cost margins, fixed costs ratio and excess profits ratio are very similar to our baseline results.

3.5.1.3 Risk premium

Next, we include a market risk premium in the calculation of our cost of capital. We source the values for this risk premium from www.market-risk-premia.com (Fenebris, 2021). Data is available from 2000

[42] (Appendix) Table 3.13 displays the corresponding actual (not smoothed) values for the price-cost margin, fixed-cost ratio and excess profits ratio. We also include standard errors and significance stars.

onwards and included in (appendix) table 3.7. Figure 3.5 visualizes the new results, and shows that the excess profits ratio follows the same trend but at a lower level.[43] The aggregate risk premium increases the cost of capital, which decreases the excess profits ratio. The price-cost margin and the fixed cost ratio follow a similar pattern as the baseline results.

3.5.2 (Un)weighted aggregate price-cost margins

This section looks into the difference between the unweighted and the weighted aggregate price-cost margin. Hall (1988) and Roeger (1995) estimate an unweighted aggregate price-cost margin. Their empirical analysis uses industry level data. The approach basically links the growth rate of inputs to the growth rate of output, thereby implicitly assuming equal weight for all the industries.

Table 3.3 Price-cost margins: Weighted and Unweighted

	(1)	(2)	(3)	(4)
Weighted	**Yes**	**No**	**Yes**	**No**
Price-Cost Margins	0.080***	0.116***	0.259***	0.416***
	(0.012)	(0.016)	(0.016)	(0.045)
Share of Fixed Capital			0.679***	0.924***
			(0.036)	(0.050)
Share of Fixed Labor			0.169***	0.331***
			(0.028)	(0.040)
Share of Fixed Intermediates			0.236***	0.419***
			(0.017)	(0.053)
Fixed Costs Ratio	-	-	.234***	.407***
	-	-	(0.016)	(0.048)
Excess Profits Ratio	-	-	.025***	.009***
	-	-	(0.002)	(0.003)
Year-Industry FE	Yes	Yes	Yes	Yes
N	280,252	280,252	280,252	280,252
r2	0.349	0.327	0.510	0.534

Notes: *Standard errors are clustered by NACE 2 digits. Standard errors in parentheses (* p < 0.05, ** p < 0.01, *** p < 0.001). Odd (even) columns are (not) weighted by operating revenue at the firm-year level.*

In order to estimate a weighted aggregate price-cost margin, we deviate on two aspects. First, we use firm level data rather than industry level data. This allows to exploit variation between industries as well as between firms within an industry. Second, we weigh our regressions. We take into account that larger firms have a stronger impact on the aggregate price-cost margin. In the absence of fixed factors, we weigh equation (3) by operating revenue at the firm-year level. The weights are allowed to vary over time. This allows to capture potential reallocation effects. In particular, assume that a large firm with a high price-cost margins is growing, then this would push the aggregate price-cost margin

[43] (Appendix) Table 3.14 displays the corresponding actual (not smoothed) values for the price-cost margin, fixed-cost ratio and excess profits ratio. We also include standard errors and significance stars.

upwards. In the presence of fixed factors, firm-year specific weights are introduced as we go from equation (11) and (17) to respectively equation (18) and (19). The former equations are multiplied by firm-year operating revenue or firm-year total costs. We divide equation (20) again by operating revenue at the firm-year level. This eliminates the firm size dimension as all firms have a 'rescaled' operating revenue of one, while the growth rates remain the same. Doing so, all firms have an equal weight and regression results are no longer driven by firm size but only by the growth rates of the (variable) inputs and output.

Table 3.3 displays a comparison of weighted and unweighted aggregate price-cost margins based on firm level data. Columns (1) and (3) display the weighted aggregate price-cost margin while columns (2) and (4) display the unweighted aggregate price-cost margin. We find that weighted price-cost margins are smaller than unweighted price-cost margins. This suggests that large firms are characterized by lower price-cost margins. This is at odds with the bulk of the literature which finds that large firms also have large markups (e.g. Autor et al., 2020; De Loecker et al., 2020). However, the literature typically assumes that price-cost margins can be interpreted as profitability and vice versa. As we already showed, this is no longer necessarily the case once fixed costs are present. Therefore, we decompose the price-cost margin into the fixed costs ratio and the excess profits ratio. We find that the estimated weighted share of factor inputs in column (3) is smaller than the estimated unweighted share of factor inputs in column (4) for each input. Therefore, large firms have lower price-cost margins as well as a lower fixed costs ratio. Ex-ante, it is not clear whether large firms have a higher profitability or not.

Therefore, we decompose the price-cost margin into a fixed costs ratio and an excess profits ratio. We find that the unweighted excess profits ratio equals 0.9% whereas the weighted excess profits ratio equals 2.5%. Therefore, we can conclude that large firms have a lower price-cost margin and a lower fixed costs ratio, however, they are able to generate a higher excess profits ratio than smaller firms. Again, this shows that fixed costs create a wedge between price-cost margins and the excess profits ratio and both concepts cannot be used interchangeably. The literature typically finds that large firms possess more market power which is in line with our finding that large firms have a higher profitability level (e.g. Autor et al., 2020; De Loecker et al., 2020).

3.5.3 Specification error

Now, we look into a possible specification error. We allow the price-cost margin and the shares of fixed factor inputs to vary by firm size. We start from equation (20), pooled over the sample period, and allow the price-cost margin and shares of fixed factor inputs to depend on firm size. We introduce the impact of firm size as follows,

$$B_i = B + \beta_1 * [PQ_{it} - mean(PQ_{it})]$$

$$sf_i^k = sf^k + \beta_2 * [PQ_{it} - mean(PQ_{it})_t]$$

$$sf_i^l = sf^l + \beta_3 * [PQ_{it} - mean(PQ_{it})_t]$$

$$sf_i^m = sf^m + \beta_4 * [PQ_{it} - mean(PQ_{it})_t]$$

and introduce this into equation (20) such that we obtain,

$$\begin{aligned}(SRQ_{it}^C - SRP_{it}^C)C_{it} - (SRQ_{it}^R - SRP_{it}^R)PQ_{it} = B * PQ_{it} * [(\Delta p + \Delta q)_{it} - (\Delta k + \\ \Delta r)_{it}] + sf^k * RK_{it} * [(\Delta p + \Delta q)_{it} - (\Delta k + \Delta r)_{it}] + sf^l * WL_{it} * [(\Delta p + \Delta q)_{it} - \\ (\Delta k + \Delta r)_{it}] + sf^m * P^M M_{it} * [(\Delta p + \Delta q)_{it} - (\Delta k + \Delta r)_{it}] + \beta_1 * PQ_{it}[PQ_{it} - \\ mean(PQ_{it})_t] * X_{1it} + \beta_2 * RK_{it} * [PQ_{it} - mean(PQ_{it})_t] * X_{2it} + \beta_3 * WL_{it} * [PQ_{it} - \\ mean(PQ_{it})_t] * X_{3it} + \beta_4 * P^M M_{it} * [PQ_{it} - mean(PQ_{it})_t] * X_{4it} + FE + \varepsilon_{it}.\end{aligned} \quad (22)$$

Assuming that fixed costs are not present and dividing again by PQ_{it}, this formula collapses to equation (23),

$$\begin{aligned}SRQ_{it}^R - SRP_{it}^R = B[(\Delta q + \Delta p)_{it} - (\Delta k + \Delta r)_{it}] + \beta_1 * [PQ_{it} \\ - mean(PQ_{it})_t][(\Delta q + \Delta p)_{it} - (\Delta k + \Delta r)_{it}] + FE + \varepsilon_{it}\end{aligned} \quad (23)$$

We divide equation (22) again by PQ_{it} and show the results in Table 3.4. This repeats the unweighted results for Belgium between 1985 and 2014 in columns (1) and (3). Columns (2) and (4) extend these estimation results by taking the components linked to firm size into account as in equation (23) and (22) respectively.

Looking at columns (1) and (2), we find that, evaluated at the mean, price-cost margins are approximately the same. As firm size increases, the estimated price-cost margin decreases. This implies that large firms are estimated to have lower price-cost margins. The estimated coefficient is significant, however, the economic magnitude is small as firms need to have an operating revenue of one billion euros above the mean value to lower the average price-cost margins by 1.35 percentage points in Belgium.[44] Next, column (4) shows that β_1 is significant and negative. Firms with an operating revenue of one billion euros above the mean value have a price-cost margin which is 4.1 percentage points lower. Larger firms also have a lower share of fixed capital, fixed labor and intermediate input. So, large firms tend to have lower price-cost margins and a lower fixed cost ratio. Nevertheless, they have a higher excess profits ratio.

[44] Firm-specific operating revenue is divided by one billion in order to be able to interpret the estimated coefficients.

Table 3.4 Price-cost margins and shares of fixed input factors: Control for firm size

	(1)	(2)	(3)	(4)
Price-cost Margins	0.116***	0.116***	0.416***	0.416***
	(0.0156)	(0.0157)	(0.045)	(0.045)
Share of Fixed Capital			0.924***	0.920***
			(0.050)	(0.050)
Share of Fixed Labor			0.331***	0.328***
			(0.040)	(0.040)
Share of Fixed Intermediates			0.419***	0.418***
			(0.053)	(0.053)
β_1		-0.0135**		-0.041**
		(0.00399)		(0.013)
β_2				-0.218*
				(0.102)
β_3				-0.154*
				(0.063)
β_4				-0.043**
				(0.015)
Year-Industry FE	Yes	Yes	Yes	Yes
N	280252	280252	280252	280252
r2	0.327	0.327	0.534	0.535

Notes: *Standard errors in parentheses (+ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001). Standard errors are clustered by NACE 2 digits.*

3.5.4 Sectoral results: Industry, Trade & Services

Aggregate price-cost margins might hide heterogeneity at a lower level. We look at the sectoral level and consider three broad sectors: Industry, Trade and Services. The sectors consists respectively of NACE rev. 2 categories 10/33, 45/47 and 49/82. This section follows the same structure as before: we start from the assumption that all inputs are fully variable after which we introduce fixed costs. Finally, we look at the evolution of the sectoral price-cost margins over time.

Table 3.5 shows the Belgian result in column (1) and the sectoral results in columns (2) until (4). This shows sizable heterogeneity among sectors. For example, price-cost margins in Services (12.6%) and Industry (9.1%) are above the Belgian price-cost margins (8.0%) while price-cost margins in Trade (5.1%) are below this value. Moreover, price-cost margins in Services are two and a half times as large as price-cost margins in Trade.

We extend our estimation framework again by allowing for variable and fixed input factors in the production process, and show these results in columns (5) until (8) in Table 3.5. This reveals two interesting findings. First, price-cost margins increase, probably because firms need part of it to cover their fixed costs. Second, the order of the price-cost margins changes once we include fixed costs. For example, Industry rather than Services has the largest price-cost margins once we account for fixed costs. The ranking reversal is mainly due to the fact that the estimated shares of fixed input factors are

higher for each input in Industry compared to Services. Firms charge a higher margin as they have to cover more fixed costs.

Further, we use the estimated shares of fixed input factors in order to calculate the fixed costs ratio. We subtract the fixed costs ratio from the price-cost margin and obtain the excess profits ratio. We include this fixed costs ratio and excess profits ratio in additional rows in Table 3.5. We observe that sectors with the highest price-cost margins also have the highest fixed costs ratio but not necessarily the highest excess profits ratio. This suggests that most of the price-cost margin goes to covering fixed costs. Looking at the excess profits ratio, we find that Trade (2.8%) and Industry (2.7%) have the highest profitability whereas Services (1.3%) has the lowest profitability.

Table 3.5 Price-cost margins: Sectoral level

	(1)	(2) Industry	(3) Trade	(4) Services	(5)	(6) Industry	(7) Trade	(8) Services
Price-cost Margins	0.080***	0.091***	0.051**	0.126***	0.259***	0.339***	0.246**	0.237***
	(0.012)	(0.008)	(0.003)	(0.010)	(0.016)	(0.029)	(0.022)	(0.025)
Share of Fixed Capital					0.679***	0.713***	0.988**	0.699***
					(0.036)	(0.045)	(0.047)	(0.069)
Share of Fixed Labor					0.169***	0.264***	0.185*	0.104*
					(0.028)	(0.044)	(0.041)	(0.046)
Share of Fixed Intermediates					0.236***	0.317***	0.219*	0.234***
					(0.017)	(0.031)	(0.022)	(0.025)
Fixed Costs Ratio	-	-	-	-	*.234****	*.311****	*.218***	*.224****
	-	-	-	-	*(0.016)*	*(0.029)*	*(0.023)*	*(0.027)*
Excess Profits Ratio	*0.080****	*0.091****	*0.051***	*0.126****	*.025****	*.027****	*.028****	*.013+*
	(0.012)	*(0.008)*	*(0.003)*	*(0.010)*	*(0.002)*	*(0.002)*	*(0.001)*	*(0.007)*
Year-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	280,252	68,703	101,709	85,671	280,252	68,703	101,709	85,671
r2	0.349	0.370	0.338	0.393	0.510	0.505	0.646	0.465

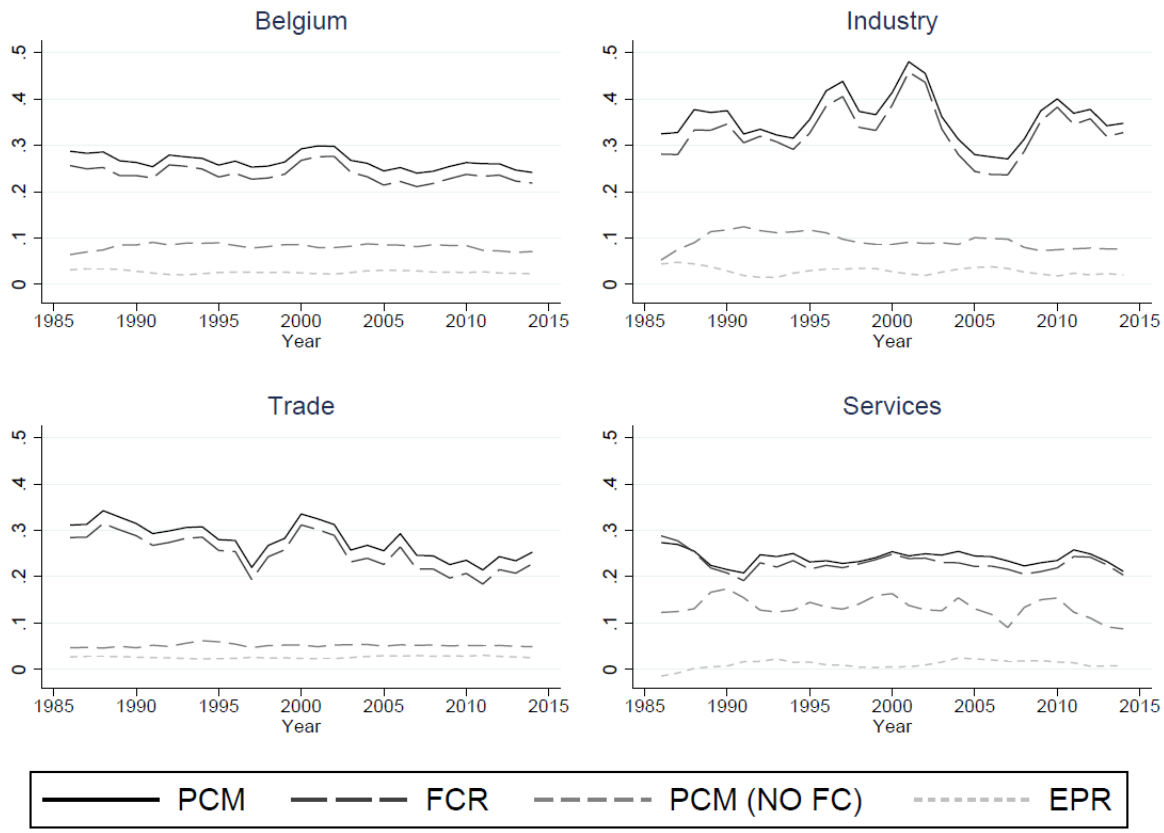
Notes: *This table shows the results from equation (22) at the sectoral level. Regressions are weighted by operating revenue at the firm-year level. Standard errors in parentheses (+ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001). Standard errors are clustered by NACE 2 digits. Industry, Trade and Services consist respectively of NACE categories 10/33, 45/47 and 49/82.*

We define the price-cost margin bias and the excess profits ratio bias as before. This confirms that ignoring fixed input factors underestimates price-cost margins while overestimating the excess profits ratio at the sectoral level. The price-cost margins bias is largest in Industry (-24.8%), followed by Trade (-19.5%) and then Services (-11.1%). On the other hand, the excess profits ratio bias is largest in Services (11.3%), followed by Industry (6.4%) and Trade (2.3%). The sum of the price-cost margins bias and the excess profits ratio bias is equal to the fixed costs ratio.

Next, we explore the time dimension of the sectoral price-cost margins. Figure 3.6 shows the evolution of aggregate and sectoral price-cost margins, and its two components, as well as the evolution of price-cost margins in the absence of fixed inputs. Due to the scale of the y-axis, it is challenging to recognize

any trend in the excess profits ratio. Therefore, we adjust the scale of the y-axis and plot the evolutions again in Figure 3.7.[45] We show the evolution of the share of fixed capital, the share of fixed labor and the share of fixed intermediate inputs at the sectoral level in (appendix) Figure 3.15.

Figure 3.6 Evolution of price-cost margins (FC): Sectors



Notes: *This figure shows the evolution of price-cost margins (equation 3), and the evolution of the price-cost margins, fixed cost ratio and the excess profits ratio (equation 20) at the yearly level. The evolution of the variables has been smoothed. Each observation is the simple average of its current observations and one observation before and after its current observation.*

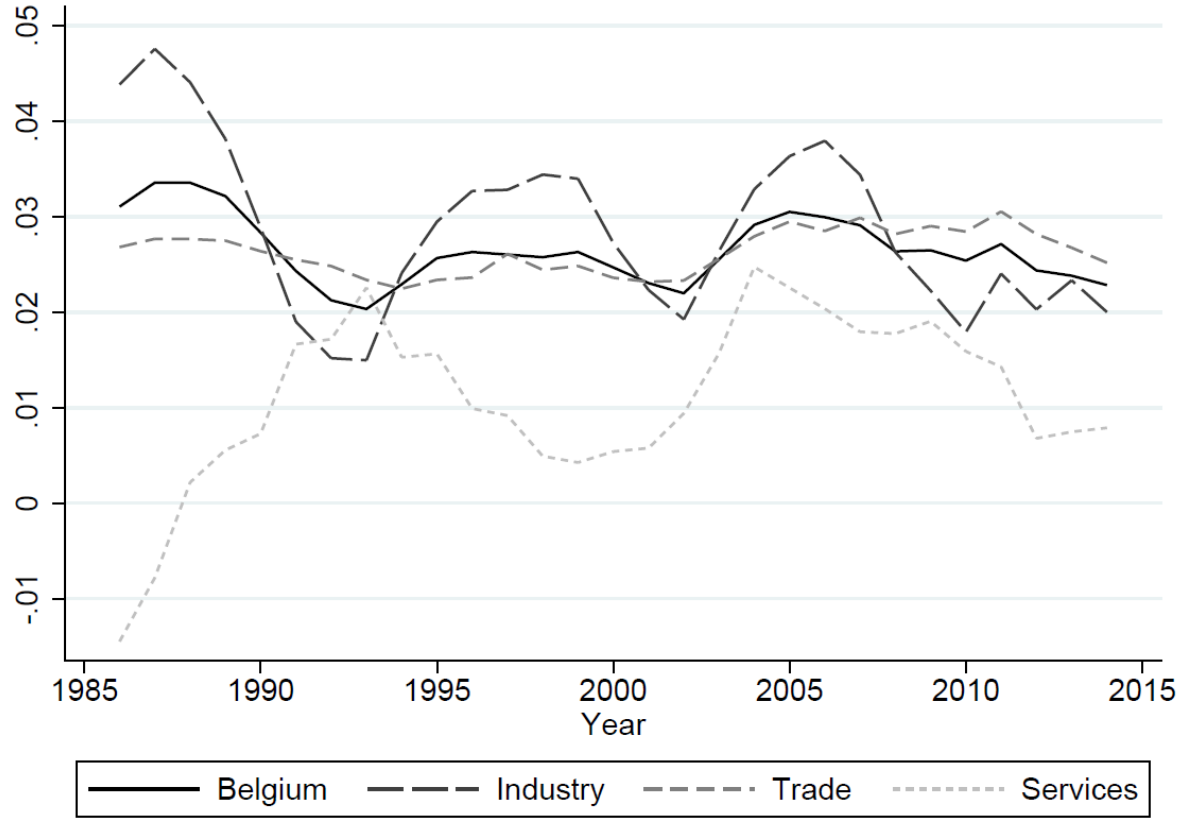
Looking first at the Belgian Industry, we find that price-cost margins and the fixed costs ratio increase over time. Price-cost margins increase from 32.5% in 1986 to 34.8% in 2014 while the fixed costs ratio rises from 28.1% to 32.8% in the same period. The rise is not always gradual, but experiences quite some fluctuation. For example, the price-cost margin and fixed costs ratio reach peak values around the early '00s whereas it reaches their minimum values on the eve of the Financial crisis. The secular increase, especially until the early '00s, suggests that firms' market power has substantially increased in Industry. However, the increasing fixed costs ratio dominates the rising price-cost margins such that the excess profits ratio has declined from 4.4% in 1986 to 2.0% in 2014. Firms are thus charging a higher price-cost margin. In the absence of fixed costs, this would also imply a higher profitability, but

[45] (Appendix) Table 3.9, 3.10 and 3.11 display the corresponding actual (not smoothed) values for the price-cost margin, fixed-cost ratio and excess profits ratio for respectively Industry, Trade and Services. We also include standard errors and significance stars.

it turns out that an even larger part of the price-cost margin is needed to cover fixed costs over time. This might be due to a change in the production process (i.e., more fixed costs and less variable costs). In the end, firms in Industry are not capturing a higher excess profits ratio in Industry but a lower one, which might be linked to the declining share of Industry in GDP.

Next, other patterns are present in Trade. In particular, price-cost margins decreased from 31.1% in 1986 to 25.3% in 2014 while the fixed costs ratio fell from 28.5% in 1986 to 22.8% in 2014. These evolutions are approximately parallel, such that the excess profits ratio is roughly constant. It goes from 2.7% in 1986 to 2.5% in 2014, while its minimum value is 2.2% and its maximum value equals 3.1% in this period. Firms in Trade are experiencing a fall in price-cost margins, but this does not correspond to a decreasing profitability due to the fact that these firms are also able to lower their fixed costs ratio. In the most recent decade, everything seems to be very stable in Trade.

Figure 3.7 Evolution of excess profit ratios (FC)



Notes: *This figure shows the evolution the excess profits ratio (equation 20) at the yearly level. The evolution of variables has been smoothed. Each observation is the simple average of its current observations and one observation before and after its current observation. Industry, Trade and Services consist respectively of NACE categories 10/33, 45/47 and 49/82.*

Further, price-cost margins and the fixed costs ratio in Services initially drop fast after which it becomes approximately stable. Price-cost margins move from 27.4% in 1986 to 21.5% in 1990 after which they remain stable. They equal 21.1% in 2014. The fixed costs ratio goes from 28.8% in 1986 to 20.8% in 1990 after which it still equals 20.4% in 2014. Looking at the evolution of the excess profits ratio in

Figure 3.7, we observe an increase until the early '90s after which it becomes rather stable, although there is still some fluctuation over the sample period.

Comparing our results with price-cost margins in the absence of fixed costs shows that these patterns are quite different in level and in trend. Price-cost margins in the absence of fixed costs do not allow to understand how the underlying components of the price-cost margins evolve. Moreover, price-cost margins without fixed costs are not able to track the evolution of the price-cost margins in the presence of fixed costs nor are they able to track the evolution of the excess profits ratio. Finally, we show the evolution of the price-cost margins and the excess profits ratio bias in (Appendix) Figure 3.16. This confirms that ignoring fixed costs underestimates price-cost margins and overestimates the excess profits ratio.

3.5.5 Longer horizon differences

This part compares five-year and ten-year differences to our benchmark result in which we use one-year differences. As we consider a longer time horizon, we would expect to find that the share of fixity decreases for each input factor such that the fixed costs ratio falls. Table 3.6 summarizes these estimation results based on five-year and ten-year differences.

Table 3.6 Price-cost margins and shares of fixed input factors: Longer horizon differences

	(1) Baseline	(2) Δ5yr	(3) Δ10yr
Price-cost Margins	0.259***	0.243***	0.214***
	(0.016)	(0.019)	(0.021)
Share of fixed capital	0.679***	0.537***	0.436***
	(0.036)	(0.048)	(0.075)
Share of fixed labor	0.169***	0.142***	0.119***
	(0.028)	(0.033)	(0.036)
Share of fixed intermediate inputs	0.236***	0.219***	0.192***
	(0.017)	(0.020)	(0.022)
Fixed costs ratio	0.234***	0.211***	0.183***
	(0.016)	(0.020)	(0.022)
Excess profits ratio	0.025***	0.032***	0.031***
	(0.002)	(0.002)	(0.002)
Year-Industry FE	YES	YES	YES
N	280,252	47,116	18,068
r2	0.500	0.586	0.606

Notes: *Standard errors in parentheses (+ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001). Standard errors are clustered by NACE 2 digits. Column (2) shows the results for the five-year differences and keeps only the years 1990, 1995, 2000, 2005, 2010 and 2014. Column (3) shows the results for the ten-year differences and keeps only the years 1995, 2005 and 2014.*

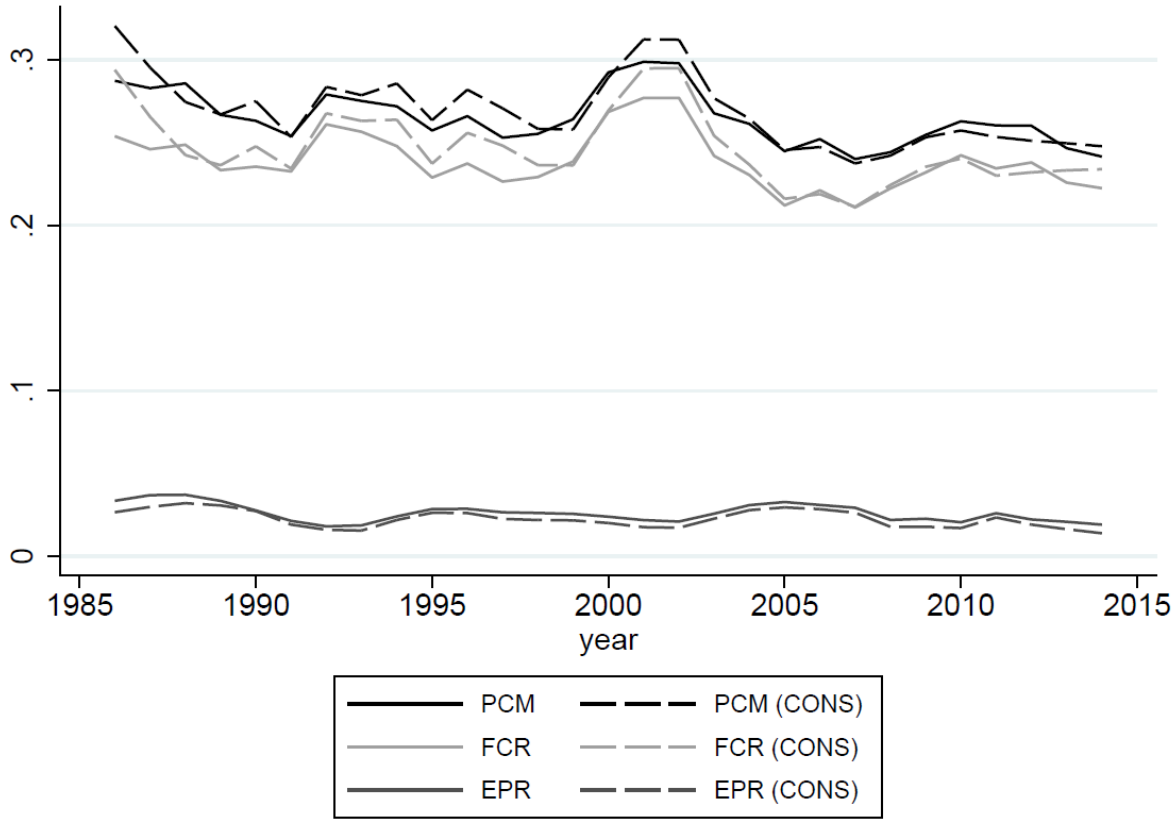
Looking at the five-year differences in column (2) and the ten-year differences in column (3), we find that the fixed costs ratio decreases to 21.1% and 18.3%, respectively, in comparison with the baseline value of 23.4% of column (1). This fall is predominantly driven by the decrease in the share of fixed capital shrinking from 67.9% to 43.6%. This is in line with the idea that capital is quasi-fixed in the short

run whereas it becomes more and more flexible over longer time periods. Additionally, comparing columns (1) and (3), we find that the share of fixed intermediate inputs falls moderately from 23.6% to 19.2% while the share of fixed labor decreases from 16.9% to 11.9%.

3.5.6 Proxy for consolidated accounts

The unit of analysis is the unconsolidated firm level account, as this is how firms report their annual income statement at the National Bank of Belgium. However, firms with a different legal VAT number might be controlled by the same parent company. Goutsmet, Lecocq & Volckaert (2017) use the concept of a 'domestic ultimate owner' to indicate whether a firm is owned by another firm within Belgium. This is the case if a firm has more than 50% of the shares of another firm. We refer to their paper for more technical details. We exploit these linkages and aggregate the Belgian annual income statements of firms which are owned by the same parent company. We use this as a proxy for consolidated firm level accounts at the Belgian level.[46]

Figure 3.8 Evolution of excess profits ratio: consolidated accounts



Notes: *This figure shows the evolution the price-cost margin, fixed costs ratio and excess profit ratio for unconsolidated and consolidated accounts based on equation (20). The evolution of the variables has been smoothed. Each observation is the simple average of its current observations and one observation before and after its current observation.*

[46] Note that this alternative definition of the frontier of a firm is a technical one and does not exist in reality.

We show the evolution of the price-cost margins, fixed costs ratio and excess profits ratio for both unconsolidated accounts and our proxy for consolidated accounts in Figure 3.8.[47] Our results are robust to this alternative boundary definition of a firm. We find that price-cost margins and the fixed costs ratio are a bit higher in some years whereas in other periods, they are a bit lower. Overall, they fluctuate around the baseline results. The new excess profits ratio displays the same evolution over time albeit being slightly smaller.

3.5.7 Exploring non-constant returns to scale and monopsony power

Now, we explore the consequences of having non-constant returns to scale as well as the existence of monopsony power in the labor and intermediate inputs market for the interpretation of our results. Although we are not able to estimate the scale parameter w.r.t. the variable inputs, γ, nor to estimate the monopsony power in the labor market and intermediate inputs market, defined by B^L and B^M, it is still valuable to understand how a deviation from these assumptions might affect our coefficients.

First, assume that our production function is extended by a scale parameter γ:

$$Q = F(\theta K^v, \theta L^v, \theta M^v)^\gamma$$

This production function is homogenous of degree γ such that,

$$Q = F(K^v, L^v, M^v)^\gamma \theta^\gamma$$

Correspondingly, assume that the variable cost function is defined as:

$$C^v = C^v(W, R, P^M, Q, \theta) = G(W, R, P^M)\theta^{-1}(Q)^{1/\gamma}$$

Following the same notation and derivation steps as before, based on the profit maximization and cost minimization procedures, leads to the following regression equation:

$$(SRQ^R - SRP^R)PQ - (SRQ^C - SRP^C)C = \big(1 - \gamma(1 - B)\big)\big((\Delta p - \Delta r) - (\Delta k - \Delta q)\big)PQ - (sf_t^k RK[(\Delta p + \Delta q) - (\Delta k + \Delta r)] - \big(sf_t^l\big)WL[(\Delta p + \Delta q) - (\Delta k + \Delta r)] - (sf_t^m)P^M M[(\Delta p + \Delta q) - (\Delta k + \Delta r)] \qquad (24)$$

This new equation shows two interesting results. First of all, the scale parameter γ does not affect our estimated shares of fixed inputs sf_t^k, sf_t^l and sf_t^m. Second, in the case that the scale parameter γ equals one, this equation collapses to equation (20).[48] However, in the case that the scale parameter γ is larger (smaller) than one, we underestimate (overestimate) the price-cost margin B. For example, if γ equals 1.1 (0.9) and estimate B in equation (20) to be 0.4, then the unbiased price-cost margin B in equation (24) equals 0.45 (0.33). Given that the excess profitability equals the difference between the

[47] (Appendix) Table 15 displays the corresponding actual (not smoothed) values for the price-cost margin, fixed-cost ratio and excess profits ratio. We also include standard errors and significance stars.
[48] Note that we make abstraction of the error term(s) in this section.

price-cost margin and the fixed costs ratio, this ratio might also be affected by a scale parameter which deviates from unity. Finally, it is not possible to separately estimate the scale parameter γ and the price-cost margin B, hence, we have assumed the scale parameter on the variable inputs to be one in this chapter.

Second, assume again that the scale parameter equals one but now we introduce monopsony power in the labor market as well as in the intermediate inputs market. Building on Curry, Love and Shumway (2007), and our own derivations, equation (20) becomes:

$$(SRQ^R - SRP^R)PQ - (SRQ^C - SRP^C)C = -B * PQ[(\Delta p + \Delta q) - (\Delta k + \Delta r)] - (sf_t^k)RK_{it}[(\Delta p + \Delta q) - (\Delta k + \Delta r)] - \left(\frac{sf_t^l + B^L}{1+B^L}\right) WL_{it}[(\Delta p + \Delta q) - (\Delta k + \Delta r)] - \left(\frac{sf_t^m + B^M}{1+B^M}\right) P^M M_{it}[(\Delta p + \Delta q) - (\Delta k + \Delta r)] \qquad (25)$$

With B^L and B^M being defined as $B^L = \frac{VMP_L - w}{w}$ and $B^M = \frac{VMP_M - P^M}{P^M}$ with VMP_L and VMP_M reflecting the value of the marginal product of labor and intermediate inputs, respectively. B^L and B^M capture the monopsony power in the labor and intermediate inputs market, respectively, with larger values indicating more market power. Note that we still assume perfectly competitive capital markets.

This derivation shows that our estimate of the price-cost margin is not affected by the presence of firms' monopsony power in the labor and/or intermediate inputs market, unlike in the previous exercise. However, the share of fixed labor and the share of fixed intermediate inputs are now intertwined with the monopsony power in the labor and intermediate inputs market, respectively. In the case that monopsony power equals zero, this equation collapses again into equation (20). From the moment that B^L and/or B^M become larger than zero, then, we overestimate the share of fixed labor and/or the share of fixed intermediate inputs. For example, if B^L equals 0.1 and sf_t^l is estimated to be 0.4 based on equation (20), then, we can find that the unbiased sf_t^l in equation (25) equals only 0.34. Our measure of excess profitability still captures the rents extracted from the output market, however, total rents are larger due to the additional rents generated from the input market(s). Again, it is not possible to separately estimate the monopsony power coefficients and the shares of fixity within this framework, nevertheless, it generates insight on how we can interpret our coefficients once the assumption of perfectly competitive input markets does not hold, and allows to evaluate our results accordingly.

3.5.8 More detailed estimates

Our methodology is also able to obtain even more detailed results than just the aggregate estimate, as we have shown with our sectoral and/or yearly results. In particular, we can estimate industry-year

level price-cost margins or firm-level (but not firm-year level) price-cost margins.[49] Furthermore, we can even exploit firm-level heterogeneity like firm age, firm size and so on by interacting the price-cost margin and the shares of fixity with these variables.

We briefly illustrate this by estimating price-cost margins, fixed costs ratios and excess profit ratios at the NACE-two digit category level for the period 1985-2014. Table 3.16 summarizes the results and shows (1) that fixed costs are sizable and significant in nearly all industries and (2) that industry-level heterogeneity matters. This opens interesting avenues for future research in which the industry or yearly dimension can be exploited in more detail.[50]

3.6 Conclusion

In this chapter, we introduce and illustrate a new method which allows to estimate aggregate price-cost margins in the presence of fixed factors of production. Our method exploits properties of the primal and dual (revenue- and cost-based) Solow residuals. It allows a flexible treatment of the input factors: labor, capital and intermediate inputs. Each input can be variable, fixed or a combination of both. Based on empirical data, the model jointly estimates price-cost margins and the share of fixity for each input. The estimated price-cost margin can be decomposed into two components: one part is needed to cover fixed costs while the other part represents firms' profitability.

We apply our method to Belgian firm level data from 1985 until 2014. Given the rich time dimension of this data set, we are able to distinguish cyclical variation from the secular trend. Our main findings can be summarized as follows. First, allowing input factors to be variable, fixed or a mix of both has a profound impact on the estimation of price-cost margins. Once fixed factors of production are taken into account, Belgian price-cost margins rise from 8.0% to 25.9%. However, this does not necessarily imply that firms' profitability has risen as well. Price-cost margins are predominantly needed to cover fixed costs (23.4%) whereas only a small fraction remains left as excess profits (2.5%). Ignoring fixed costs underestimates price-cost margins while it overestimates firms' profitability. Second, the evolution of price-cost margins consists of the evolution of the fixed costs ratio and the evolution of the excess profits ratio. These components can reinforce or offset each other. Looking at the Belgian economy, we find that both the fixed costs ratio (-3.7%) and the excess profits ratio (-0.9%) have fallen between 1985 and 2014 such that price-cost margins decreased by 4.6%. Finally, heterogeneity across

[49] This implies that we estimate an 'aggregate' price-cost margin at the industry-year level. On the other hand, we are able to estimate firm-level price-cost margins by assuming a constant price-cost margin at the firm-level during a fixed time horizon. Estimates at the firm-year level are not possible as we would have to estimate four coefficients based on one observation.

[50] See Bormans, Konings and Muraközy (2020) for an application at the industry-year level discussing the issue of fixed costs during the COVID-19 crisis.

time and among sectors matters. For example, price-cost margins exhibit an increase in Industry but this evolution is dominated by an even larger increase in the fixed costs ratio in this sector, hence, firms' profitability falls.

Understanding the decomposition and evolution of price-cost margins is an important tool to assess firms' market power and its evolution. The presence of fixed costs implies that price-cost margins might change not only due to a change in firms' market power, but also due to changes in the production process (i.e., the mix between variable and fixed costs) or even due to a combination of both. Our novel methodology is able to distinguish these underlying mechanisms, thereby providing an additional layer of insight to the ongoing academic and policy debate on firms' market power.

3.7 Appendix

3.7.1 Data appendix

Our application uses Belgian unconsolidated firm level accounts from the National Bank of Belgium (1985-2014).[51] Firms are identified as a legal entity by their unique VAT number. NACE rev. 2 codes are used to assign a firm to an industry (NACE 2-digit).[52] The dataset includes all for-profit firms which file an annual income statement, however, 'small firms' do not have to report this information.[53] They can choose to do this at a voluntary basis. The dataset does not include data on self-employed people.

We obtain the following balance sheet variables: operating revenue, wage costs, intermediate inputs, depreciation and tangible fixed assets. We have 358,143 firm-year observations. From 1996 onwards, firms report employment in terms of full-time equivalents (FTE).[54] Our dataset covers an increasing number of employees over time: total employment in FTE equals 1,042,861.8 in 1996. This increases to 1,298,381.4 in 2014.

Before running our regressions, we need to make some data adjustments. First, we only keep firms which belong to NACE rev. 2 categories 10/82. Next, we solely keep firms which have no missing values for operating revenue, wage costs, intermediate inputs, tangible fixed assets, depreciation and their NACE two digits code. We drop firms with a negative or zero value for operating revenue, wage costs,

[51] Belgian annual accounts are freely accessible through the NBB. The past ten years can be downloaded online. Older firm accounts can be requested at a cost.
[52] NACE is the industry standard classification system used in the European Union. It is the acronym of the French translation of the Statistical Classification of Economic activities in the European Community. The first four digits are common across all European countries.
[53] We refer to Bijnens & Konings (2018) for more detailed information on the filing requirements. Small firms are firms that do not exceed the following criteria: average number of employees above 50 FTE, €7.3 million for turnover and €3.65 for balance sheet total (2014 levels).
[54] Before 1996, firms report the number of jobs instead of full-time equivalents.

intermediate inputs, tangible fixed assets or depreciation. We drop firms which have a labor or intermediate input share above one and winsorize the labor and intermediate input share at the 95th percentile.[55] Finally, we winsorize the components for the regressions at the 1st and 99th percentiles to account for outliers in terms of growth rates.

In order to calculate the nominal rental cost of capital $R_{it} = P_{I_t}(r_t - \pi_t + \delta_{it})$ for firm i in year t, we start from Hall & Jorgenson (1967). We calculate the depreciation rate δ_{it} as the ratio of depreciation in year t-1 and tangible fixed assets in year t for firm i, thereby following Konings, Van Cayseele and Warzynski (2005).[56] The cost of capital does not include a cost for intangible assets. The price index of investment goods P_I is obtained from the World Bank. Inflation π and the nominal interest rate r are sourced from the OECD (2021).[57] The three latter variables are at the Belgian country-year level.

Further, we extend the calculation of the cost of capital by accounting for capital allowances (Asen & Bunn, 2019) and the statutory tax rate as follows: $R^{ADJ} = R_{it} * \frac{(1-(CA_t)*\tau_t)}{(1-\tau_t)}$ with CA[58] and τ representing respectively the Belgian capital allowance and the statutory tax rate. Both measures are made available by the OECD (2021). In most countries, like in Belgium, depreciation schedules do not allow to take the time value of money into account. The time value of money consists of inflation and a normal return. Assume that a firm invests €1000 in a machine and it uses the straight-line depreciation method over a time horizon of five years. Further, assume an inflation rate of 2% and a normal return of 5%. In the first year, the firm depreciates €200. In the second year, again, the firm depreciates €200, however, the present value of this amount equals only €187. After five years, the firm is able to deduct only €877. The capital allowance, defined as the percentage of the initial investment which can be fully deducted, equals 87.7% in this case. The capital allowance becomes lower as the time horizon increases and/or the time value of money rises. A lower (than 100%) capital allowance increases the cost of capital. We use the adjusted cost of capital as our measure of cost of capital in the main text.

We plot the evolution of the nominal interest rate r in Figure 3.9, the evolution of inflation π in Figure 3.10, the evolution of the weighted depreciation rate δ in Figure 3.11, the evolution of the (adjusted) real rental cost of capital $(r_t - \pi_t + \delta_{it}) * \frac{(1-(CA)*\tau)}{(1-\tau)}$ in Figure 3.12, the evolution of the price index of

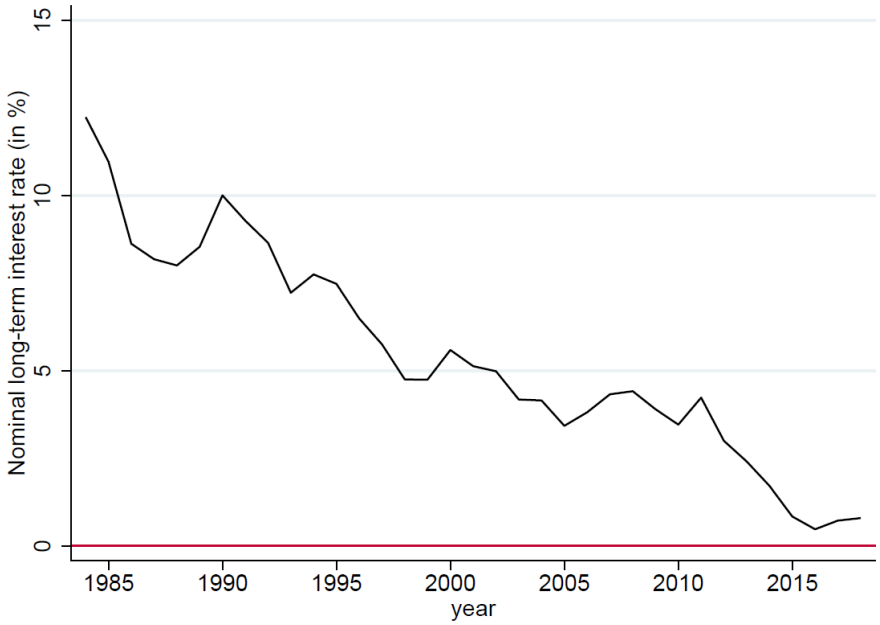
[55] Under the assumption of constant returns to scale, a labor (intermediate input) share larger than one implies that the capital share would be negative. We only retain observations which have a labor (intermediate input) share smaller or equal to one. We replace negative capital shares by a value of zero.
[56] We limit the depreciation rate at 100%.
[57] Inflation refers to the yearly growth rate of the consumer price index. The nominal interest rate refers to the long-term (10 years) government bond yield. The OECD (2021) reports these indices in a consistent manner since 1985.
[58] We calculate the capital allowance as the weighed sum of the capital allowance of each component, divided by tangible fixed assets. The weights are the corresponding shares of the component in tangible fixed assets.

investment goods P_I in Figure 3.13 and the evolution of the (adjusted) nominal rental cost of capital R^{ADJ} in Figure 3.14. Appendix Table 3.7 displays the values for the nominal interest rate, statutory tax rate and capital allowances.

A limitation of our Belgian data is that depreciation is only reported from 1996 onwards while we observe all other variables from 1985 onwards. Therefore, we assume that the depreciation rate in and before 1995 equals the depreciation rate in 1996 at the firm level.

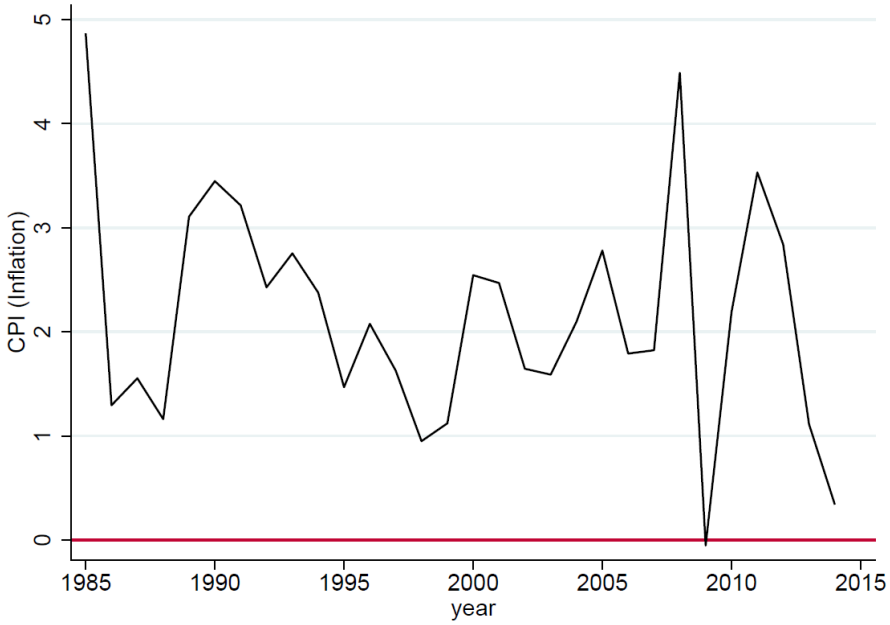
3.7.2 Figures appendix

Figure 3.9 Evolution of the nominal long-term interest rate



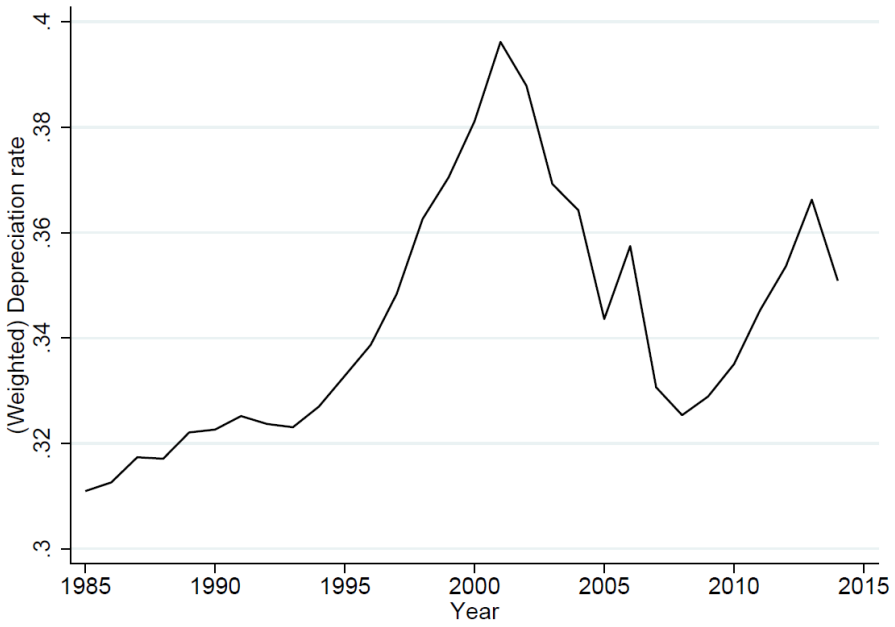
Notes: *This figure plots the long-term government bond yield (10 years). Data is obtained from the OECD (2021) and is consistently calculated throughout the sample period.*

Figure 3.10 Evolution of the consumer price index



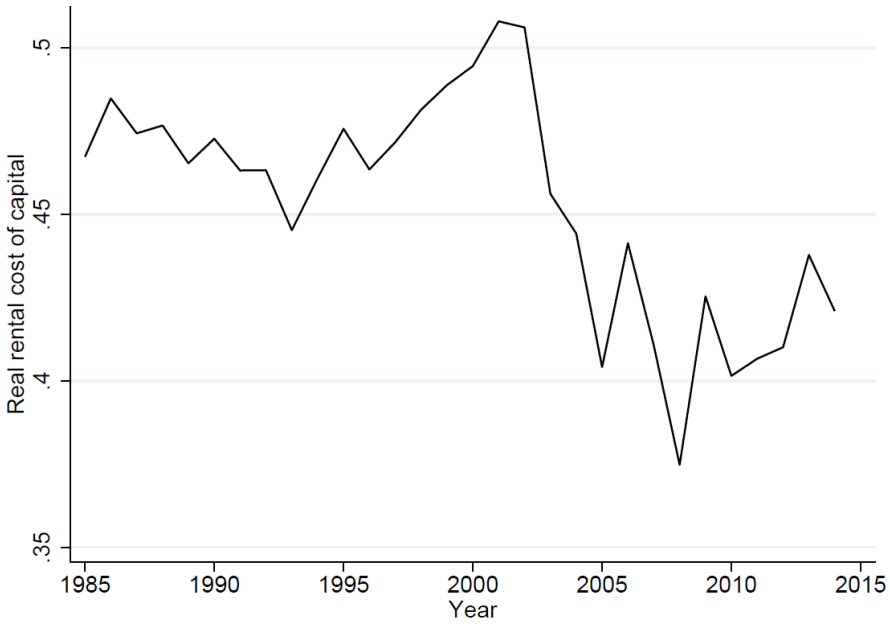
Notes: *This figure plots the yearly Belgian consumer price index (CPI) change. Data is obtained from the OECD (2021) and is consistently calculated throughout the sample period.*

Figure 3.11 Evolution of the weighted depreciation rate



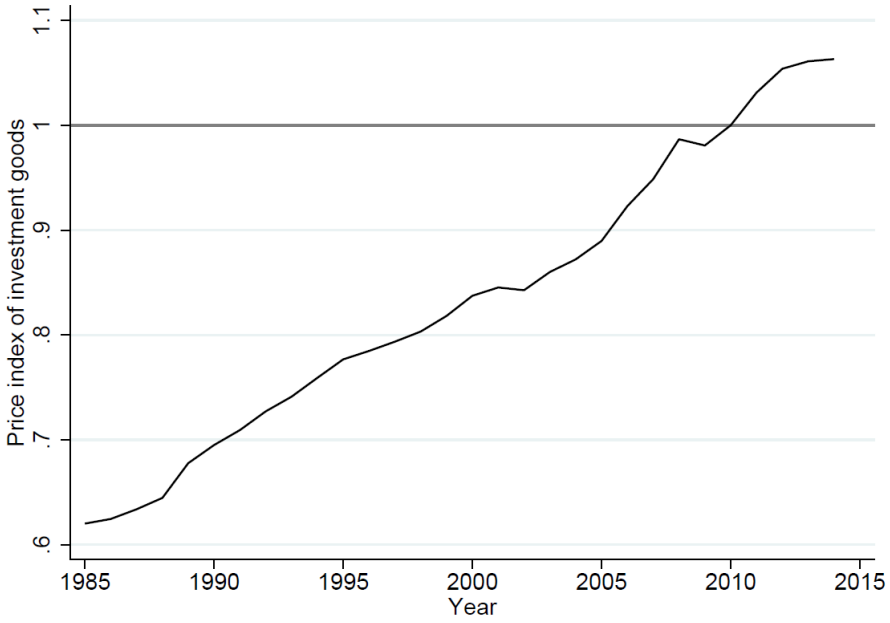
Notes: *This figure shows the weighted depreciation rate. We weigh the depreciation rate by operating revenue at the firm-year level.*

Figure 3.12 Evolution of the weighted real rental price of capital



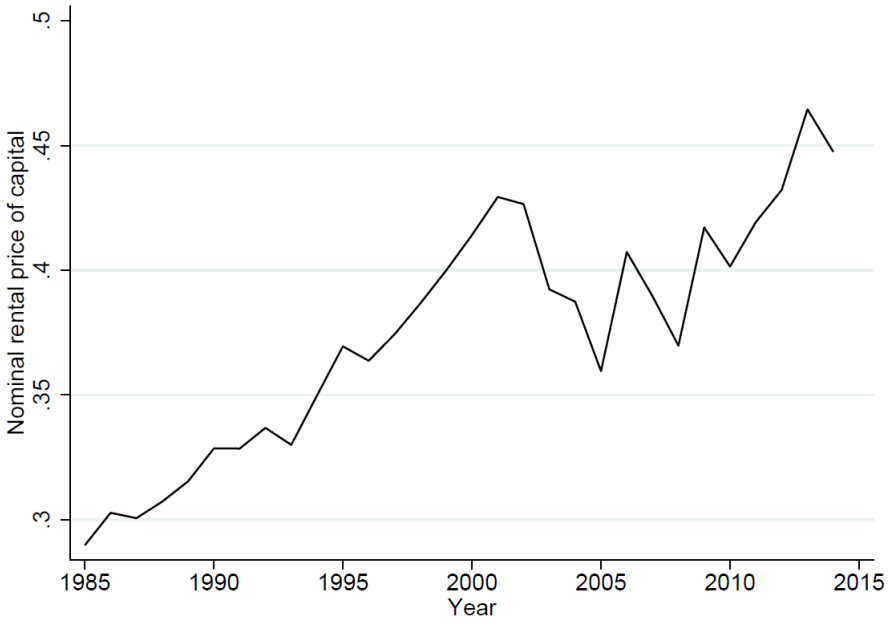
Notes: *This figure shows the weighted real rental price of capital. Depreciation is only available since 1996 for Belgian firms. We weigh the depreciation rate by operating revenue at the firm-year level.*

Figure 3.13 Evolution of the price index of investment goods



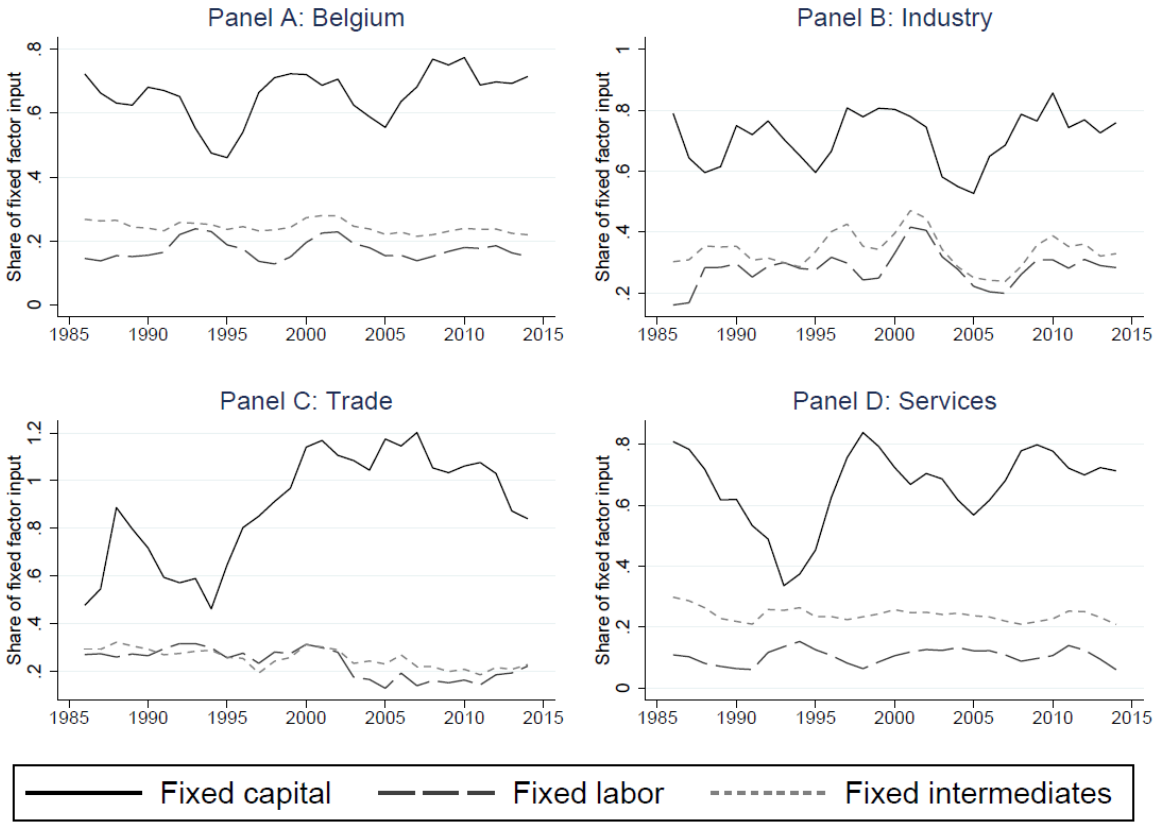
Notes: *This figure shows the Belgian price index of investment goods with 2010 as reference year. We source this data from the World Bank (2021).*

Figure 3.14 Evolution of the weighted nominal rental price of capital



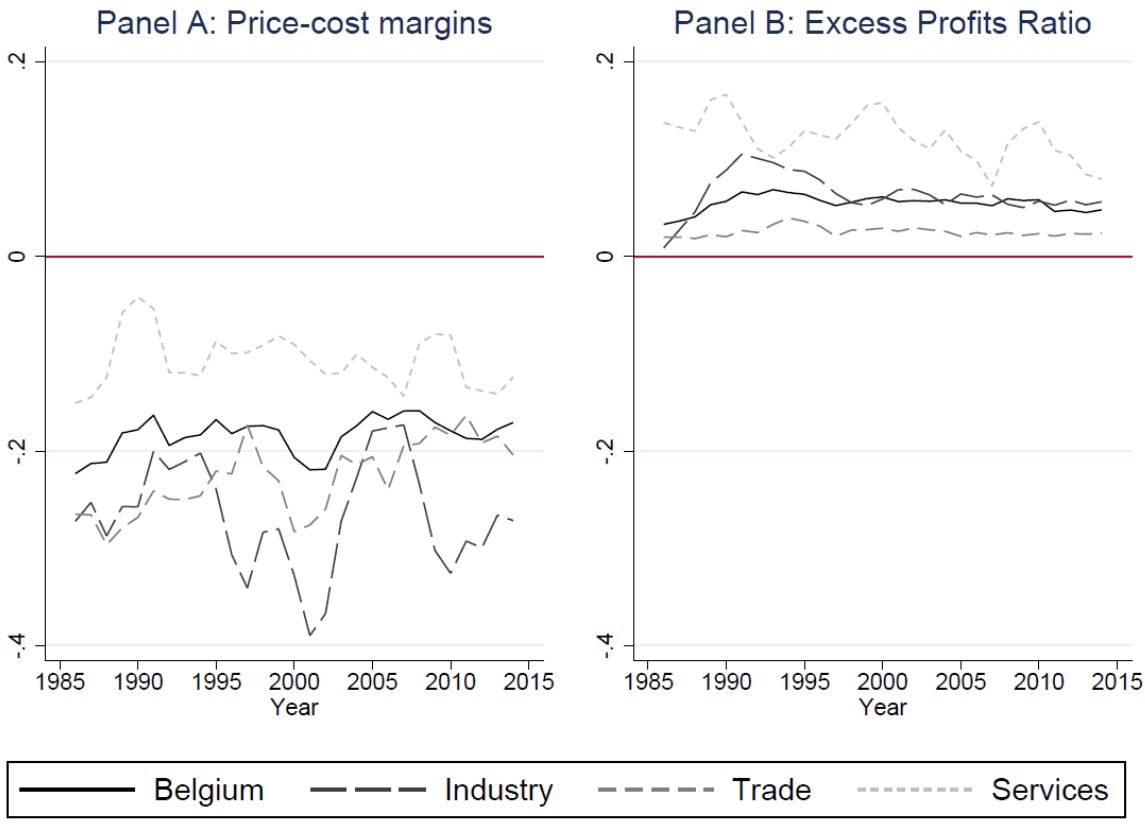
Notes: *This figure shows the weighted nominal rental price of capital. Depreciation is only available since 1996 for Belgian firms. We weigh the depreciation rate by operating revenue at the firm-year level.*

Figure 3.15 Evolution of estimated share of fixed inputs



Notes *Each panel plots the evolution of the estimated share of fixed capital, the estimated share of fixed labor and the estimated share of fixed intermediates. These evolutions have been smoothed. Each observation is the simple average of its current observations and two observations before and after its current observation.*

Figure 3.16 Evolution of PCM and EPR bias



Notes *This figure shows the price-cost margins and excess profits ratio, at the aggregate and sectoral level.*

3.7.3 Table appendix

Table 3.7 Raw data for robustness tests for the cost of capital

Year	Nominal Interest Rate	Tax Rate	Loan Rate	CA (Machines)	CA (Buildings)	CA (Patents)	Market Risk Premium
1985	10.97	45	-	83.8	62.2	-	-
1986	8.63	45	-	83.8	62.2	-	-
1987	8.18	43	-	83.8	62.2	-	-
1988	8.01	43	-	83.8	62.2	-	-
1989	8.54	43	-	83.8	62.2	-	-
1990	10.01	41	-	83.8	62.2	-	-
1991	9.29	39	-	83.8	62.2	-	-
1992	8.65	39	-	83.8	62.2	-	-
1993	7.23	40.2	-	83.8	62.2	-	-
1994	7.75	40.2	-	83.8	62.2	87	-
1995	7.48	40.2	-	83.8	62.2	87	-
1996	6.49	40.2	-	83.8	62.2	87	-
1997	5.75	40.2	-	83.8	62.2	87	-
1998	4.75	40.2	-	88.2	62.2	87	-
1999	4.75	40.2	-	88.2	62.2	87	-
2000	5.59	40.17	-	88.2	62.2	87	4.29
2001	5.13	40.17	-	88.2	62.2	87	5.63
2002	4.99	40.17	-	88.2	62.2	87	4.72
2003	4.18	33.99	3.78	88.2	62.2	87	6.87
2004	4.15	33.99	3.58	88.2	62.2	87	5.16
2005	3.43	33.99	3.43	88.2	62.2	87	5.27
2006	3.82	35.97	4.04	88.2	62.2	87	5.46
2007	4.33	33.99	5.15	88.2	62.2	87	4.72
2008	4.42	33.99	5.44	88.2	62.2	87	6.09
2009	3.90	33.99	2.62	88.2	62.2	87	6.97
2010	3.46	33.99	2.27	88.2	62.2	87	6.84
2011	4.23	33.99	2.83	88.2	62.2	87	7.26
2012	3.00	33.99	2.40	88.2	62.2	87	9.57
2013	2.41	33.99	2.28	88.2	62.2	86	7.33
2014	1.71	33.99	2.26	88.2	62.2	85	6.30

Notes: *All values in this table are denoted in percentages.*

Table 3.8 Yearly estimates: Belgium

Year	PCM	PCM (SE)		FCR	FCR (SE)		EPR	EPR (SE)	
1986	0.280	0.033	***	0.247	0.032	***	0.033	0.003	***
1987	0.294	0.040	***	0.260	0.039	***	0.034	0.004	***
1988	0.274	0.033	***	0.230	0.031	***	0.044	0.004	***
1989	0.289	0.044	***	0.255	0.044	***	0.034	0.003	***
1990	0.237	0.025	***	0.214	0.026	***	0.023	0.003	***
1991	0.263	0.025	***	0.237	0.025	***	0.026	0.003	***
1992	0.261	0.030	***	0.246	0.032	***	0.015	0.005	**
1993	0.313	0.041	***	0.300	0.041	***	0.013	0.005	*
1994	0.251	0.028	***	0.223	0.028	***	0.028	0.003	***
1995	0.251	0.035	***	0.220	0.036	***	0.031	0.004	***
1996	0.269	0.030	***	0.243	0.030	***	0.026	0.004	***
1997	0.277	0.027	***	0.249	0.027	***	0.029	0.004	***
1998	0.212	0.031	***	0.188	0.031	***	0.025	0.004	***
1999	0.276	0.027	***	0.251	0.028	***	0.025	0.003	***
2000	0.304	0.030	***	0.277	0.030	***	0.027	0.003	***
2001	0.297	0.023	***	0.278	0.023	***	0.020	0.002	***
2002	0.295	0.026	***	0.276	0.026	***	0.019	0.003	***
2003	0.301	0.024	***	0.277	0.024	***	0.024	0.002	***
2004	0.206	0.031	***	0.172	0.031	***	0.034	0.002	***
2005	0.276	0.030	***	0.242	0.030	***	0.034	0.002	***
2006	0.252	0.023	***	0.222	0.024	***	0.030	0.002	***
2007	0.228	0.026	***	0.200	0.027	***	0.029	0.002	***
2008	0.240	0.020	***	0.211	0.021	***	0.029	0.002	***
2009	0.264	0.028	***	0.256	0.028	***	0.008	0.002	***
2010	0.260	0.026	***	0.229	0.027	***	0.031	0.002	***
2011	0.264	0.019	***	0.242	0.020	***	0.023	0.002	***
2012	0.257	0.023	***	0.233	0.024	***	0.024	0.002	***
2013	0.259	0.017	***	0.239	0.017	***	0.020	0.002	***
2014	0.224	0.017	***	0.205	0.018	***	0.018	0.002	***

Notes: *This table shows the estimated Belgian price-cost margins, fixed costs ratio and excess profits ratio, with corresponding standard errors and significance level. Standard errors ($^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). Standard errors are clustered by NACE 2 digits.*

Table 3.9 Yearly estimates: Industry

Year	PCM	PCM (SE)		FCR	FCR (SE)		EPR	EPR (SE)	
1986	0.316	0.063	***	0.268	0.062	***	0.047	0.004	***
1987	0.334	0.082	***	0.290	0.079	***	0.044	0.006	***
1988	0.333	0.074	***	0.276	0.069	***	0.058	0.006	***
1989	0.464	0.051	***	0.423	0.050	***	0.040	0.004	***
1990	0.315	0.047	***	0.294	0.048	***	0.021	0.004	***
1991	0.345	0.078	***	0.320	0.079	***	0.025	0.004	***
1992	0.313	0.055	***	0.312	0.056	***	0.001	0.007	.
1993	0.346	0.163	*	0.347	0.163	*	-0.001	0.008	.
1994	0.308	0.084	***	0.283	0.082	***	0.026	0.004	***
1995	0.292	0.087	***	0.256	0.086	**	0.035	0.005	***
1996	0.468	0.103	***	0.435	0.102	***	0.033	0.005	***
1997	0.493	0.078	***	0.453	0.077	***	0.040	0.005	***
1998	0.353	0.100	***	0.321	0.099	**	0.033	0.006	***
1999	0.273	0.050	***	0.241	0.050	***	0.032	0.004	***
2000	0.472	0.064	***	0.438	0.064	***	0.034	0.004	***
2001	0.497	0.057	***	0.480	0.058	***	0.017	0.004	***
2002	0.472	0.042	***	0.446	0.043	***	0.025	0.003	***
2003	0.397	0.043	***	0.369	0.043	***	0.028	0.004	***
2004	0.217	0.063	***	0.181	0.063	**	0.036	0.003	***
2005	0.326	0.048	***	0.287	0.047	***	0.039	0.004	***
2006	0.297	0.047	***	0.258	0.047	***	0.039	0.003	***
2007	0.203	0.049	***	0.169	0.048	***	0.034	0.003	***
2008	0.313	0.033	***	0.287	0.034	***	0.026	0.004	***
2009	0.425	0.044	***	0.420	0.043	***	0.005	0.004	.
2010	0.386	0.055	***	0.351	0.056	***	0.035	0.004	***
2011	0.390	0.046	***	0.371	0.048	***	0.019	0.004	***
2012	0.332	0.062	***	0.306	0.065	***	0.026	0.005	***
2013	0.411	0.037	***	0.391	0.037	***	0.020	0.002	***
2014	0.284	0.071	***	0.265	0.072	***	0.019	0.004	***

Notes: *This table shows the estimated Belgian price-cost margins, fixed costs ratio and excess profits ratio, with corresponding standard errors and significance level. Standard errors ($^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). Standard errors are clustered by NACE 2 digits.*

Table 3.10 Yearly estimates: Trade

Year	PCM	PCM (SE)		FCR	FCR (SE)		EPR	EPR (SE)	
1986	0.288	0.027	***	0.257	0.034	***	0.032	0.007	***
1987	0.335	0.014	***	0.302	0.014	***	0.033	0.001	***
1988	0.316	0.023	***	0.282	0.025	***	0.035	0.002	***
1989	0.377	0.051	***	0.345	0.048	***	0.032	0.004	***
1990	0.293	0.020	***	0.262	0.020	***	0.031	0.001	***
1991	0.275	0.017	***	0.244	0.015	***	0.031	0.002	***
1992	0.312	0.026	***	0.287	0.023	***	0.025	0.004	***
1993	0.310	0.034	***	0.281	0.033	***	0.029	0.001	***
1994	0.297	0.005	***	0.269	0.002	***	0.028	0.004	***
1995	0.317	0.033	***	0.289	0.035	***	0.028	0.002	***
1996	0.226	0.019	***	0.201	0.020	***	0.026	0.001	***
1997	0.291	0.029	***	0.269	0.032	***	0.022	0.003	***
1998	0.143	0.029	***	0.117	0.031	***	0.026	0.002	***
1999	0.369	0.047	***	0.344	0.047	***	0.025	0.001	***
2000	0.337	0.019	***	0.311	0.019	***	0.026	0.001	***
2001	0.300	0.033	***	0.277	0.033	***	0.024	0.000	***
2002	0.338	0.058	***	0.316	0.060	***	0.021	0.003	***
2003	0.300	0.011	***	0.273	0.010	***	0.027	0.001	***
2004	0.135	0.017	***	0.102	0.017	***	0.033	0.001	***
2005	0.368	0.020	***	0.335	0.022	***	0.033	0.002	***
2006	0.264	0.031	***	0.236	0.031	***	0.028	0.000	***
2007	0.246	0.030	***	0.216	0.030	***	0.030	0.001	***
2008	0.229	0.019	***	0.199	0.020	***	0.030	0.002	***
2009	0.260	0.023	***	0.235	0.023	***	0.025	0.002	***
2010	0.190	0.019	***	0.160	0.021	***	0.030	0.001	***
2011	0.257	0.003	***	0.228	0.004	***	0.029	0.002	***
2012	0.197	0.026	***	0.169	0.028	***	0.028	0.002	***
2013	0.276	0.024	***	0.251	0.027	***	0.025	0.003	***
2014	0.230	0.023	***	0.204	0.025	***	0.026	0.002	***

Notes: *This table shows the estimated Belgian price-cost margins, fixed costs ratio and excess profits ratio, with corresponding standard errors and significance level. Standard errors ($^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). Standard errors are clustered by NACE 2 digits.*

Table 3.11 Yearly estimates: Services

Year	PCM	PCM (SE)		FCR	FCR (SE)		EPR	EPR (SE)	
1986	0.269	0.054	***	0.289	0.062	***	-0.021	0.023	.
1987	0.279	0.071	***	0.266	0.080	***	0.013	0.022	.
1988	0.262	0.045	***	0.242	0.042	***	0.019	0.017	.
1989	0.225	0.047	***	0.207	0.052	***	0.019	0.015	.
1990	0.187	0.029	***	0.167	0.030	***	0.020	0.010	*
1991	0.234	0.031	***	0.219	0.035	***	0.015	0.013	.
1992	0.204	0.033	***	0.169	0.042	***	0.035	0.012	**
1993	0.304	0.040	***	0.284	0.037	***	0.020	0.017	.
1994	0.222	0.031	***	0.187	0.039	***	0.036	0.018	*
1995	0.224	0.048	***	0.211	0.053	***	0.013	0.014	.
1996	0.249	0.036	***	0.237	0.043	***	0.012	0.013	.
1997	0.231	0.030	***	0.223	0.031	***	0.007	0.010	.
1998	0.206	0.032	***	0.202	0.035	***	0.004	0.010	.
1999	0.261	0.037	***	0.255	0.039	***	0.006	0.010	.
2000	0.256	0.037	***	0.244	0.038	***	0.012	0.007	+
2001	0.245	0.021	***	0.226	0.024	***	0.019	0.008	*
2002	0.234	0.024	***	0.236	0.028	***	-0.003	0.010	.
2003	0.270	0.035	***	0.254	0.038	***	0.016	0.008	*
2004	0.236	0.051	***	0.203	0.054	***	0.033	0.008	***
2005	0.258	0.045	***	0.227	0.047	***	0.031	0.010	**
2006	0.240	0.038	***	0.223	0.043	***	0.017	0.007	*
2007	0.233	0.040	***	0.209	0.044	***	0.024	0.007	***
2008	0.230	0.030	***	0.204	0.033	***	0.026	0.007	***
2009	0.207	0.029	***	0.219	0.033	***	-0.011	0.009	.
2010	0.253	0.031	***	0.233	0.034	***	0.021	0.008	**
2011	0.244	0.031	***	0.231	0.036	***	0.013	0.009	.
2012	0.276	0.035	***	0.269	0.038	***	0.007	0.006	.
2013	0.227	0.025	***	0.223	0.030	***	0.004	0.009	.
2014	0.196	0.019	***	0.189	0.020	9.251	***	0.007	0.814

Notes: *This table shows the estimated Belgian price-cost margins, fixed costs ratio and excess profits ratio, with corresponding standard errors and significance level. Standard errors ($^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). Standard errors are clustered by NACE 2 digits.*

Table 3.12 Yearly estimates (Robustness: Loan Rate)

Year	PCM	PCM (SE)		FCR	FCR (SE)		EPR	EPR (SE)	
2004	0.218	0.032	***	0.184	0.032	***	0.034	0.002	***
2005	0.291	0.029	***	0.257	0.029	***	0.034	0.002	***
2006	0.263	0.025	***	0.234	0.026	***	0.029	0.002	***
2007	0.226	0.029	***	0.200	0.029	***	0.027	0.002	***
2008	0.252	0.018	***	0.227	0.019	***	0.025	0.002	***
2009	0.296	0.022	***	0.285	0.022	***	0.011	0.003	***
2010	0.293	0.025	***	0.261	0.024	***	0.032	0.002	***
2011	0.265	0.020	***	0.239	0.021	***	0.026	0.003	***
2012	0.256	0.022	***	0.230	0.022	***	0.025	0.002	***
2013	0.262	0.020	***	0.242	0.021	***	0.020	0.003	***
2014	0.230	0.018	***	0.213	0.018	***	0.017	0.003	***

Notes: *This table shows the estimated Belgian price-cost margins, fixed costs ratio and excess profits ratio, with corresponding standard errors and significance level. Standard errors ($^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). Standard errors are clustered by NACE 2 digits.*

Table 3.13 Yearly estimates (Robustness: Capital Allowances)

Year	PCM	PCM (SE)		FCR	FCR (SE)		EPR	EPR (SE)	
1995	0.255	0.031	***	0.223	0.032	***	0.031	0.004	***
1996	0.271	0.030	***	0.244	0.031	***	0.027	0.004	***
1997	0.295	0.030	***	0.265	0.030	***	0.030	0.004	***
1998	0.210	0.032	***	0.185	0.032	***	0.025	0.004	***
1999	0.268	0.031	***	0.242	0.031	***	0.026	0.004	***
2000	0.323	0.035	***	0.295	0.035	***	0.028	0.003	***
2001	0.295	0.024	***	0.275	0.025	***	0.020	0.002	***
2002	0.297	0.026	***	0.277	0.026	***	0.019	0.003	***
2003	0.320	0.027	***	0.295	0.028	***	0.025	0.002	***
2004	0.210	0.033	***	0.175	0.033	***	0.034	0.002	***
2005	0.276	0.030	***	0.240	0.030	***	0.035	0.002	***
2006	0.258	0.024	***	0.227	0.025	***	0.031	0.002	***
2007	0.226	0.029	***	0.196	0.029	***	0.030	0.002	***
2008	0.244	0.019	***	0.214	0.020	***	0.030	0.002	***
2009	0.268	0.028	***	0.260	0.028	***	0.008	0.003	***
2010	0.270	0.026	***	0.239	0.026	***	0.032	0.002	***
2011	0.264	0.020	***	0.241	0.020	***	0.024	0.002	***
2012	0.261	0.023	***	0.236	0.024	***	0.025	0.002	***
2013	0.261	0.019	***	0.240	0.019	***	0.020	0.002	***
2014	0.231	0.018	***	0.212	0.018	***	0.020	0.002	***

Notes: *This table shows the estimated Belgian price-cost margins, fixed costs ratio and excess profits ratio, with corresponding standard errors and significance level. Standard errors ($^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). Standard errors are clustered by NACE 2 digits.*

Table 3.14 Yearly estimates (Robustness: Risk Premium)

Year	PCM	PCM (SE)		FCR	FCR (SE)		EPR	EPR (SE)	
2001	0.310	0.026	***	0.302	0.027	***	0.008	0.002	***
2002	0.320	0.030	***	0.309	0.030	***	0.012	0.003	***
2003	0.316	0.031	***	0.306	0.031	***	0.009	0.003	***
2004	0.212	0.033	***	0.187	0.032	***	0.025	0.003	***
2005	0.285	0.030	***	0.258	0.031	***	0.027	0.003	***
2006	0.250	0.025	***	0.229	0.026	***	0.021	0.002	***
2007	0.230	0.030	***	0.206	0.030	***	0.024	0.002	***
2008	0.243	0.025	***	0.224	0.025	***	0.019	0.002	***
2009	0.254	0.022	***	0.264	0.022	***	-0.010	0.003	***
2010	0.260	0.024	***	0.244	0.024	***	0.016	0.003	***
2011	0.262	0.023	***	0.256	0.023	***	0.007	0.002	***
2012	0.207	0.027	***	0.206	0.026	***	0.002	0.002	.
2013	0.245	0.022	***	0.242	0.023	***	0.003	0.002	.
2014	0.238	0.023	***	0.234	0.023	***	0.005	0.002	*

Notes: *This table shows the estimated Belgian price-cost margins, fixed costs ratio and excess profits ratio, with corresponding standard errors and significance level. Standard errors ($^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). Standard errors are clustered by NACE 2 digits.*

Table 3.15 Yearly estimates (Robustness: Consolidated accounts)

Year	PCM	PCM (SE)		FCR	FCR (SE)		EPR	EPR (SE)	
1986	0.364	0.051	***	0.336	0.052	***	0.028	0.004	***
1987	0.277	0.038	***	0.252	0.039	***	0.025	0.004	***
1988	0.245	0.053	***	0.209	0.052	***	0.036	0.003	***
1989	0.301	0.051	***	0.267	0.050	***	0.035	0.004	***
1990	0.254	0.032	***	0.233	0.033	***	0.021	0.003	***
1991	0.269	0.049	***	0.243	0.049	***	0.026	0.004	***
1992	0.236	0.030	***	0.226	0.031	***	0.010	0.005	+
1993	0.345	0.069	***	0.333	0.070	***	0.012	0.006	+
1994	0.254	0.035	***	0.229	0.037	***	0.025	0.004	***
1995	0.258	0.040	***	0.228	0.040	***	0.029	0.004	***
1996	0.279	0.033	***	0.254	0.034	***	0.025	0.004	***
1997	0.309	0.045	***	0.285	0.045	***	0.024	0.004	***
1998	0.224	0.036	***	0.205	0.036	***	0.019	0.004	***
1999	0.241	0.039	***	0.219	0.039	***	0.023	0.004	***
2000	0.308	0.028	***	0.285	0.029	***	0.024	0.003	***
2001	0.319	0.035	***	0.305	0.036	***	0.014	0.003	***
2002	0.310	0.028	***	0.295	0.029	***	0.015	0.004	***
2003	0.308	0.028	***	0.285	0.029	***	0.023	0.003	***
2004	0.212	0.028	***	0.182	0.029	***	0.030	0.002	***
2005	0.273	0.032	***	0.243	0.032	***	0.031	0.002	***
2006	0.251	0.031	***	0.223	0.032	***	0.027	0.003	***
2007	0.218	0.041	***	0.190	0.040	***	0.027	0.002	***
2008	0.244	0.023	***	0.220	0.024	***	0.024	0.003	***
2009	0.265	0.025	***	0.263	0.025	***	0.002	0.003	.
2010	0.251	0.023	***	0.224	0.023	***	0.027	0.003	***
2011	0.256	0.024	***	0.235	0.024	***	0.022	0.002	***
2012	0.253	0.033	***	0.232	0.034	***	0.021	0.003	***
2013	0.244	0.027	***	0.229	0.028	***	0.014	0.003	***
2014	0.252	0.022	***	0.238	0.023	***	0.013	0.003	***

Notes: *This table shows the estimated Belgian price-cost margins, fixed costs ratio and excess profits ratio, with corresponding standard errors and significance level. Standard errors ($^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). Standard errors are clustered by NACE 2 digits.*

Table 3.16 Industry estimates

Industry	Description	PCM	PCM (SE)		FCR	FCR (SE)		EPR	EPR (SE)	
10	Manufacture of food products	0.29	0.05	***	0.27	0.05	***	0.02	0.00	***
11	Manufacture of beverages	0.46	0.07	***	0.37	0.07	***	0.09	0.00	***
12	Manufacture of tobacco products	0.25	0.08	**	0.23	0.09	*	0.02	0.01	*
13	Manufacture of textiles	0.68	0.07	***	0.65	0.06	***	0.03	0.00	***
15	Manufacture of leather and related products	0.89	0.08	***	0.84	0.08	***	0.06	0.00	***
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	0.67	0.06	***	0.62	0.06	***	0.05	0.01	***
17	Manufacture of paper and paper products	0.40	0.13	**	0.37	0.13	**	0.03	0.00	***
18	Printing and reproduction of recorded media	0.62	0.05	***	0.62	0.05	***	0.01	0.00	*
19	Manufacture of coke and refined petroleum products	0.14	0.04	***	0.11	0.04	**	0.03	0.01	**
20	Manufacture of chemicals and chemical products	0.36	0.03	***	0.33	0.03	***	0.03	0.00	***
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	0.25	0.03	***	0.23	0.03	***	0.03	0.01	**
22	Manufacture of rubber and plastic products	0.46	0.06	***	0.42	0.06	***	0.04	0.00	***
23	Manufacture of other non-metallic mineral products	0.59	0.05	***	0.58	0.05	***	0.01	0.00	**
24	Manufacture of basic metals	0.27	0.04	***	0.25	0.04	***	0.02	0.00	***
25	Manufacture of fabricated metal products, except machinery and equipment	0.51	0.07	***	0.49	0.06	***	0.02	0.00	***
26	Manufacture of computer, electronic and optical products	0.31	0.06	***	0.28	0.06	***	0.03	0.00	***
27	Manufacture of electrical equipment	0.34	0.06	***	0.30	0.06	***	0.03	0.00	***
28	Manufacture of machinery and equipment n.e.c.	0.35	0.04	***	0.31	0.04	***	0.04	0.00	***
29	Manufacture of motor vehicles, trailers and semi-trailers	0.18	0.04	***	0.16	0.05	***	0.03	0.00	***
30	Manufacture of other transport equipment	0.42	0.05	***	0.42	0.05	***	0.00	0.01	.
31	Manufacture of furniture	0.87	0.09	***	0.83	0.09	***	0.03	0.01	***
32	Other manufacturing	0.28	0.03	***	0.25	0.04	***	0.03	0.00	***
33	Repair and installation of machinery and equipment	0.22	0.07	***	0.21	0.07	**	0.01	0.00	***
35	Electricity, gas, steam and air conditioning supply	0.19	0.03	***	0.14	0.04	***	0.05	0.01	***
36	Water collection, treatment and supply	0.26	0.03	***	0.34	0.04	***	-0.09	0.01	.
37	Sewerage	0.24	0.06	***	0.24	0.08	**	0.00	0.03	.

38	Waste collection, treatment and disposal activities; materials recovery	0.33	0.04	***	0.31	0.03	***	0.03	0.01	***
39	Remediation activities and other waste management services	1.00	0.04	***	0.95	0.04	***	0.04	0.00	***
41	Construction of buildings	0.43	0.03	***	0.40	0.03	***	0.02	0.00	***
42	Civil engineering	0.57	0.03	***	0.52	0.03	***	0.05	0.00	***
43	Specialised construction activities	0.26	0.03	***	0.25	0.03	***	0.01	0.00	***
45	Wholesale and retail trade and repair of motor vehicles and motorcycles	0.38	0.05	***	0.36	0.05	***	0.02	0.00	***
46	Wholesale trade, except of motor vehicles and motorcycles	0.23	0.02	***	0.20	0.02	***	0.03	0.00	***
47	Retail trade, except of motor vehicles and motorcycles	0.37	0.02	***	0.35	0.02	***	0.02	0.00	***
49	Land transport and transport via pipelines	0.08	0.02	***	0.13	0.02	***	-0.05	0.00	.
50	Water transport	0.28	0.06	***	0.32	0.06	***	-0.05	0.01	.
51	Air transport	0.16	0.05	**	0.16	0.06	**	0.01	0.01	.
52	Warehousing and support activities for transportation	0.24	0.01	***	0.25	0.01	***	-0.01	0.00	.
53	Postal and courier activities	0.27	0.05	***	0.31	0.09	**	-0.04	0.06	.
55	Accommodation	0.38	0.07	***	0.42	0.07	***	-0.04	0.01	.
56	Food and beverage service activities	0.34	0.05	***	0.33	0.05	***	0.02	0.00	***
58	Publishing activities	0.50	0.05	***	0.43	0.05	***	0.07	0.00	***
59	Motion picture, video and television programme production, sound recording and music publishing activities	0.63	0.10	***	0.58	0.09	***	0.05	0.01	***
60	Programming and broadcasting activities	0.64	0.07	***	0.64	0.08	***	0.00	0.01	.
61	Telecommunications	0.39	0.03	***	0.39	0.04	***	0.00	0.02	.
62	Computer programming, consultancy and related activities	0.36	0.02	***	0.33	0.02	***	0.03	0.00	***
63	Information service activities	0.24	0.22	.	0.23	0.23	.	0.01	0.02	.
64	Financial service activities, except insurance and pension funding	0.26	0.02	***	0.23	0.02	***	0.03	0.00	***
65	Insurance, reinsurance and pension funding, except compulsory social security	0.84	0.05	***	0.75	0.05	***	0.09	0.00	***
66	Activities auxiliary to financial services and insurance activities	0.27	0.04	***	0.17	0.04	***	0.10	0.00	***
68	Real estate activities	0.31	0.03	***	0.31	0.03	***	0.00	0.02	.
69	Legal and accounting activities	0.24	0.03	***	0.19	0.03	***	0.06	0.00	***
70	Activities of head offices; management consultancy activities	0.29	0.02	***	0.26	0.02	***	0.03	0.00	***

71	Architectural and engineering activities; technical testing and analysis	0.31	0.05	***	0.28	0.05	***	0.03	0.00	***
72	Scientific research and development	0.32	0.05	***	0.31	0.04	***	0.01	0.01	.
73	Advertising and market research	0.11	0.01	***	0.09	0.01	***	0.02	0.00	***
74	Other professional, scientific and technical activities	0.40	0.09	***	0.37	0.09	***	0.03	0.01	**
77	Rental and leasing activities	0.27	0.01	***	0.32	0.02	***	-0.05	0.01	.
78	Employment activities	0.07	0.01	***	-0.24	0.01	.	0.31	0.01	***
79	Travel agency, tour operator and other reservation service and related activities	0.13	0.02	***	0.12	0.03	***	0.01	0.00	**
80	Security and investigation activities	0.13	0.01	***	-0.07	0.01	.	0.20	0.01	***
81	Services to buildings and landscape activities	0.18	0.02	***	0.04	0.03	.	0.14	0.01	***
82	Office administrative, office support and other business support activities	0.29	0.02	***	0.28	0.02	***	0.01	0.00	**

Notes: *Standard errors are clustered by year. Standard errors in parentheses (* p < 0.05, ** p < 0.01, *** p < 0.001). An industry is defined as a two-digit category. We estimate equation (20) by industry (NACE two-digit categories). Fixed effects include year fixed effects.*

3.7.4 Methodology appendix

We start from a production function which is homogeneous of degree one with respect to the variable inputs of production. Θ denotes neutral technical progress as each production factor is multiplied with the same technology component. Hence, we have:

$$Q = F(K^v, L^v, M^v)\Theta \tag{4}$$

The Lagrangian of the static profit maximization problem of firm *i* in year *t* becomes,

$$\max P(Q)Q - (WL^v + RK^v + P^M M^v) - \lambda(Q - (F(K^v, L^v, M^v)\Theta$$

which yields the following first-order-conditions,

$$\Theta * \frac{\partial F(.)}{\partial L^v} = \mu * \frac{w}{p}$$

$$\Theta * \frac{\partial F(.)}{\partial K^v} = \mu * \frac{r}{p}$$

$$\Theta * \frac{\partial F(.)}{\partial M^v} = \mu * \frac{P^M}{p}$$

Euler's law states that,

$$\frac{\partial F(.)}{\partial L^v} * L^v + \frac{\partial F(.)}{\partial k^v} * K^v + \frac{\partial F(.)}{\partial M^v} * M^v = F(.) = \frac{Q}{\Theta}$$

And can be rewritten, due to the first-order conditions as,

$$\left(\frac{Q}{F(.)}\right)\left(\frac{\partial F(.)}{\partial L^v} * L^v + \frac{\partial F(.)}{\partial k^v} * K^v + \frac{\partial F(.)}{\partial M^v} * M^v\right) = Q = \frac{RK^v}{(1-B)P} + \frac{WL^v}{(1-B)P} + \frac{P^M M^v}{(1-B)P}$$

Logarithmic differentiation of the production function leads to,

$$\Delta q = \frac{\partial F(.)}{\partial k^v}\Theta\frac{K^v}{Q}\Delta k^v + \frac{\partial F(.)}{\partial L^v}\Theta\frac{L^v}{Q}\Delta l^v + \frac{\partial F(.)}{\partial M^v}\Theta\frac{M^v}{Q}\Delta m^v + F(K^v, L^v, M^v)\frac{\Theta}{Q}\Delta\theta$$

Which can be rewritten, due to the first-order conditions and Euler's law, as,

$$\Delta \mathrm{q} = \frac{\mathrm{P}}{\mathrm{MC}}\left(\frac{\mathrm{sv^k RK}}{\mathrm{PQ}}\Delta \mathrm{k^v} + \frac{\mathrm{sv^l WL}}{\mathrm{PQ}}\Delta \mathrm{l^v} + \frac{\mathrm{sv}^m P^M M}{\mathrm{PQ}}\Delta \mathrm{m^v}\right) + \Delta\theta \tag{6}$$

Similarly, cost minimization, logarithmic differentiation of the marginal costs and Shepard's lemma allows to obtain equation (9) in the main text.

3.8 References

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Chapter 4

Targeting government aid during COVID-19: the issue of fixed costs

4.1 Introduction

The ongoing COVID-19 pandemic leads to an unprecedented drop in economic activity around the world. GDP losses are estimated at 11.5% in the Euro Area and 8.5% in the United States (OECD, 2020).[1] Many firms, as well as households and governments, have experienced a sharp decrease in income even though they still have to pay fixed expenses, i.e., costs which by definition do not change as production changes. Governments reacted almost instantly and implemented measures like furlough schemes or moratory on rent or interest payments (see Bennedsen, Larsen, Schmutte & Scuret, 2020 for an overview). Meanwhile, government budgets are very tight as budget deficits are widening and public debts are rising, which makes the effective targeting and design of the different policy instruments crucial. Regarding subsidizing firms, a common idea is that firms do not need to be compensated for their entire operating revenue loss during and after the lockdown, because - unlike fixed costs - variable costs related to the foregone production can be avoided. Relatedly, a fall in demand is more likely to lead to inefficient bankruptcy and exit in industries, where fixed costs are high. Motivated by such ideas, several governments are targeting firms or industries in which not only operating revenue losses are high but fixed costs are also considered to be substantial and set the generosity of the subsidy to be in line with the share of fixed costs in firms production. For example, the Danish government covers 25% to 80% of the fixed costs if turnover falls by 35% to 100% (Bennedsen et al., 2020). Other examples are the Norwegian or the Flemish government which implemented a policy change (Alstadsæter, Bjørkheim, Kopczuk & Økland, 2020; De Tijd, 2020), thereby moving from a lump-sum subsidy to a targeted program in which they compensate (partly) for fixed, unavoidable costs if firms experience substantial revenue losses.

Although the conceptual difference between variable and fixed costs is straightforward, they are harder to quantify in practice. Firms are not required to report this distinction and even if they would

[1] This chapter has benefitted from comments and suggestions at seminars at the University of Leuven, the 9th Workshop on Industrial and Public Economics, the 13th FIW Research Conference International Economics and the Scottish Economic Society Annual Conference. I am grateful for the financial support from Methusalem that made this study possible. A previous version of this chapter was published as "Targeting government aid during COVID-19: The issue of fixed costs (Bormans, Konings & Muraközy, 2020; VIVES Discussion Paper 91).

choose to do so, accounting concepts differ from economic categories. This chapter exploits a novel methodology (Abraham, Bormans, Konings and Roeger, 2020) which disentangles variable and fixed costs at the industry-level based on firm-level accounts, by relying on identities derived from profit maximization under very weak assumptions. This approach allows to estimate and decompose the industry-level price-cost margin (PCM) into two components: the part required to cover fixed costs, the fixed cost ratio (FCR) and the remaining excess profits ratio (EPR). Importantly, these two components depend on different economic forces: the FCR is mainly determined by technology and demand, while the EPR depends mainly on the strength of competition. Therefore, even if two industries have very similar price-cost margins, they may differ substantially in terms of competition and/or technology. Importantly, the two components respond very differently to economic shocks, and therefore, two industries with a similar price-cost margin can behave very differently under a crisis.

The two components of the price-cost margins tend to react differently to economic downturns. Increased competition resulting from a fall in demand tends to reduce the excess profit ratio, therefore the EPR is likely to be procyclical. In contrast, the share of fixed costs is likely to increase when sales fall. Firms produce less, but they can only cut their variable costs, hence, fixed costs represent a larger share of the total costs, making the FCR countercyclical. Furthermore, the dynamics of the two components may also differ over time. The evolution of the PCM reflects a sum of these two opposing forces, and, therefore, its reaction to a crisis is ambiguous. If fixed costs are high relative to profits, then the price-cost margin should be countercyclical. Vice versa, if excess profits are high relative to fixed costs, then the price-cost margin should be procyclical.

This price-cost margin and its components are illustrated in Figure 4.1 for Belgium, Hungary and the UK for the period around the 2008/2009 recession (see Section 4.2 and 4.3 for details about the methodology and data, respectively). Panel A shows the estimated price-cost margins. The pattern is not especially clear-cut, with somewhat different trends in the different countries. Panel B shows the evolution of the excess profitability, which fell sharply in all three countries in 2009 but recovered quickly afterwards. Panel C shows the fixed cost ratio, which clearly increased in all three countries between 2007 and 2009 but it fell back again in Belgium and the UK, thanks to the relatively swift recovery, while increased further for a couple of years afterwards in Hungary where recovery was more staggered.[2] The contrast between the swift recovery of the EPR and the much slower change in the FCR in Hungary shows that the two components may often follow very different dynamics. The

[2] GDP growth in 2010 was already 2.9% and 1.9% in Belgium and the UK, respectively, compared to 0.7% in Hungary, which also faced another dip of 1.5% GDP decline in 2012 (World Bank, 2020).

dynamics of the PCM follow a combination of these forces, but seem to be correlated more closely with the FCR.

Figure 4.1 Evolution of price-cost margin, excess profitability and fixed costs ratio for various countries



Notes: *This figure has three panels which show the evolution of the estimated price-cost margin, the excess profits ratio and the fixed costs ratio, respectively, for Belgium, Hungary and the United Kingdom. All evolutions are filtered with the Hodrick-Prescott filter. The y-axis shows the cyclical component in percentage points. Grey areas indicate recession times, defined as years in which real GDP decreased in Belgium, UK and Hungary. We use firm-level data from the National Bank of Belgium (Belgium), KRTK Databank (Hungary) and Orbis Global (United Kingdom).*

We analyze these patterns more quantitatively and in more detail by using exceptionally long and detailed Belgian firm level accounts from 1985 until 2014. We confirm that the fixed cost ratio is indeed negatively linked to the business cycle while the excess profitability is positively linked to the business cycle. Empirically, we find that fixed costs are high relative to excess profits such that price-cost margins are countercyclical in Belgium. During the Great Recession, price-cost margins increased by approximately 4.8pp. This is the sum of a 6.3pp increase in the fixed cost share and a 1.5pp decrease in the excess profitability.

From a policy side of view, the results from the Great Recession could be useful when designing policies during the COVID-19 crisis. The ongoing pandemic is likely to have even stronger effects, hence, industries with high operating revenue losses, high fixed costs and low pre-crisis profitability might run

into financial trouble. Government aid should be targeted to these industries to make sure that no inefficient exit takes place. After all, the pandemic should be temporary rather than structural.

This chapter supports policymakers by providing and implementing a methodology to identify which industries are most vulnerable to the issue of fixed costs. We introduce a new crisis vulnerability index taking into account the fall in revenues, the increase in fixed cost shares and the pre-crisis profitability. Especially the sector Food & Accommodation ranks high on this index, indicating that government aid is essential for firms in this industry to survive the crisis. Moreover, also Wholesale & Retail; Administrative and support service activities; and Manufacturing display moderately high values and might need support.

From an academic point of view, this chapter fits into a long-standing empirical literature on price-cost margin cyclicality. This strand explores how price-cost margins evolve over the business cycle. A countercyclical price-cost margin is a theoretical key feature in macroeconomic models (see Rotemberg & Woodford, 1992; Smets & Wouters, 2003, 2007). Most empirical papers find evidence for this relationship (Rotemberg & Woodford, 1992; Bils, Klenow & Malin, 2018) although other scholars disagree and show evidence for a positive link (Nekarda & Ramey, 2013; Kim, 2015). Empirical evidence, therefore, is still ambiguous. Our chapter contributes to this debate by emphasizing that price-cost margins are the sum of the fixed cost ratio and excess profitability, which have different cyclicality patterns. In particular, with falling demand the share of fixed cost will increase while stronger competitive pressure will push down profits. These effects are large in economic terms: according to our estimates, during the COVID-19 crisis the fixed cost ratio will increase by 16.0 percentage points (compared to its average value of 38.8pp) while profit ratios are estimated to fall by 3.8 percentage points. As price-cost margin cyclicality is the sum of the cyclicality of the fixed cost ratio and the cyclicality of the excess profitability, the different cyclicality of the two components can lead to ambiguous patterns of price-cost margin cyclicality.

This chapter also relates to literature on the cleansing effect during recessions, i.e., recession periods push the least productive firms out of the market and reallocate resources towards more productive firms (see Foster, Grim & Haltiwanger, 2015; Van den bosch & Vanormelingen, 2017 for evidence from US and Belgium, respectively). This implies a trade-off between saving efficient firms facing only temporary financial issues on the one hand and allowing for efficient reallocation on the other hand. Saving all firms would be expensive as well as disruptive for efficient reallocation while withdrawing all support would lead to inefficient liquidation of healthy firms. Hence, government aid measures should be well-designed and targeted.

This chapter contains various remaining main parts. Section 4.2 discusses the methodology. The baseline idea is presented in the main text. More technical details are available in the Methodology appendix (section 4.8.1). The third part discusses the data while the fourth section presents the results. The fifth section contains a discussion which makes the bridge from the academic insights towards policy recommendations. Section 4.6 presents a robustness test and section 4.7 concludes. The appendix (section 4.8) and the references (section 4.9) are available at the end of this chapter.

4.2 Methodology

4.2.1 Estimating price-cost margins, fixed cost ratios and excess profitability

Our estimation strategy builds on Abraham et al. (2020), which estimates price-cost margins in the presence of fixed costs. The model exploits characteristics of profit maximizing behaviour and relies on very mild assumptions. A key advantage is that one does not have to make assumptions about which input is fixed or to what extent, rather, it estimates the proportion of fixed costs for the three key types of inputs (capital, labor and intermediate inputs) alongside the price-cost margin. For example, the *share of fixed cost for capital* shows the share of capital stock that is fixed. Assume that fixed and variable capital equal respectively €80 and €20, then the estimated share of fixed capital should equal 0.80.

The price-cost margin (PCM) is defined as the difference between the price and the marginal cost divided by the price: $PCM \equiv \frac{P-MC}{P}$. The price-cost margin can be converted into a mark-up through $\mu = \frac{1}{1-PCM}$. For example, a price-cost margin of 0.20 corresponds to a mark-up of 1.25.

The model contrasts different ways of representing the relationship between the growth rate of the output on one hand and the growth rate of the three types of inputs on the other hand at the firm-year level. The starting point is the Solow residual, which is a measure of total factor productivity (TFP) growth in the absence of fixed costs and imperfect competition. It subtracts a weighted average of the growth in input use from the output growth. Importantly, the Solow residual can be written up in four different ways which differ in two main components. First, the weights used for the inputs can come from the shares of inputs either in costs or revenues. Second, one can model the production (primal) or the cost functions (dual).

The logic of the method builds on two principles derived from profit maximizing behaviour. First, comparing the output changes relative to a weightedchange in inputs will inform us about how different prices are from costs, or, equivalently, how large is the margin. Second, when expanding output, only variable inputs increase, therefore total input use will increase more if the share of fixed

inputs is lower. Capturing the relationship between input and output growth allows us to quantify the share of fixed costs. The method combines these two principles and, by contrasting the four types of Solow residuals, it allows one to decompose price-cost margins into a part needed to cover fixed costs and another part which remains left as excess profits.

This section presents the main equations and their interpretation. A technical derivation and a detailed definition of the components can be found in the Methodology appendix (section 4.8.1). We refer to Abraham et al. (2020) for an in-depth technical discussion.

Our main equation to estimate price-cost margins looks as follows:

$$\Delta y_{it} = -PCM_{st} * \Delta x_{1_{it}} + sf_{st}^{k} * \Delta x_{2_{it}} + sf_{st}^{l} * \Delta x_{3_{it}} + sf_{st}^{m} * \Delta x_{4_{it}} + \epsilon_{it} \qquad (1)$$

where all components in Δy and Δx (see Methodology appendix) are readily available in firm-level accounts for each firm-year combination. Δy represents a combination of the four Solow residuals while the various Δx components are linked to changes in output (operating revenue) and changes in the various input factors capital, labor and intermediate inputs for firm *i* in year *t,* respectively. The coefficients from estimating equation (1) are direct estimates of the *price-cost margins* PCM_{st}, the *share of fixed capital* sf_{st}^{k}, the *share of fixed labor* sf_{st}^{l} and the *share of fixed intermediate inputs* sf_{st}^{m} for industry *s* in year *t*.[3]

Having estimated these coefficients, this method allows one to decompose the price-cost margins into a *fixed costs ratio* and an *excess profits ratio*. The first part of the PCM is necessary to cover fixed costs while the second component represents the excess profitability.[4] Price-cost margins are defined as the sum of the fixed costs ratio and the excess profits ratio as shown in equation (2):

$$\widehat{PCM}_{st} \equiv \widehat{FCR}_{st} + \widehat{EPR}_{st} \qquad (2)$$

Consider, for example, an industry which needs 60% of their operating revenue to pay their variable cost such that their price-cost margin equals 40%. Assume further that 35% is needed to cover the fixed costs, then, 5% remains as excess profitability. As a result of this procedure, we can estimate the price-cost margin, the fixed cost shares for every input and the two ratios for each industry-year combinations. Importantly, this method allow to estimate these parameters at the industry-level, but does not allow estimating them at the firm-level.

[3] We assume that ϵ_{it} represents an i.i.d. error term which is not subject to any specification nor measurement error. For a detailed discussion about misspecification errors, see Abraham et al. (2020).

[4] The fixed cost ratio is calculated from the share of the different inputs in production and the fixed cost shares. For example, if the input share of materials, labour and capital are 70, 20 and 10 percent in production, respectively, and sf_t^m=0.3, sf_t^l=0.3 and $sf_t^k = 0.8$, $\widehat{FCR} = 0.7 * 0.3 + 0.2 * 0.3 + 0.1 * 0.8 = 0.35$. In other words, 35 percentage points from the PCM are needed to cover the fixed costs.

4.2.2 Estimating the relationship between GDP growth and price-cost margins

As we have already discussed briefly, the two main components of the price-cost margins are likely to display different cyclicality. It seems reasonable to expect that the excess profits ratio is positively linked to the business cycle, i.e. firms or industries become more (less) profitable as the economy is growing (shrinking). In contrast, fixed costs become relatively more (less) dominant in bad (good) economic times.

The price-cost margin cyclicality combines how the fixed cost share and the excess profitability move over the business cycle and, *a priori*, it is not clear which of the two effects dominates. The price-cost margin cyclicality may be negative, insignificant or positive depending on the relative importance of the fixed costs ratio cyclicality and the excess profits ratio cyclicality. This might explain why ambiguous results are still found in the literature. For example, in an industry with high fixed costs and almost no excess profits, the price-cost margin cyclicality should be close to the fixed costs cyclicality and thus countercyclical. On the other hand, consider an industry with almost no fixed costs and a high excess profitability. In this case, the price-cost margin cyclicality should be close to the excess profits ratio cyclicality for which our maintained hypothesis is procyclical.

We answer this cyclicality question empirically by investigating how the estimated price-cost margin and ratios co-move with the state of the economy in the long run. In particular, we proxy the business cycle by the growth rate of aggregate GDP.[5] Writing this more formally, we obtain:

$$Y_{st} = \beta * X_t + \delta_s + \varepsilon_{st}, \qquad (3)$$

where Y_{st} represents the objects of interest (PCM, FCR and EPR) for industry *s* in year *t*, X_t is aggregate GDP growth and δ_s represents industry fixed effects, while ε_{st} is the error term. The slope of the regression, β, shows the sign and magnitude of the cyclicality for the different components, with $\beta > (<) 0$ suggesting procyclicality (countercyclicality).

4.3 Data

We make use of Belgian unconsolidated firm level data, obtained from the National Bank of Belgium. This unique data set covers all for-profit firms and is particularly rich in terms of the time dimension between 1985 and 2014, thereby making it an ideal data set to study business cycle movements in the long run. We rely on the following balance sheet variables: operating revenue, wage bill, intermediate inputs, tangible fixed assets and depreciation.

[5] We follow Bils et al. (2018) and apply the Hodrick-Prescott (HP) filter in order to capture the cyclical component.

Table 4.1 Summary statistics: Firm-level

Variable	Mean	SD	P25	Median	P75	N
PQ	38.4	304.9	4.1	8.9	21.2	305,404
WL	5.2	32.2	0.6	1.4	3.1	305,404
$P^M M$	29.9	278.9	2.3	6.1	15.6	305,404
TFA	7.6	87.3	0.2	0.7	0.2	305,404
Depreciation	1.5	15.0	0.1	0.2	0.1	305,404
ΔPQ	6.8%	23.5%	-2.5%	4.7%	13.6%	269,789
ΔWL	4.7%	19.3%	-1.9%	3.7%	9.9%	269,789
$\Delta P^M M$	7.1%	25.4%	-3.1%	4.9%	15.2%	269,789
ΔTFA	1.7%	33.3%	-11.4%	-1.5%	10.4%	269,789
LS	0.13	0.14	0.03	0.09	0.19	305,404
MS	0.77	0.19	0.68	0.83	0.93	305,404
CS	0.10	0.11	0.04	0.06	0.11	305,404

Notes: *The top panel shows the descriptive statistics in nominal million EUR. The middle and bottom panel show the descriptive statistics in units. The number of observations is always shown in units. Summary statistics for the growth rates and the input share are weighted by operating revenue at the firm-year level. Note that price deflators are not used as we do not need them in the model.*

Table 4.1 shows the firm-level summary statistics. Our sample contains 305,404 firm-year observations. The 'average' Belgian firm has an operating revenue of 38.4 million EUR, pays 5.2 million EUR in wage costs and 29.9 million EUR in intermediate input costs. Its tangible fixed assets are worth 7.6 million EUR and the firm depreciates 1.5 million EUR on a yearly basis.

This typical Belgian firm is able to increase its yearly nominal operating revenue by 6.8%. Meanwhile, labor costs, intermediate input costs and tangible fixed assets rise by 4.7%, 7.1% and 1.7%, respectively. The intermediate input share is by far the most dominant input factor (77%), followed by the labor share (13%) and the capital share (10%).

Finally, we exploit two indicators for the business cycle in equation (3). First, we make use of the real Belgian aggregate GDP growth sourced from Eurostat (2021). Second, we calculate yearly industry value added growth rates, based on our final sample and use this as a robustness test (section 4.6).

4.4 Results

This section consists of two main parts. The first part provides a picture about the importance of fixed costs in production. The second part takes the long term perspective and investigates how price-cost margins, fixed cost shares and excess profitability co-move with the business cycle based on three decades of firm-level data.

4.4.1 Fixed costs and margins in Belgium

Table 4.2 shows the distribution of the price-cost margin, the fixed cost ratio and the excess profit ratio across Belgian industry-years. We find that an 'average' Belgian industry in our sample period has a price-cost margin of .388, i.e., for every €100 in operating revenue, it pays €61.2 in variable costs and

retains €38.8 in price-cost margin.[6] Almost all of it is needed to cover the fixed costs (€38.6)[7] such that the excess profitability is 0.2% of operating revenue (or nearly 0.87% of value added)[8] indicating that 'on average', competition pushes down these profits to low levels. Clearly, considering the strength of competition based on price-cost margins would paint a very different picture compared to the excess profit ratios.

Table 4.2 Summary statistics: Industry-level estimates

Variable	Mean	SD	P10	P25	Median	P75	P90	N
PCM	0.388	0.228	0.161	0.216	0.307	0.554	0.743	1,285
FCR	0.386	0.232	0.153	0.212	0.297	0.554	0.753	1,285
EPR	0.002	0.040	-0.033	-0.017	-0.002	0.013	0.040	1,285

Notes: *This table shows the mean, standard deviation, the 10th percentile, quartiles, 90th percentile and number of observations in units for the price-cost margin (PCM), the fixed costs ratio (FCR) and the excess profits ratio (EPR). Summary statistics are weighted by operating revenue at the industry-year level.*

Three additional things are noteworthy. First, the average hides substantial heterogeneity at the industry level. For example, price-cost margins represent less than a quarter of revenues in more than 25 percent of the industries while the margins constitute more than 55% of revenue in the top 25 percent of industries. This heterogeneity in PCM is largely a result of the variation in the fixed cost shares, which span a similar range. The excess profit ratio varies on a smaller range, but that range spans around that critical number, zero. It turns out that it is close to zero in most industries but it exceeds 1% of the revenue for the top quartile and even 4% in the top decile. When interpreting these numbers, it is important to recall that they represent industry averages and might hide substantial differences among firms within an industry. Some firms might be able to extract a lot of the economic rents while others are barely surviving and even making losses. Finally, the cost of capital is broadly defined such that it includes depreciation costs as well as a compensation for the real interest rate, i.e., the excess profitability ratio measures economic profit rather than accounting profitability.

4.4.2 Cyclicality in the long term

Figure 4.2 has three panels and shows how the price-cost margin, excess profits ratio and the fixed costs ratio evolve along the business cycle, respectively. We add the evolution of the HP filtered GDP growth and consider a longer time span. The main patterns in Figure 4.2 indicate that the patterns

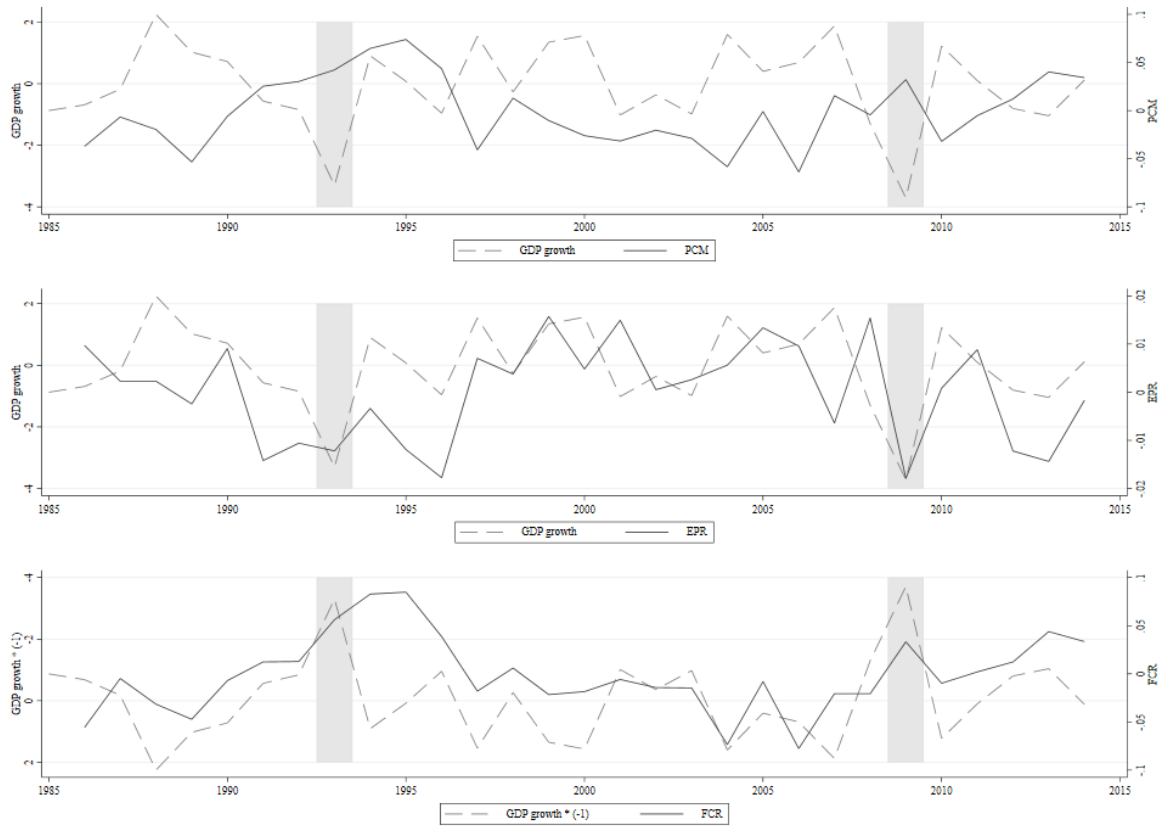
[6] The average share of fixed capital, labor and intermediate inputs is 0.857, 0.347 and 0.341 respectively. This confirms the intuition that capital displays the largest fixity among all inputs, however, the fixed costs ratio is remarkably closer to the estimated share of intermediate inputs due to the fact the intermediate input share dominates the other input shares.

[7] Note that we multiply both sides of equation (A15) by $\frac{C}{PQ}$ to get the same denominator, as is also done in the robustness section in Abraham et al. (2020). Our estimated price-cost margin, fixed cost share and excess profitability are very much comparable to the their results. The main takeaway remains that price-cost margins are sizable and remarkably larger than the excess profitability due to the fact that fixed costs drive a wedge between them. Moreover, fixed costs are larger in comparison with the excess profitability.

[8] Excess profitability is 0.2% of operating revenue. Given that the intermediate input share is 0.77 on average, we find that excess profitability is 0.87% of value added (= 0.2% * (1/(1-0.77)).

already observed in Figure 4.1 can be generalized to this long period. There is no clear correlation between the price-cost margin and GDP growth but it seems to be the case that the price-cost margin tends to be high whenever GDP growth is low, e.g. during the Great Recession, and vice versa. Decomposing the price-cost margin into the excess profits ratio and the fixed costs ratio in the second and third panel, respectively, suggests that the excess profits ratio evolves procyclical with GDP growth. Visually, we infer that the profitability rises whenever GDP growth is increasing (e.g. from the early '90s until 2000) and vice versa (e.g. during the Great Recession). In the third panel, we reverse the axis of GDP growth and observe that the fixed costs ratio seems to rise whenever GDP growth is decreasing. In particular, firms pay more fixed costs (as a % of operating revenues) during the Great Recession. The opposite happened between 1993 and 2000, i.e., as GDP growth increases, firms use a smaller part of their operating revenues to cover the fixed costs. While these correlations are suggestive, we build on this and use a regression framework to identify conditional correlations while controlling for industry fixed effects.

Figure 4.2 Cyclicality: Price-cost margins, fixed costs ratio and excess profits ratio



Notes: *This figure has three panels which show the evolution of the estimated price-cost margin, the excess profits ratio and the fixed costs ratio respectively, as well as the evolution of GDP growth. All evolutions are filtered with the Hodrick-Prescott filter. Grey areas indicate recession times, defined as years in which the real Belgian GDP decreased (Source: World Bank, 2021). The y-axis (left) for GDP growth is reversed in the third panel.*

Table 4.3 shows the regression results based on equation (3). The business cycle indicator X_t is proxied by aggregate GDP growth while price-cost margins, the fixed costs ratio and the excess profits ratio are estimated at the industry-year level. The first three columns show results weighted by operating revenue at the industry-year level while the last three columns show the unweighted results. Weighted regression results take into account that larger industries drive the aggregate results while unweighted regressions give equal importance to each industry.

This confirms our hypotheses. In particular, as expected, the fixed costs ratio and excess profits ratio are counter- and procyclical, respectively. This means that industries experience a decrease in their fixed costs ratio as aggregate GDP is growing. Vice versa, an industry encounters an increasing fixed costs ratio whenever the economy is shrinking. Furthermore, industries enjoy increased profitability as the economy is booming while they suffer whenever the economy is going through recession times. Second, given that the price-cost margin is the sum of the fixed costs ratio and the excess profits ratio, the price-cost margin cyclicality in column (1) equals the sum of the cyclicality of the fixed costs ratio and the excess profits ratio. Empirically, we find that the price-cost margin is countercyclical due to the fact that the fixed costs ratio is by far the largest component of the price-cost margin in Belgium, i.e. the price-cost margin cyclicality is very close to the fixed cost ratio cyclicality.[9] On a smaller note, we find that the weighted and the unweighted regression results point to the same results.

Table 4.3 Cyclicality: Aggregate results

	Weighted			**Unweighted**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	PCM	FCR	EPR	PCM	FCR	EPR
ΔGDP	-.013***	-.017***	.004***	-.011***	-.013***	.003**
	(.0027)	(.0028)	(.00065)	(.0032)	(.0032)	(.00100)
Industry FE	YES	YES	YES	YES	YES	YES
N	1763	1763	1763	1763	1763	1763
R^2	0.015	0.024	0.022	0.008	0.011	0.008

Notes: *This table shows the estimation results from equation (3). Columns (1)-(3) show the weighted results. Columns (4)-(6) show the unweighted results. Standard errors in parentheses (+ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001). All coefficients remain significant when clustering standard errors at the year-level.*

Table 4.4 investigates whether these patterns persist in the different large sectors of the economy. In particular, the regression is run separately for Manufacturing, Trade and Services. We confirm the countercyclical fixed cost share and the procyclical excess profits ratio in all sectors although the coefficient for the fixed cost share cyclicality in Trade is insignificant. We find countercyclical price-cost margins in Manufacturing, Trade and Services albeit not significant in Trade.

[9] El Gallaa (2018) finds procyclical markups for the Belgian Manufacturing industry. Implicitly, fixed costs are assumed away in the methodology. These results might be in line with our positive coefficient on the excess profits ratio cyclicality. Additionally, we find countercyclicality for the fixed cost share such that the price-cost margins are countercyclical.

Table 4.4 Cyclicality: Sectoral results

	Manufacturing			Trade			Services		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
	PCM	FCR	EPR	PCM	FCR	EPR	PCM	FCR	EPR
ΔGDP	-.012*	-.024***	.0052***	-.0083	-.0098	.0019^{+}	-.013***	-.013**	.0023^{+}
	(.0054)	(.0055)	(.0012)	(.0081)	(.0084)	(.0010)	(.0038)	(.0042)	(.0012)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	676	676	676	87	87	87	800	800	800
R^2	0.008	0.031	0.033	0.013	0.017	0.038	0.019	0.015	0.008

Notes: *This table shows the estimation results from equation (3). Columns (1)-(3), (4)-(6) and (7)-(9) show results for Manufacturing (10/33), Trade (45/47) and Services (49/82), respectively. Standard errors in parentheses ($^{+}$ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001). Coefficients in columns (1) until (3) remain significant when clustering at the year-level. Other coefficients lose significance.*

These effects are significant in economic terms and can help us in forecasting the effects of the COVID-19 recession. During the Great Recession, GDP growth fell by about 3.7pp in Belgium compared to its trend value in 2009. This implies that, according to the regression, the PCM was expected to increase by 4.8pp compared to its mean of 38.8%. This is the sum of a 6.3pp increase in the fixed cost ratio and a 1.5pp fall in excess profit rate. Given that that the typical values of the EPR are around zero and even the 75 percentile of its distribution is only 1.3 percent, this fall has very strongly affected most industries' profitability.

The Great Recession has mainly affected the price-cost margins through the fixed costs ratio mechanism. In particular, industries experience an increase in their fixed cost share once the crisis hits. Meanwhile, they generate less profits which might cause many industries to run into financial trouble, even though they are healthy during normal times. This suggests that the fixed cost channel is quite strong during crisis times and likely to have even more adverse effects during the COVID-19 crisis.

With predictions of GDP falling by around 9.4pp during the COVID-19 recession,[10] price-cost margins could rise by 12.2pp which combines a rise of 16.0pp in the fixed cost share and a fall of 3.8pp in excess profitability. This could push even industries around the 90th percentile of the EPR distribution into negative profitability.

4.5 Discussion

The ongoing COVID-19 pandemic led many governments, including the Belgian, to implement a lockdown to contain the spread of the virus. This lockdown has inflicted an unprecedented blow for the economy, estimated at a decrease of 7.4% for the Belgian economy in 2020 (Federal Planning Bureau, 2020). The various governments (federal, regional and municipalities) reacted instantly and tried to control the damage to the economy through a system of temporarily economic unemployment and subsidies. The high cost of some of these measures make effective targeting and credible exit

[10] The Federal Planning Bureau predicts a 7.4% GDP decline for the Belgian economy (Federaal Planbureau, 2020) which is around a 9.4% change compared to a trend growth rate of approximately 2%.

strategies fundamental. This involves a delicate trade-off: saving all firms would be both expensive and hinder efficient reallocation, while withdrawing support for all firms would lead to inefficient liquidation of healthy firms.

The approach in this chapter provides a simple guide for governments when deciding on which industries and firms to target. The financial strain on firms depends on how much their fixed cost ratio increases during the crisis: the larger the increase in the FCR, the larger fraction of revenue is eaten up. The change in the FCR during a crisis, in turn, depends on the fall in revenue and the original fixed cost ratio. The larger the fall in revenue, the smaller the number of output units will be between which the fixed costs should be divided. Also, the larger the fixed cost ratio, the larger the expected change in the fixed cost share will be as a percentage of output.[11]

Based on these observations, we provide an estimate on the "mechanical effect" of the fall in revenue on the FCR during the COVID-19 crisis.[12] In order to calculate this, one needs information on the fall in demand and the pre-crisis fixed cost ratio. Regarding the changes in turnover, we use Eurostat's (2021) Short Term Business Statistics, which report changes in turnover by two digit industry. We quantify the change in turnover during the start of the lockdown by the change in turnover between 2019Q2 and 2020Q2.[13]

Fixed costs, in contrast, are hard to observe as firms do not have to classify their expenses as variable or fixed and accounting conventions do not follow the economic distinction in this respect. However, the framework used in this article allows to estimate the pre-crisis fixed costs ratio based on firms' balance sheet information, which is publicly available. We use the estimated fixed costs ratio by two digit industry, averaged over the period 1985-2014 for this purpose.

Based on these two pieces of information, we can predict the expected (mechanical) effect of the COVID-19 lockdown on the fixed cost ratio in each industry, denoted by $\widehat{\Delta FCR}$. Figure 4.3 shows these estimates, together with the change in operating revenue and the estimated initial fixed cost ratios.[14]

The figure shows that there are important differences in terms of the initial fixed cost share as well as in the change in operating revenue. For example, fixed costs are relatively low, around (0.28), in

[11] Let us denote the initial fixed cost ratio by FCR_0 and assume that the change in sales is g. Then $FCR_1 = FCR_0/(1+g)$, therefore $\Delta FCR = -\frac{g}{1+g}FCR_0$, which is proportional in FCR_0 and (nearly) inversely proportional in g, if g is not too large.

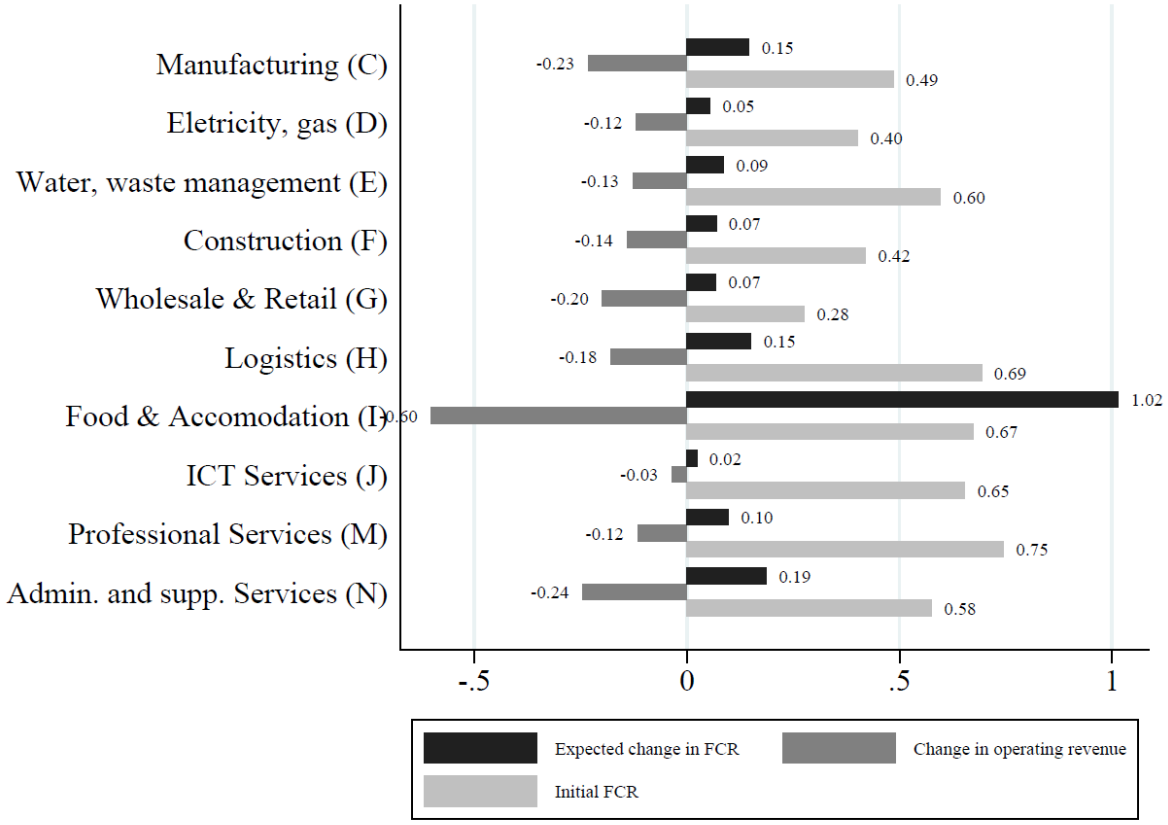
[12] Naturally, this only quantifies the mechanical effect of having to divide the same fixed costs across a smaller number of units, while many other factors – including input and output prices, wages etc. will change during the crisis. Our previous regression results estimated the "full effect" of GDP changes on fixed cost shares, while here, we just quantify this mechanical effect to illustrate a potential use of our estimates.

[13] Making use of the change between 2019Q2 and 2020Q2, rather than yearly data, allows to capture the short-term change in operating revenue more closely. The Belgian government imposed the first COVID lockdown at March 18, 2020. We use yearly data to estimate the initial fixed cost ratio, excess profitability and price-cost margin.

[14] (Appendix) Table 4.6 includes a full list of two-digit industries and their corresponding fixed cost share.

Wholesale and retail, where cost of goods sold is the dominant element in the cost structure. In contrast, fixed cost tend to be quite important in professional services (0.75). Fixed costs are also relatively large in Logistics (Transportation and Warehousing, 0.69) and Food and Accommodation (0.67), where large, fixed capital items or rents are a very significant item in the cost structure. Probably surprisingly but plausible, the fixed cost share in Manufacturing (0.49) is somewhat lower compared to many service sectors. Further, we observe decreases in operating revenue between 12% and 24% for the most sectors. The fall is more pronounced in Food & Accommodation (-60%) whereas there is almost no decrease in ICT Services (-3%).

Figure 4.3 Expected change in FCR and its components



Notes: *This figure shows the expected change in FCR (between 2019Q2 and 2020Q2), the change in operating revenue (between 2019Q2 and 2020Q2) and the initial pre-crisis FCR. Sectors are identified by their corresponding NACE letter code.*

The expected change in the fixed cost ratio depends both on the initial fixed cost ratio and the fall in operating revenue. The figure shows an enormous predicted increase in the FCR in Food and Accommodation, so that fixed cost during the lockdown substantially exceed revenues. This is a consequence of the 60% fall in revenues in this sector combined with the high initial cost share (0.67). Administrative & Support Services (which includes travel agencies) were also strongly hit, because of the 24% fall in revenue in that sector in combination with a relatively high initial fixed cost share (0.58). On the other hand, ICT Services has a rather high fixed cost share (0.65) but this industry should not

run into trouble as operating revenue falls by a modest 3% such that the expected change in fixed costs ratio equals only 0.02.

Furthermore, a larger decrease in operating revenue does not necessarily imply a higher expected change in the fixed costs ratio. For example, operating revenue decreases by 18% in Logistics while it falls by 20% in Wholesale & Retail. Nevertheless, the expected change in the fixed costs ratio is higher in Logistics (0.15) than in Wholesale & Retail (0.07) due to the larger initial fixed cost share (0.69 in Logistics versus 0.28 in Wholesale & Retail).

While the change in the fixed cost ratio is clearly related to the strain on company finances, the probability of inefficient liquidation will also depend on the financial buffer firms have. A firm in a less competitive industry with a higher EPR can weather the crisis even if there is a substantial increase in the fixed cost ratio, while firms in highly competitive industries with a low EPR may not even survive a limited increase in the FCR.

We build on this insight when proposing a novel *crisis vulnerability index* which takes into account both of these factors. We do so in two steps. First, we calculate the difference between the predicted change in the fixed cost ratio (ΔFCR) and the initial excess profitability. This number shows the predicted fall in the EPR if the PCM remains unchanged; in other words, this shows how large losses the firm would face compared to its initial output. Second, we normalize this difference with the price-cost margin to calculate the index itself. This allows us to calculate how large this shortfall is relative to the PCM. In particular:

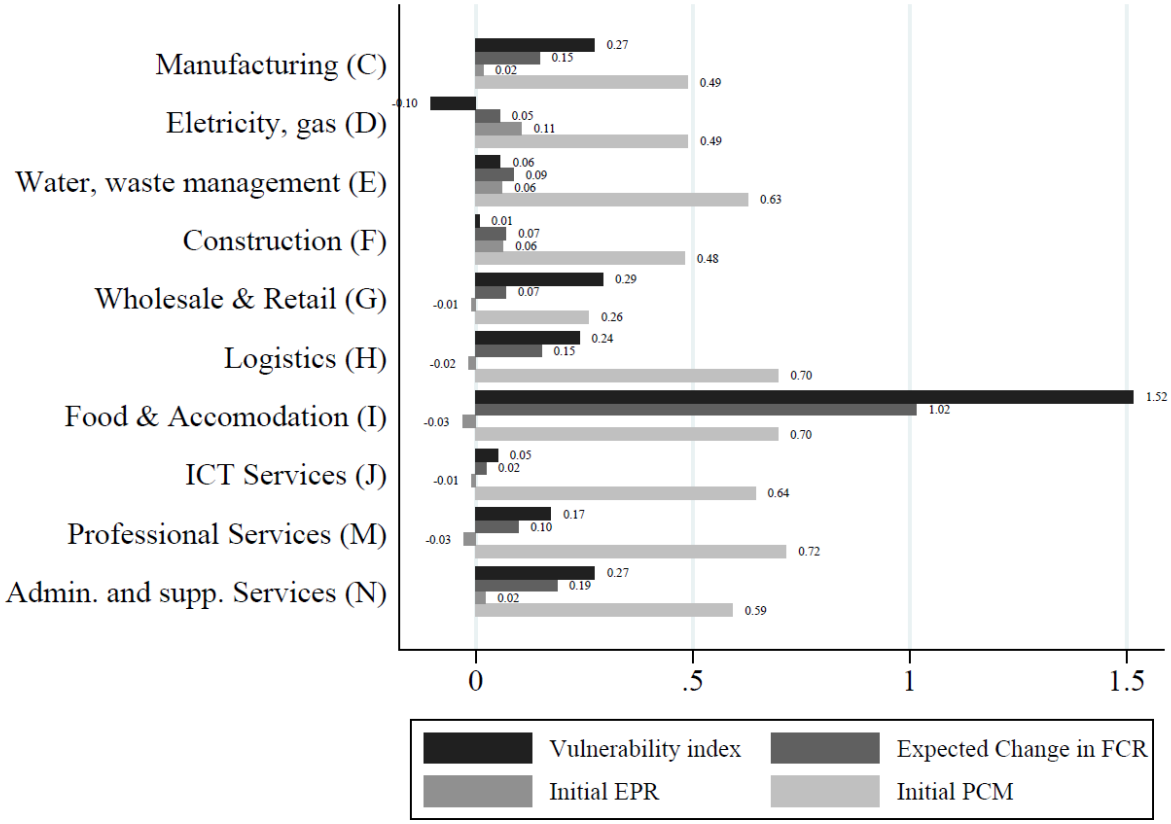
$$Vulnerability\ index = \frac{\widehat{\Delta FCR} - EPR_0}{PCM_0} \qquad (4)$$

Where EPR_0 and PCM_0 are the pre-crisis EPR and PCM levels, respectively.

Let us illustrate how this works. Let us assume that in an industry FCR_0=20%, EPR_0=5%, PCM_0=25%, $\widehat{\Delta FCR}$=10%. As a result of the crisis, the industry would face a loss of $\widehat{\Delta FCR} - EPR_0$=5% of its revenue. This loss is 20% of its initial PCM, therefore the industry's vulnerability index is 20%. This also means that the industry would have to increase its PCM by 20% to remain profitable. We can compare these numbers to a similar industry, where the only difference is that EPR_0=0%, and, also PCM_0=20%. The predicted loss is 10%, and the industry's vulnerability index is, therefore, 50%. So this second industry would need to raise its PCM by 50% in order to remain profitable. This industry is more likely to face inefficient exit.

Figure 4.4 shows the vulnerability index and the expected changes in the fixed cost ratio, as well as the initial excess profitability and the initial price-cost margin.[15] The rankings of the vulnerability index and the changes in the fixed cost shares are quite similar – thanks to the fact that EPRs tend to be much smaller than FCRs – but there are some differences. Food and Accommodation is again a clear outlier, reflecting both the large increase in the expected change in FCR and the low profitability of this strongly competitive sector. Comparing Manufacturing and Wholesale & Retail shows that the vulnerability index ranking can be different from the one based on the expected change in the fixed cost ratio: thanks to its better profitability and its larger price-cost margin, Manufacturing's vulnerability index is lower than the one for Wholesale & Retail. Finally, the vulnerability index is negative (-0.10) for Electricity and Gas showing that the initial excess profitability is larger than the expected change in fixed cost share. Even though operating revenue falls by 12%, excess profits are large enough to cover the rise in fixed cost share such that the sector remains profitable on average.

Figure 4.4 Vulnerability index and its components

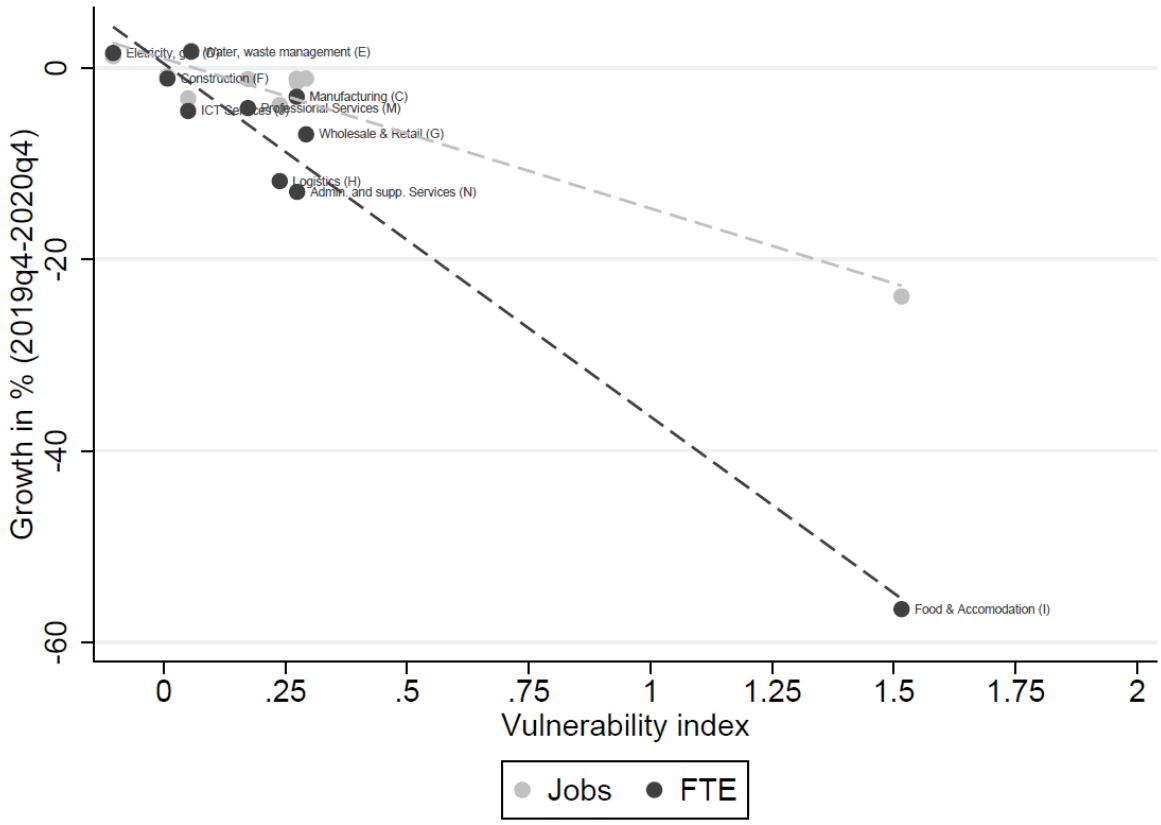


Notes: *This figure shows the vulnerability index, the expected change in FCR (between 2019Q2 and 2020Q2), the initial EPR and the initial PCM by one digit industry.*

[15] The figure shows intermediate components which are rounded off while the vulnerability index is based on numbers which are not rounded off.

As a final exercise, we want to have a look whether sectors with a higher value on the vulnerability index are also related to worse ex-post outcome. In Figure 4.5, we link the vulnerability index (calculated at 2020Q2) to the change in jobs as well as to the change in full-time equivalents, which are respectively looking at the number of jobs and the number of hours worked. The change in jobs and FTE is calculated for the most recent period available at the time of writing, namely, the change between 2019Q4 and 2020Q4.

Figure 4.5 Vulnerability index and ex-post outcomes



Notes: *This figure shows the vulnerability index on the x-axis and the change in jobs and the change in FTE (between 2019Q4 and 2020Q4) on the y-axis by sector. The dotted line represents the fitted linear trend line.*

This leads to twee main results. First, as expected, we find a strong negative correlation between the vulnerability index and the change in jobs/FTE, an effect which is also present even if we disregard Food & Accommodation.[16,17] Second, we observe that the fall in jobs is clearly less pronounced than the fall in full-time equivalents. This is due to the fact that firms can make use of temporarily economic

[16] The correlation, at the industry level, between the vulnerability index and the change in jobs/FTE is respectively -0.57 and -0.65 while the correlation between the change in turnover and the change in jobs/FTE is respectively 0.54 and 0.61, hence, the vulnerability index is slightly more correlated to ex-post outcomes in terms of the number of jobs and full-time equivalents.

[17] Regressing the change in jobs and the change in FTE on the vulnerability index, leads to estimated coefficients of -15.7 and -36.9, respectively. A one point increase in the vulnerability index is associated to a decrease of 15.7% and 36.9% for the number of jobs and the number of FTE, respectively.

unemployment. This ensures that although employees experience a decrease in their number of hours worked, due to COVID measures imposed by the Belgian government, firms are not forced to fire them. Rather, the Belgian government intervenes and provides unemployment benefits. This has the advantage that employees can keep (most of) their wages as well as their job while the firm receives financial support during this COVID crisis. For example, the number of jobs falls by 24% in Food & Accommodation whereas the number of hours worked (expressed in full-time equivalents) decreases by 56%.

Our vulnerability index is one of the criteria which governments should use when designing targeted policies. It adds additional insight, above the change in operating revenue, by looking into initial fixed cost shares, excess profitability and price-cost margin across sectors. The vulnerability index can be decomposed into its components to understand better why a certain sector might be at risk once a lockdown is implemented, as well as to gain insight into the magnitude of this risk among sectors. Nevertheless, notable differences remain to exist between firms, even within the same industry. Governments should take these firm-level differences into account. Moreover, other dimensions (e.g. international competitiveness, solvability and so on) might also play a role in the implementation of a credible exit, and recovery, strategy.

4.6 Robustness test

We consider one robustness test to validate our main result. In particular, we use GDP growth at the industry-year level as business cycle indicator rather than aggregate GDP growth. This allows to explore the price-cost margin cyclicality at an industry-level, thereby inducing more variation to exploit in subsequent research. More specifically, we use equation (3) with the industry-level GDP growth as measure of the business cycle. We show the general regression results in Table 4.5.

Table 4.5 Cyclicality: Industry results

	(1) PCM	(2) FCR	(3) EPR
Industry GDP growth	-.046	-.086*	.027***
	(.034)	(.035)	(.0082)
N	1699	1699	1699
R^2	0.003	0.006	0.009

Notes: *This table shows the estimation results from equation (3). The business cycle indicator is the industry-level GDP growth. Standard errors in parentheses ($^{+}$ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001). All coefficients become insignificant when clustering standard errors at the year-level.*

Table 4.5 shows that our main results are robust to this alternative business cycle indicator, i.e., we find countercyclicality for the fixed costs ratio and procyclicality for the excess profits ratio. Combining these two effects, we observe that price-cost margins are countercyclical albeit insignificantly.

4.7 Conclusion

The current COVID-19 pandemic leads to a sharp fall in operating revenue for many industries and firms. Although variable costs related to the foregone production can be avoided, fixed expenses still have to be paid. Firms which are no longer able to do so might run rapidly into liquidity problems leading to inefficient exit. Governments reacted instantly and initiated various aid programs to guide healthy firms through the crisis, however, budget deficits are widening and public debt is increasing. Therefore, it is essential that policy measures are targeted rather than broad-based.

This chapter argues that the case for support is high in industries which are characterized by the following criteria: 1) a substantial loss of operating revenue, 2) a high initial fixed cost share and 3) a low pre-crisis profitability. We combine these criteria into a novel vulnerability index: sectors with larger values on this vulnerability index are more prone to inefficient exit, and should be targeted by government aid. The first component can be obtained from accounting information, however, the latter two components cannot easily be identified. Firms are not required to report the distinction between variable and fixed costs in their accounts. Based on a novel methodology (Abraham et al., 2020), we estimate industry-level price-cost margins and decompose them into a part needed to pay for fixed costs and a part which remains left as excess profitability.

We illustrate this methodology via microdata from 3 countries during the Great Recession on the one hand and detailed Belgian firm-level data from 1985 until 2014 on the other hand. For the Belgian economy, we identify the industries which should be targeted, i.e. Food & Accommodation in the first place followed by Wholesale & Retail; Manufacturing; and Administrative & Support Services.

Finally, we contribute to the academic literature on price-cost margin cyclicality by showing that the fixed costs ratio and the excess profits ratio evolve differently during crisis times. The fixed cost share is countercyclical while the excess profitability is procyclical, i.e., fixed cost shares rise in crisis times while profitability decreases. The ongoing COVID-19 pandemic is likely to amplify this channel even more: according to our calculations, the share of fixed costs might increase by 16.0 percentage points and the excess profit ratio might fall by 3.8 percentage points, on average.

One key dimension of an economic exit, and recovery, strategy is to target government aid based on the vulnerability index, towards industries which are prone to high revenue losses, high fixed cost shares and low pre-crisis profitability buffers.

4.8 Appendix

4.8.1 Methodology appendix

We follow Abraham et al. (2020) and start from a standard short run production function which is homogeneous of degree one in variable capital K^v, variable labor L^v and variable intermediate inputs M^v. The returns to scale are constant for *variable* inputs for firm *i* in year *t*,

$$Q_{it} = F(K_{it}^v, L_{it}^v, M_{it}^v)\Theta_{it} \qquad \text{(A1)}$$

where production function F(.) uses inputs capital, labor and intermediate inputs to produce physical output Q. Θ represents an index of Hicks-neutral technological change.

A variable input is defined is defined as an input which adjusts within one time period without frictions. Likewise, a fixed input is defined as an input which does not adjust within one time period and/or experiences frictions. The share of variable (fixed) capital sv^k (sf^k), the share of variable (fixed) labor sv^l (sf^l) and the share of variable (fixed) intermediate inputs sv^m (sf^m) are defined as the share of the input which is variable (fixed). For example, a firm has €100 in total capital costs of which €20 (€80) is needed to pay variable (fixed) capital costs, then, the share of variable (fixed) capital is 20% (80%). In the remainder of the derivation, we omit the subscripts for firms and time after which we add them again in the final main equation.

Allowing for the presence of fixed costs and imperfect competition in the product market, output growth is defined as a weighted sum of the variable input growth augmented by the mark-up and the growth rate of productivity as,

$$\Delta \mathrm{q} = \frac{\mathrm{P}}{\mathrm{MC}}\left(\frac{\mathrm{sv^k RK}}{\mathrm{PQ}}\Delta \mathrm{k^v} + \frac{\mathrm{sv^l WL}}{\mathrm{PQ}}\Delta \mathrm{l^v} + \frac{\mathrm{sv}^{m} P^M M}{\mathrm{PQ}}\Delta \mathrm{m^v}\right) + \Delta\theta \qquad \text{(A2)}$$

where $\frac{\mathrm{sv^k RK}}{\mathrm{PQ}}$, $\frac{\mathrm{sv^l WL}}{\mathrm{PQ}}$ and $\frac{\mathrm{sv}^{m} P^M M}{\mathrm{PQ}}$ are defined as the share of variable capital cost, variable labor cost and variable intermediate input cost in revenue, respectively. Growth rates are shown by Δ and are defined as the difference between the value in year *t* and year *t-1* divided by the mean of the values in year *t* and year *t-1*. The primal revenue-based Solow residual is defined as,

$$SRQ^R \equiv \Delta q - \frac{WL}{PQ}\Delta l - \frac{P^M M}{PQ}\Delta m - (1 - \frac{WL}{PQ} - \frac{P^M M}{PQ})\Delta k \qquad \text{(A3)}$$

with $\Delta q, \Delta l, \Delta m \; and \; \Delta k$ defined as the growth rate of physical output *q*, number of employees *l*, units of intermediate inputs *m* and capital units *k*. The Solow residual is positive if the growth rate of the output exceeds the weighted growth rate of the inputs. For example, the growth rate of output equals

5% while all inputs increase by 3%, then the Solow residual equals 2%. Hence, the firm or the industry becomes more productive.

Substituting equation (A2) in the primal revenue-based Solow residual defined in equation (A3), allows to rewrite the primal revenue-based Solow residual as follows:

$$SRQ^R = PCM(\Delta q - \Delta k) + \frac{(1-\mathrm{sv}^{\mathrm{l}})WL}{PQ}(\Delta k - \Delta l) + \frac{(1-\mathrm{sv}^{\mathrm{m}})P^M M}{PQ}(\Delta k - \Delta m) + \frac{\mathrm{sv}^{\mathrm{k}}RK}{PQ}(\Delta \mathrm{k}^{\mathrm{v}} - \Delta k) +$$

$$\frac{\mathrm{sv}^{l}WL}{PQ}(\Delta l^{\mathrm{v}} - \Delta l) + \frac{\mathrm{sv}^{\mathrm{m}}P^M M}{PQ}(\Delta \mathrm{m}^{\mathrm{v}} - \Delta m) + (1 - PCM)\Delta\theta \qquad \text{(A4)}$$

Equation (A4) shows that the primal revenue-based Solow residual captures the growth rate of productivity as well as additional wedges introduced by the presence of price-cost margins on the one hand and fixed factors of production on the other hand. Under the simplifying assumptions that fixed costs and price-cost margins do not exist, i.e. these components equal zero, all components except the final one in equation (A4) drop out such the primal revenue-based Solow residual only captures the growth rate of technology.

Following Roeger (1995), we exploit the dual revenue-based Solow residual to eliminate the unobservable productivity growth. Define the cost function $C(W, R, P^M, Q, \theta) = \frac{G(W,R,P^M)Q}{\theta}$ with G(.) the marginal costs and being homogeneous of degree one. The growth rate of product price Δp is defined as,

$$\Delta p = \frac{P}{MC}\left(\frac{\mathrm{sv}^{\mathrm{k}}\mathrm{RK}}{\mathrm{PQ}}\Delta r + \frac{\mathrm{sv}^{\mathrm{l}}\mathrm{WL}}{\mathrm{PQ}}\Delta w + \frac{\mathrm{sv}^{m}P^M M}{\mathrm{PQ}}\Delta p^M\right) - \Delta\theta \qquad \text{(A5)}$$

with $\Delta r, \Delta w \; and \; \Delta p^M$ defined as the growth rate of the cost of capital, the average firm-level wage and the price of the intermediate input. Define the dual revenue-based Solow residual as,

$$SRP^R \equiv \frac{WL}{PQ}\Delta w + \frac{P^M M}{PQ}\Delta p^M + \left(1 - \frac{WL}{PQ} - \frac{P^M M}{PQ}\right)\Delta r - \Delta p \qquad \text{(A6)}$$

The dual revenue-based Solow residual is negative (positive) if the growth rate of the product price exceeds (is less than) the weighted growth rate of the inputs. Substituting equation (A5) into equation (A6) leads to,

$$SRP^R = -B(\Delta p - \Delta r) + \frac{(1-\mathrm{sv}^{\mathrm{l}})WL}{PQ}(\Delta w - \Delta r) + \frac{(1-\mathrm{sv}^{\mathrm{m}})P^M M}{PQ}(\Delta p^M - \Delta r) + (1 - PCM)\Delta\theta \qquad \text{(A7)}$$

Taking the difference of equations (A3) and (A7) gives,

$$SRQ^R - SRP^R = PCM[(\Delta p + \Delta q) - (\Delta k + \Delta r)] + \frac{(1-\mathrm{sv}^{\mathrm{l}})WL}{PQ}(\Delta k + \Delta r) + \frac{(1-\mathrm{sv}^{\mathrm{m}})P^M M}{PQ}(\Delta k + \Delta r) +$$
$$\frac{(\mathrm{sv}^{\mathrm{l}}-1)WL}{PQ}(\Delta w + \Delta l) + \frac{(\mathrm{sv}^{\mathrm{m}}-1)P^M M}{PQ}(\Delta p^M + \Delta m) + \frac{\mathrm{sv}^{\mathrm{k}}\mathrm{RK}}{\mathrm{PQ}}(\Delta \mathrm{k}^{\mathrm{v}} - \Delta \mathrm{k}) + \frac{\mathrm{sv}^{\mathrm{l}}\mathrm{WL}}{\mathrm{PQ}}(\Delta \mathrm{l}^{\mathrm{v}} - \Delta \mathrm{l}) +$$
$$\frac{\mathrm{sv}^{\mathrm{m}} P^M M}{\mathrm{PQ}}(\Delta m^v - \Delta \mathrm{m}) \qquad \text{(A8)}$$

and allows to eliminate the unobservable growth rate of productivity $\Delta\theta$. The difference of the primal and dual revenue-based Solow residual can be explained by a price-cost margin component and the presence of fixed factors of production. There is still more than one unobservable in the latter three components, making it impossible to disentangle these components. In order to resolve this issue, we exploit the primal and dual *cost-based* Solow residuals as well. We follow the same roadmap to obtain the difference between the primal and dual cost-based Solow residual after which we exploit the difference between the four Solow residuals.

Using cost shares and the assumption of constant returns to scale for *variable* inputs, we obtain $MC * Q = C^v$ with MC and C^v defined as the marginal cost and the total variable costs respectively, we can rewrite equation (A2), based on cost shares now, as,

$$\Delta \mathrm{q} = \frac{\mathrm{sv}^{\mathrm{k}}\mathrm{RK}}{\mathrm{C}^{\mathrm{v}}}\Delta \mathrm{k}^{\mathrm{v}} + \frac{\mathrm{sv}^{\mathrm{l}}\mathrm{WL}}{\mathrm{C}^{\mathrm{v}}}\Delta \mathrm{l}^{\mathrm{v}} + \frac{sv^m \mathrm{P}^{\mathrm{M}}\mathrm{M}}{\mathrm{C}^{\mathrm{v}}}\Delta \mathrm{m}^v + \Delta\theta \qquad \text{(A9)}$$

which we then substitute in the primal cost-based Solow residual

$$SRQ^C \equiv \Delta q - \frac{WL}{C}\Delta l - \frac{P^M M}{C}\Delta m - \frac{RK}{C}\Delta k \qquad \text{(A10)}$$

to obtain the alternative primal cost-based Solow residual,

$$\mathrm{SRQ}^{\mathrm{C}} = \left(1 - \mathrm{sv}^{\mathrm{k}}\right)\frac{\mathrm{RK}}{\mathrm{C}}(\Delta \mathrm{q} - \Delta \mathrm{k}) + \left(1 - \mathrm{sv}^{\mathrm{l}}\right)\frac{\mathrm{WL}}{\mathrm{C}}(\Delta \mathrm{q} - \Delta \mathrm{l}) + (1 - \mathrm{sv}^{\mathrm{m}})\frac{P^M M}{\mathrm{C}}(\Delta \mathrm{q} - \Delta \mathrm{m}) +$$
$$\mathrm{sv}^{\mathrm{k}}\frac{\mathrm{RK}}{\mathrm{C}}(\Delta \mathrm{k}^{\mathrm{v}} - \Delta \mathrm{k}) + \mathrm{sv}^{\mathrm{l}}\frac{\mathrm{WL}}{\mathrm{C}}(\Delta \mathrm{l}^{\mathrm{v}} - \Delta \mathrm{l}) + \mathrm{sv}^{\mathrm{m}}\frac{P^M M}{\mathrm{C}}(\Delta \mathrm{m}^{\mathrm{v}} - \Delta \mathrm{m}) + \frac{\mathrm{C}^{\mathrm{v}}}{\mathrm{C}}\Delta\theta \qquad \text{(A11)}$$

We exploit the dual cost-based Solow residual and define the growth rate of the product price as,

$$\Delta p = \frac{\mathrm{sv}^{\mathrm{k}}\mathrm{RK}}{\mathrm{C}^{\mathrm{v}}}\Delta r + \frac{\mathrm{sv}^{\mathrm{l}}\mathrm{WL}}{\mathrm{C}^{\mathrm{v}}}\Delta w + \frac{sv^m \mathrm{P}^{\mathrm{M}}\mathrm{M}}{\mathrm{C}^{\mathrm{v}}}\Delta p^M - \Delta\theta \qquad \text{(A12)}$$

and substitute it in the dual cost-based Solow residual defined in equation (A13),

$$SRP^C \equiv \frac{RK}{C}\Delta r + \frac{WL}{C}\Delta w + \frac{P^M M}{C}\Delta p^M - \Delta p \qquad \text{(A13)}$$

to get,

$$SRP^C = -\left(1 - \mathrm{sv}^{\mathrm{k}}\right)\frac{RK}{C}(\Delta p - \Delta r) - (1 - \mathrm{sv}^{\mathrm{l}})\frac{WL}{C}(\Delta p - \Delta w) - (1 - \mathrm{sv}^{m})\frac{P^M M}{C}(\Delta p - \Delta p^M) + \frac{\mathrm{C}^{\mathrm{v}}}{\mathrm{C}}\Delta\theta$$

(A14)

Combining the primal and dual cost-based Solow residual from equations (A11) and (A14) gives,

$$SRQ^C - SRP^C = \left(1 - \mathrm{sv}^{k}\right)\frac{RK}{C}[(\Delta p + \Delta q) - (\Delta k + \Delta r)] + \left(1 - \mathrm{sv}^{\mathrm{l}}\right)\frac{WL}{C}[(\Delta p + \Delta q) - (\Delta w + \Delta l)] + (1 - \mathrm{sv}^{\mathrm{m}})\frac{P^M M}{C}[(\Delta p + \Delta q) - (\Delta m + \Delta p^M)] + \frac{\mathrm{sv}^{k} RK}{C}(\Delta k^v - \Delta k) + \frac{\mathrm{sv}^{l} WL}{C}(\Delta l^v - \Delta l) + \frac{\mathrm{sv}^{m} P^M M}{C}(\Delta m^v - \Delta m) \qquad \text{(A15)}$$

which shows that the difference of the two cost-based Solow residuals is not subject to the growth rate of productivity nor to the price-cost margin. Nevertheless, the fourth, fifth and sixth still have more than one unobservable such that we cannot uniquely identify all unobserved components.

We resolve this by exploiting the difference between the difference between the primal and dual cost-based Solow residual on the one hand and the difference between the primal and dual revenue-based Solow residual on the other hand, which looks like a "difference-in-difference" (DID) approach. We multiply both sides of equation (A15) by $\frac{C}{PQ}$ to get the same denominator, as is also done in the robustness section in Abraham et al. (2020).

Finally, we obtain our main equation (1) as introduced in the main text.

$$\Delta y_{it} = -PCM_{st} * \Delta x_{1_{it}} + sf_{st}^{k} * \Delta x_{2_{it}} + sf_{st}^{l} * \Delta x_{3_{it}} + sf_{st}^{m} * \Delta x_{4_{it}} + \epsilon_{it} \qquad (1)$$

where $\Delta y_{it} = \left(SRQ_{it}^{C} - SRP_{it}^{C}\right)\frac{C_{it}}{PQ_{it}} - \left(SRQ_{it}^{R} - SRP_{it}^{R}\right)$, $\Delta x_{1_{it}} = [(\Delta p + \Delta q)_{it} - (\Delta k + \Delta r)_{it}]$, $\Delta x_{2_{it}} = \frac{RK_{it}}{PQ_{it}}[(\Delta p + \Delta q)_{it} - (\Delta k + \Delta r)_{it}]$, $\Delta x_{3_{it}} = \frac{WL_{it}}{PQ_{it}}[(\Delta p + \Delta q)_{it} - (\Delta k + \Delta r)_{it}]$ and $\Delta x_{4_{it}} = \frac{P^M M_{it}}{PQ_{it}}[(\Delta p + \Delta q)_{it} - (\Delta k + \Delta r)_{it}]$. $(\Delta p + \Delta q)_{it}$ and $(\Delta k + \Delta r)_{it}$ are defined as the growth rate of operating revenue and the growth rate of total cost of capital, respectively. SRQ(C), SRP(C), SRQ(R) and SRP(R) are defined as in equations A10, A13, A3 and A6 respectively. We weigh equation (1) by operating revenue at the firm-year level.

Having estimated both the price-cost margin and the shares of fixity for each input factor, we can now decompose the price-cost margins into a fixed costs ratio and an excess profits ratio. The former component is needed to cover fixed costs while the latter component represents the excess profitability. Price-cost margins are defined as the sum of the fixed costs ratio and the excess profits ratio as shown in equation (2):

$$\widehat{PCM}_{st} \equiv \widehat{FCR}_{st} + \widehat{EPR}_{st} \qquad (2)$$

with $\widehat{FCR}_{st} \equiv \frac{\left(\widehat{sf^k_{st}} * RK_{st} + \widehat{sf^l_{st}} * WL_{st} + \widehat{sf^m_{st}} * P^M M_{st}\right)}{PQ_{st}}$; $\widehat{EPR}_{st} = \widehat{PCM}_{st} - \frac{\left(\widehat{sf^k_{st}} * RK_{st} + \widehat{sf^l_{st}} * WL_{st} + \widehat{sf^m_{st}} * P^M M_{st}\right)}{PQ_{st}}$

where RK_{st}, WL_{st}, $P^M M_{st}$ and PQ_{st} represent respectively total capital costs, total labor costs, total intermediate input costs and operating revenue at the industry-year level.

4.8.2 Data appendix

This chapter uses balance sheet data from Belgian unconsolidated firms. The sample period goes from 1985 until 2014. Firms are identified by their unique VAT number and assigned to a NACE rev. 2 two-digit industry.[18] The data set covers all for-profit firms which are legally required to report an annual income statement. Small firms are not obliged to report, however, some of them still choose to do so voluntarily. Small firms are firms that do not exceed one of the following criteria (2014 levels): average number of employees above 50 full-time equivalents, €7.3 million turnover and €3.65 million balance sheet total (Bijnens & Konings, 2018). Self-employed people are not included. The data set covers an increasing number of employees: employment is 881,701 in 1985 and 1,496,192 in 2014.

Variable definition – We follow Hall & Jorgenson (1967) and define the nominal rental cost of capital as $R_{it} = P_{I_t}(r_t - \pi_t + \delta_{it})$ for firm *i* in year *t*. We follow Konings, Van Cayseele and Warzynski (2005) in order to calculate the depreciation rate δ_{it}, defined as the ratio of depreciation in year t-1 and tangible fixed assets in year t for firm i. We limit the depreciation rate at 100%. Note that Belgian firms report depreciation only since 1996, therefore, we assume that the depreciation rate before 1996 equals the depreciation rate in 1996. Furthermore, we obtain the price index of investment goods P_I from the World Bank (2021). Inflation π and the nominal interest rate r are sourced from the OECD. The three latter variables are at the Belgian country-year level.

Data cleaning (firm-level) – As part of the data cleaning process, we keep only firms which belong to the private sector (NACE codes: 10/82). We keep firms which have a nonnegative value for operating revenue, wage costs, intermediate input costs, tangible fixed assets and which report their NACE rev. 2 two-digit code. We drop firms with a negative or zero value for depreciation. We drop firms with a labor share or an intermediate input share larger than one. We replace negative capital shares by a value of zero. Finally, we winsorize the variables in equation (1) at the 1st and 99th percentile at the sector level to account for outliers. We define four sectors: Industry (10/33), Trade (45/47), Services (49/82) and Other. The numbers in parentheses refer to the NACE rev. 2 two-digit codes.

Data cleaning (industry-level) – We estimate equation (1) and (2) at the industry-year level. We remove industries-years which have an estimated price-cost margin or fixed costs ratio below 0% or

[18] NACE is the standard industry classification system used in the European Union.

above 100% as well as industries with an excess profits ratio below -10% or above 100%. We interpolate the price-cost margin, fixed costs ratio and the excess profits ratio after which we obtain the HP filtered components, by industry.

4.8.3 Table appendix

Table 4.6 Industry description

Sector	NACE	Fixed costs ratio	P-value (FCR)	Industry description
G	46	.23	<.001	Wholesale trade, except of motor vehicles and motorcycles
G	45	.25	<.001	Wholesale and retail trade and repair of motor vehicles and motorcycles
G	47	.30	<.001	Retail trade, except of motor vehicles and motorcycles
C	10	.35	<.001	Manufacture of food products
F	41	.36	<.001	Construction of buildings
C	18	.37	<.001	Printing and reproduction of recorded media
C	13	.38	<.001	Manufacture of textiles
C	20	.40	<.001	Manufacture of chemicals and chemical products
D	35	.40	<.001	Electricity, gas, steam and air conditioning supply
N	79	.41	<.001	Travel agency, tour operator and other reservation service and related activities
C	17	.41	<.001	Manufacture of paper and paper products
C	29	.41	<.001	Manufacture of motor vehicles, trailers and semi-trailers
C	28	.42	<.001	Manufacture of machinery and equipment n.e.c.
C	19	.43	<.001	Manufacture of coke and refined petroleum products
C	25	.43	<.001	Manufacture of fabricated metal products, except machinery and equipment
C	22	.44	<.001	Manufacture of rubber and plastic products
C	23	.45	<.001	Manufacture of other non-metallic mineral products
E	37	.45	<.001	Sewerage
J	61	.46	<.001	Telecommunications
N	77	.46	<.001	Rental and leasing activities
E	38	.46	<.001	Waste collection, treatment and disposal activities; materials recovery
C	16	.46	<.001	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
N	80	.46	<.001	Security and investigation activities
C	27	.48	<.001	Manufacture of electrical equipment
C	32	.50	<.001	Other manufacturing

F	42	.51	<.001	Civil engineering
F	43	.51	<.001	Specialised construction activities
L	68	.52	<.001	Real estate activities
C	26	.54	<.001	Manufacture of computer, electronic and optical products
N	81	.55	<.001	Services to buildings and landscape activities
H	52	.56	<.001	Warehousing and support activities for transportation
C	30	.56	<.001	Manufacture of other transport equipment
C	24	.56	<.001	Manufacture of basic metals
C	33	.57	<.001	Repair and installation of machinery and equipment
H	50	.58	<.001	Water transport
N	78	.62	<.001	Employment activities
C	31	.63	<.001	Manufacture of furniture
C	15	.63	<.001	Manufacture of leather and related products
C	14	.64	<.001	Manufacture of wearing apparel
I	55	.64	<.001	Accommodation
K	65	.65	<.001	Insurance, reinsurance and pension funding, except compulsory social security
I	56	.68	<.001	Food and beverage service activities
K	64	.69	<.001	Financial service activities, except insurance and pension funding
C	11	.69	<.001	Manufacture of beverages
N	82	.69	<.001	Office administrative, office support and other business support activities
H	49	.70	<.001	Land transport and transport via pipelines
J	58	.71	<.001	Publishing activities
M	70	.71	<.001	Activities of head offices; management consultancy activities
J	59	.71	<.001	Motion picture, video and television programme production, sound recording and music publishing activities
E	36	.72	<.001	Water collection, treatment and supply
K	66	.72	<.001	Activities auxiliary to financial services and insurance activities
E	39	.72	<.001	Remediation activities and other waste management services
C	21	.72	<.001	Manufacture of basic pharmaceutical products and pharmaceutical preparations
M	71	.73	<.001	Architectural and engineering activities; technical testing and analysis
H	53	.74	<.001	Postal and courier activities

M	73	.76	<.001	Advertising and market research
J	62	.78	<.001	Computer programming, consultancy and related activities
M	69	.78	<.001	Legal and accounting activities
M	72	.78	<.001	Scientific research and development
C	12	.80	<.001	Manufacture of tobacco products
H	51	.80	<.001	Air transport
J	63	.81	<.001	Information service activities
J	60	.86	<.001	Programming and broadcasting activities
M	74	.87	<.001	Other professional, scientific and technical activities
M	75	.93	<.001	Veterinary activities

Notes: *This table contains the sector code in column (1), the NACE two digit code in column (2), the estimated fixed costs ratio averaged over the sample period in column (3) and the industry description name. The table is sorted by estimated fixed costs ratio.*

4.9 References

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