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The impact of superstar firms on the labor share

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Evidence from a small, open economy: Belgium*

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Abstract

The Belgian labor share, measured as the part of GDP going to labor, is declining. This evolution fits into the global secular trend of decreasing labor shares. A novel strand in the literature focusses on its firm-level drivers. Recent research in the United States claims that superstar firms, defined as large firms with a dominant market share, are increasing their market share and link this to the fall of the labor share (Autor, Dorn, Katz, Patterson & Van Reenen, 2017). Using a long time series of Belgian firm-level data from 1985 – 2014, we link the rise of superstar firms to the decrease of the labor share in Manufacturing, Wholesale & Retail and Transportation & Storage. These three sectors represent approximately two-thirds of the Belgian economy.

Keywords: Labor share, Superstar firms, Market concentration, Firm-level data

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1. Introduction

The part of GDP which goes to workers is defined as the labor share. Nowadays, there is compelling evidence that the labor share is declining in the vast majority of the countries around the world (Karabarbounis & Neiman, 2014). The ILO & the OECD (2015) documented the evolution of the labor share across a variety of developed and emerging countries. They show that the labor share decreases in developed countries like Spain, Italy, United States, Japan, Australia, Canada, Germany, France and the United Kingdom. The same pattern is also apparent in most emerging economies. The labor share declined in Turkey, Saudi Arabia, Mexico, South Africa, China, India and Brazil. One exception is the Russian Federation, the labor share has moderately increased.

The fall of the labor share is an important policy issue for at least two reasons. First, a secular decline in the labor share implies that productivity is growing structurally faster than real wages. Bivens, Gould, Mishel & Shierholz (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 108.1% and 93.4%, but between 1979 and 2013, productivity increased by 64.9% while wages increased only by 8.2% . This evolution might be perceived as unfair by (groups of) workers. They might feel left behind. Second, a falling labor share has recently been linked to a rise in income inequality. This follows from the fact that labor income is known to be more equally distributed than capital income (Dao, Das, Koczan & Lian, 2017).

Which mechanisms can explain the decline in the labor share? One dominant strand in the literature points to the rapid advancement of technology as well as to the globalization of trade and capital (Dao et al., 2017). Karabarbounis & 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 & Wan (2017) support the importance of international trade. They show that exports depress the labor share whereas imports increase the labor share.

Another strand in the literature remains inconclusive about the impact of other determinants like a mark-up increase, 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 recent strand in the literature focusses on the granularity approach. Autor et al. (2017) relate the rise of superstar firms to the fall of the labor share. Superstar firms are large firms with a dominant market share in terms of value added in their industry – like Apple, Walmart and so on. These firms are characterized by a lower labor share. They achieve this through lower average costs, superior quality and/or greater innovation. The authors show that these superstar firms are expanding their market share. The combination of a lower labor share and a growing market share causes the aggregate labor share to decline over time. They define this mechanism as the superstar firm hypothesis.

Autor et al. (2017) provide evidence for the link between the growing dominance of large firms and the fall of the labor share in a variety of sectors in the United States. However, large firms are often considered to be less important in Europe. Nevertheless, evidence from a European country is still lacking. It serves as an interesting research opportunity to investigate to what extent the U.S. findings generalize (De Loecker, Fuss & Van Biesebroeck, 2018). We contribute to the literature by investigating the impact of superstar firms on the labor share in the Belgian economy.

Belgium stands out as an interesting case study as it differs notably from the economy in the United States. Belgium has a small, open economy unlike the United States. Further, Belgium is part of the ongoing integration happening in the European Union, a process not present in the United States. Finally, the labor market differs considerably. For example, trade union density is 53.8% in Belgium whereas it is only 10.7% in the United States in 2014 (OECD, 2019).

The remainder of the paper contains five parts. Section 2 discusses the empirical strategy, which closely follows the approach used by Autor et al. (2017). We continue by presenting our Belgian firm-level data, going from 1985 until 2014, in section 3. Next, we present the results in section 4. We show that the increase in market share of superstar firms is linked to the fall of the labor share in Manufacturing, Wholesale & Retail and Transportation & Storage. We provide multiple robustness checks in section 5, which confirm our findings. We conclude in section 6.

2. Empirical strategy

2.1. Terminology

In this part, we introduce some basic terminology. We define the aggregate labor share as,

$$LS_t = \sum_{1}^{i} ms_{it} * LS_{it} \, , \tag{1}$$

with ms_{it} and LS_{it} representing respectively the market share 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 the 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. LS_t represents the aggregate labor share. For example, assume an economy with two firms, namely firm A and firm B. Firm A produces a value added of €100 and pays its workers €60. The labor share is .60 for firm A. Firm B produces a value added of €400 and pays its workers €140. The labor share equals .35 for firm B. The market share of firm A equals .20 while the market share of firm B equals .80 . We apply equation (1), taking into account the weights of each firm, and obtain an aggregate labor share of .40 for this economy.

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 market shares, leads to a biased aggregate labor share as this implicitly assumes an equal market share for each firm. Weighing gives more (less) importance to the labor share of a large (small) firm.

The market and aggregate labor shares can be calculated for different levels of aggregation. We can do this on an industry, sector, country or even a global level.

2.2. The superstar firm hypothesis

Autor et al. (2017) 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 further over time, they turn into so-called superstar firms. The reallocation of market shares to dominant firms increases market concentration within an industry. Besides, superstar firms in the United States are characterized by a lower labor share. They achieve this through lower average costs, superior quality and/or greater innovation. As the importance of the low labor share of these superstar firms rises, their weight in formula (1) grows as well. This leads to a gradual decline in the aggregate U.S. labor share over time. Thus, value added reallocates to superstar firms causing the aggregate U.S. labor share to fall.

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 in 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: Increasing market concentration

We define three market concentration measures, namely C4, C10 and C20 which respectively represent the market share of the four, ten and twenty largest firms within their industry. We aggregate this industry-specific concentration measure to a sector-specific concentration measure while taking into account the different weight of each industry within a sector. 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 industry output of €100. The four largest firms in the second industry create a value added of €120 relative to a total industry output 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, leads to an aggregate market concentration of .40 in this sector. The aggregate market concentration lies closer to the market concentration of the second industry because the total value added of the second industry is four times as large as the total value added of the first industry.

At this stage, we are only interested in providing descriptive figures showing the evolution of the market concentration measures C4, C10 and C20. We want to observe if we can identify (periods in) sectors with a declining labor share and an increasing market concentration. We try to link these evolutions in a more formal way and turn to econometrics in the next prediction.

Prediction 2: An increase in the market concentration ratio leads to a decrease in the labor share

The second prediction states that industries with the highest increase in the concentration ratio will experience the largest drop in the labor share. We follow the regression specification used by Autor et al. (2017) 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.[3] Time dummies are represented by γ_t and the error term is given by ε_{jt}. We run separate regressions for each sector. The regression coefficient β_s is estimated uniquely for each sector.[4]

[3] We provide the results for market concentration measures C10 and C20 in the robustness section.
[4] We use heteroscedasticity-robust standard errors in equation (2). Abadie, Athey, Imbens & 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.

The second prediction requires that the market concentration and 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 reallocation effect drives the fall of the labor share

The third prediction states that the reallocation effect, also called 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 the two components resulting from the Olley & Pakes (1996) decomposition. The between-firm component describes factors influencing firms 'in a different way'. An example clarifies this component. 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. Firms are thus affected in a different way. 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. All firms are affected in the same way, they all grow equally.

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

The third prediction thus states 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 & Pakes (1996) decomposed industry productivity into two components, a within-firm and a between-firm component. Their method can be applied in an analogous way to decompose the evolution of the labor share. Define the aggregate labor share decomposition, based on Olley & Pakes (1996) as,

$$\begin{aligned} LS_t &= \sum_{1}^{i} w_{it} * LS_{it} \\ &= \underbrace{\overline{LS}_t}_{Within-firm} + \underbrace{\sum_{1}^{i} (w_{it} - \overline{w}_t)(LS_{it} - \overline{LS}_t)}_{Between-firm}, \end{aligned} \tag{3}$$

with the unweighted average firm weight $\overline{w}_t$ and the unweighted average labor share $\overline{LS}_t$.[5] Other variables are defined as before. The first term on the right-hand side is the within-firm component, the second term is the between-firm component.

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 for surviving firms. 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,

$$\Delta LS = LS_t - LS_{t-1}$$
$$= \underbrace{\Delta \overline{LS}}_{\Delta Within-firm} \underbrace{+\Delta \sum_{1}^{i} (w_i - \overline{w})(LS_i - \overline{LS}).}_{\Delta Between-firm} \quad (4)$$

Melitz & 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 aggregate labor share decomposition, based on Melitz and Polanec (2015) as,

[5] 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.

$$\Delta LS = \underbrace{\Delta\overline{LS}^S}_{\Delta Within\ (Survivors)} + \underbrace{\left\{\Delta\sum_{1}^{i}(w_i - \overline{w})(LS_i - \overline{LS})\right\}^S}_{\Delta Between\ (Survivors)} \tag{5}$$
$$+ \underbrace{w_{t-1}^X\left(LS_{t-1}^S - LS_{t-1}^X\right)}_{Exit\ term} + \underbrace{w_t^E\,(LS_t^E - LS_t^S)}_{Entry\ term},$$

with the superscript S, X and E abbreviating 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 aggregate 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 & Maliranta (2016). Providing standard errors is becoming common practice in the field of productivity decompositions (Fuss & Theodorakopoulos, 2018) but is barely done in labor share decomposition papers.

> Prediction 4: An increase in the market concentration ratio leads to a decrease in the between-firm component

The fourth prediction states that industries with the highest increase in the concentration ratio will experience the largest fall in the between-firm component. We use the same approach as before and use the following regression specification based on Autor et al. (2017),

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

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.[6] The regression coefficient should be significantly negative in order to confirm the fourth hypothesis.

[6] We use robust standard errors in equation (6). Abadie et al. (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.

3. Data

We use firm-level data sourced from the National Bank of Belgium. The time period ranges from 1985 to 2014. We use the 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). The numbers between parentheses refer to the codes in the Belgian financial statement. 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[7]. We only keep observations with a strictly positive value for remuneration. We have 4.016.033 unique firm-year combinations (of which 73.659 in 1985 and 162.333 in 2014).

Our dataset contains firm-level observations for 21 sectors but we include only the eight largest sectors in our analysis. These eight sectors represent 82.5% and 88.0% of value added in respectively 1985 and 2014. 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.

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 then 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 dataset, 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

[7] 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 in this paper.

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 becomes negative when value added drops below zero. We solve this by replacing negative value added observations by a value added of one. Doing so, the labor share is defined while the firm's contribution to aggregate value added is approximately zero. However, these observations now also experience the second issue. If the value added of a firm goes to 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 & Polanec (2015) decomposition. We solve this by replacing the labor share by a value of two if its original value is higher than two. We test alternative specifications in our robustness section at the end of the paper and show that our results are robust to different treatments of these outliers.

4. Results

4.1. Summary statistics

We show the summary statistics for our variables of interest: remuneration, value added, firm labor share and market concentration in **Table 1**. This reveals that the mean value for remuneration and value added is well above the median, which is the 50th percentile. This implies that the distribution of remuneration and value added is not symmetric, but heavily skewed towards large firms. The highest value for remuneration is €2.17 billion while the largest value added equals €2.8 billion.

Table 1: *Summary statistics*

	mean	sd	p25	p50	p75	min	max
Remuneration	533 713	9 037 716	19 212	57 974	189 929	1	2 171 158 016
Value Added	874 769	15 015 619	43 084	110 796	308 132	1	2 822 272 256
Firm Labor Share (orig.)	4003.14	204754.06	0.37	0.62	0.82	0.00	89 974 000
Firm Labor Share (adj.)	0.66	0.45	0.37	0.62	0.82	0.00	2.00
Market Concentration	0.44	0.25	0.23	0.40	0.63	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.*

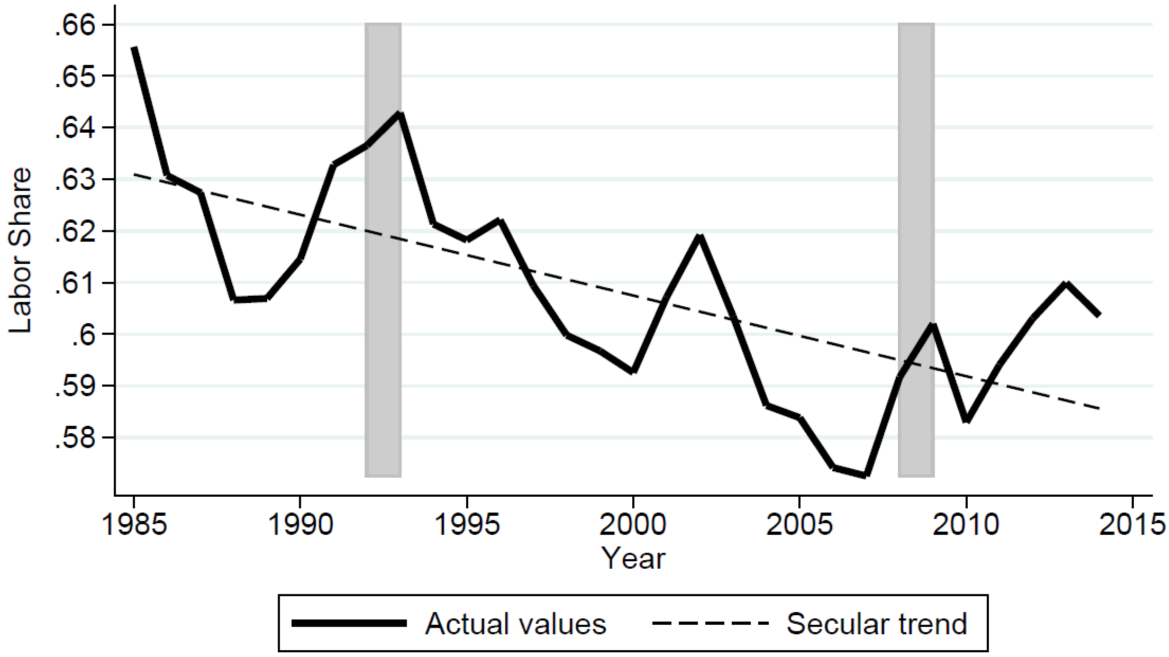
The original firm-specific labor share displays plausible values for the 25th, 50th and 75th percentile, but the maximum value equals roughly 90 million. This implies that a firm would pay its workers 90 million times their value added, which does not make any sense at all. This is why we adjust the labor share as we have explained before. The adjusted firm-specific labor share has a maximum value of two. The mean and standard deviation of this adjusted labor share equals respectively .66 and .45 now.

Finally market concentration ranges from 0.02 to 0.99, indicating that some industries are not concentrated at all whereas other industries are completely captured by large firms. The mean and the median values are respectively .44 and .40 indicating that the four largest firms produce roughly 40%-45% of value added in an average industry.

4.2. Descriptive statistics

We start this part by plotting the evolution of the Belgian labor share in **Figure 1**. We add a linear trend (dashed line) through the actual values (solid line) to represent the secular trend of the labor share.

Figure 1: Evolution 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. It is expressed as a ratio and typically lies between zero and one. The shaded grey areas represent periods of recessions as indicated by the OECD.

This leads to five main results. First, the Belgian labor share is declining. It shrinks from approximately .66 in 1985 to less than .61 in 2014, a drop of more than five percentage points. Second, both the absolute levels and the decreasing trend are reasonably similar to the evolution observed in the United States. The U.S. labor share decreases from roughly .65 in 1977 to .59 in 2010 according to Autor et al. (2017). Third, the slope of the secular trend line in **Figure 1** equals -.00156 (p-value = .000). This slope follows from the regression of the Belgian labor share on year as shown in **Table 2**. This means that the labor share drops on average by .156 percentage point per year. Translating this into an economically meaningful number means that a Belgian worker would lose on average €139 of labor income per year. We based this back-on-the-envelope calculation on Eurostat data from 2014. In that year, Belgian GDP and its labor force equals respectively ±€400 billion and 4 497 200 employees. Dividing the 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 -.00156 leads ceteris paribus to the estimated yearly loss of €139 per employee.

Table 2: *Estimated decline of the Belgian labor share*

	(1) **Belgian labor share**
Year	-0.00156***
	(0.000310)
Constant	3.733***
	(0.620)
Observations	30
R-squared	0.476

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

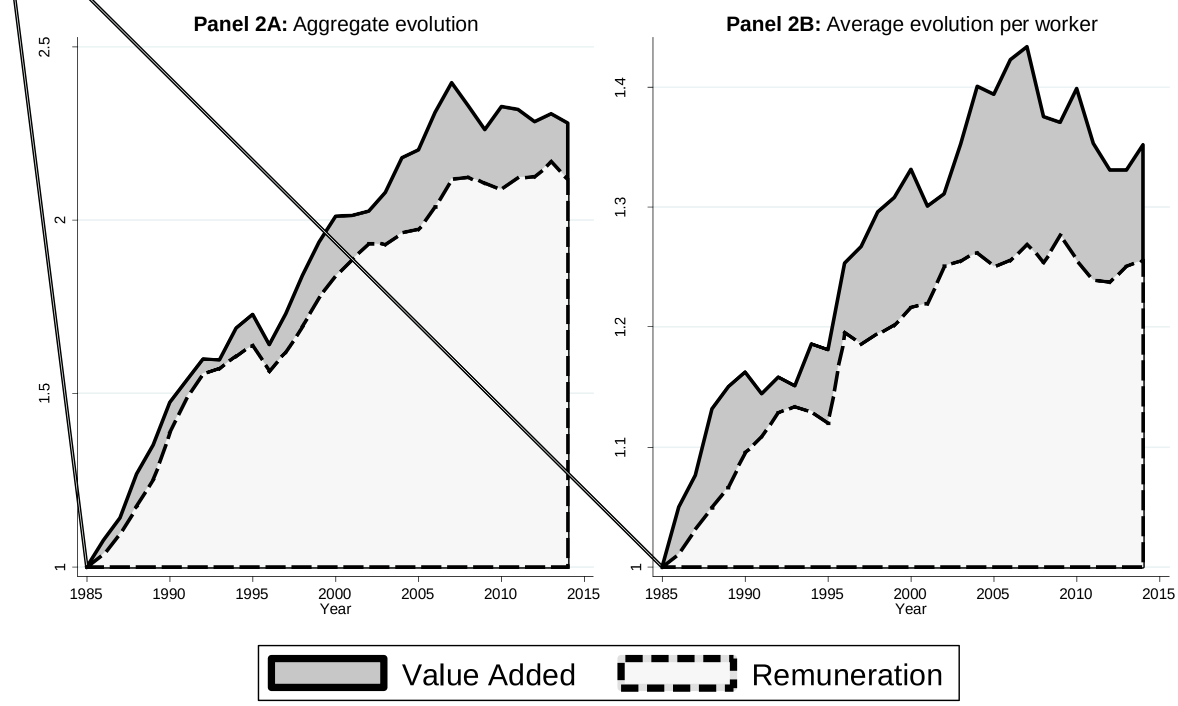
Fourth, the labor share evolves countercyclically over time. It reaches a temporarily peak during periods of recessions, while it decreases again during periods of recovery and economic upturn. This countercyclical pattern is in line with research done by Rios-Rull & Santaeulalia-Llopis (2010).[8] Finally, 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. This states that firms might be less tempted to hire and fire workers in respectively good and bad times. Stronger Belgian labor unions might indeed induce more barriers to do so. De Mulder & Druant (2011) document the case of labor hoarding in Belgium.

The labor share is defined as the ratio of remuneration and value added. We delve now further into the evolution of each component separately. **Figure 2** describes the evolution of remuneration and value added on the aggregated Belgian level.

[8] 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 .97.

Panel 2A shows the aggregate evolution.[9] 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 2B** visualizes the evolution of the average value added and average remuneration per worker.[10] We can interpret this as average productivity and average wages. We observe that the wage (+25%) and productivity (+35%) rise over time. Nevertheless, the increasing real wage per worker is unable to follow the faster increase in real value added per worker.

Figure 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.

We continue by calculating the labor share on a sector-level and show the results in **Figure 3**. We show the sectors by their market share in terms of value added in 1985. Manufacturing is the largest sector and Financial & Insurance Activities is the smallest of these eight sectors. The yearly sectoral market shares are shown in **Figure A1** (with A referring to an appendix figure/table from now on).

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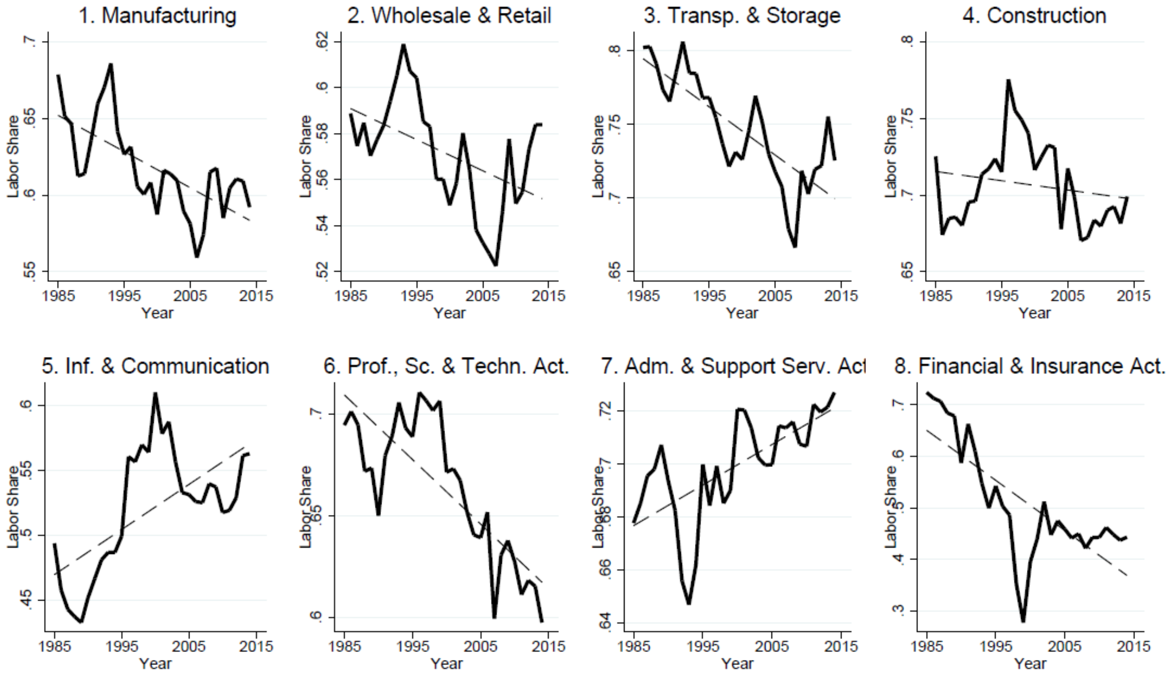
[9] The Belgian labor share can be defined as $LS = \frac{w*L}{VA} = \frac{w/p*L}{VA/p} = \frac{(\bar{w}*L)}{\overline{VA}}$ with w, L, p and VA denoting respectively nominal mean wage per worker, total employment, the CPI price index and nominal value added . Variables with a bar are denoted in real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

[10] 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.

Figure A1 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 stood at .60 in Manufacturing in 2014. We observe a higher labor share in Construction in the same year as it equals .70. On the other hand, the labor share equals only .45 in Financial & Insurance Activities in the final year of our data.

Figure 3: Sectoral evolution of the 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 show that the secular labor share trend (dashed line) 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.

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 explained by the dot-com bubble[11]. 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 trend.

[11] 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

To sum up, we observe a decrease in the Belgian labor share. It closely resembles the one observed in the United States. The Belgian secular labor share evolution is driven by the fact that productivity rises faster than wages albeit both rose considerably. Additionally, sectoral labor share variation plays an important role in Belgium.

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 in these eight Belgian sectors. We test the predictions of the superstar firm hypothesis step by step.

Prediction 1: Increasing market concentration

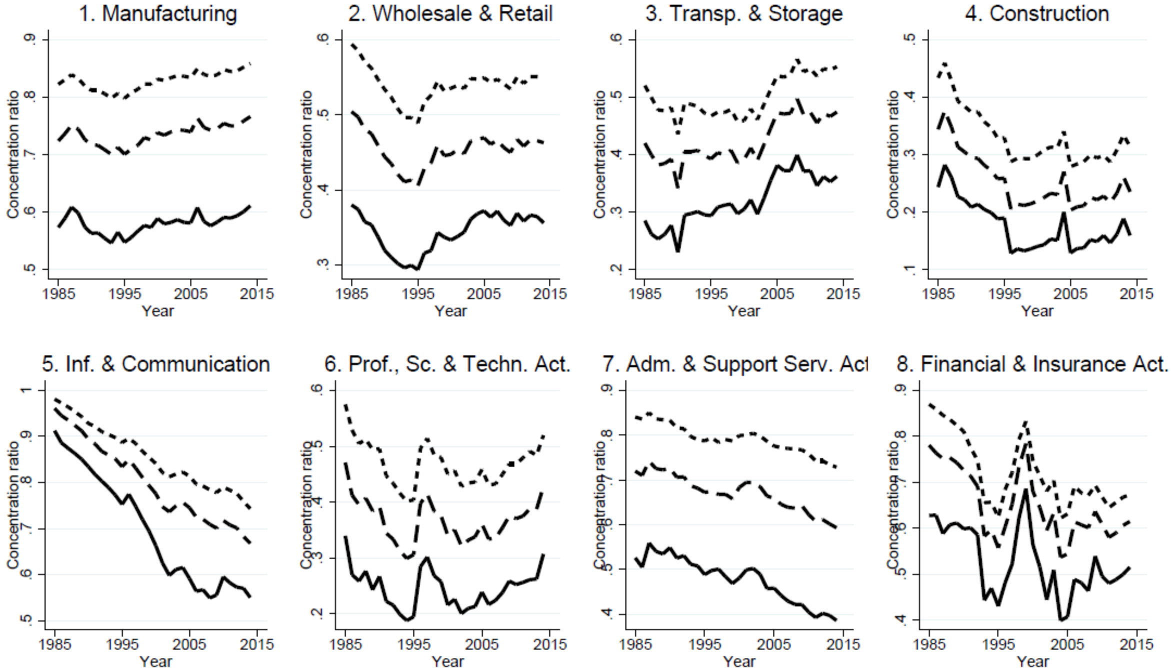
Figure 4 plots the sectoral evolution of the market concentration ratios C4, C10 and C20 in Belgium. The three concentration measures move very much in parallel which means that the concentration of the four biggest firms, in terms of value added, has a big impact in calculating the concentration of the ten and twenty largest firms within an industry. This is the reason why we use C4 as market concentration measure in the remaining analysis. We include robustness checks with C10 and C20 for the other predictions in the robustness section as well.

The concentration ratio increases in Manufacturing and in Transportation & Storage. The market concentration ratio first drops in Wholesale & Retail and Professional, Scientific & Technic activities and increases since the mid ‘90s. The market concentration ratio decreases in the four other sectors. Combining **Figure 3** and **Figure 4** allows us to find suggestive evidence for a negative link between labor share and market concentration. For example, this seems to be apparent in Manufacturing as the two evolutions move in opposing directions.

We link the evolution of the labor share and the market concentration in a more formal way in the next prediction. Thus, we confirm the first prediction of Autor et al. (2017) for a variety of sectors, especially since the mid ‘90s, albeit not for each Belgian sector.

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.

Figure 4: Evolution of sectoral concentration ratio



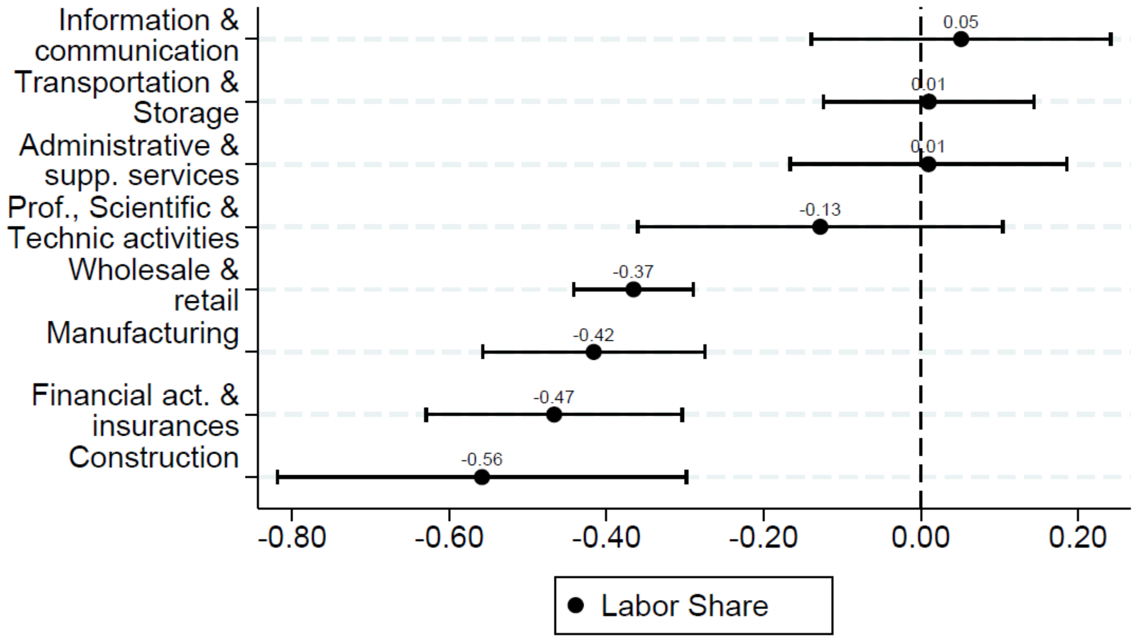
Notes: Each panel plots the evolution of C4 (solid), C10 (dash) and C20 (shortdash). This captures the share value added generated by respectively the four, ten and twenty largest firms within an industry. We then aggregate this into a sectoral concentration ratio.

<u>Prediction 2:</u> An increase in the market concentration ratio leads to a decrease in the labor share

Figure 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 for 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 -.42 percentage points in its labor share. The regression coefficient is not significant for Prof. Sc. & Technical activities, Support and Administrative activities, Transportation & Storage and Information & Communication.

Figure 5: The effect of the change in the concentration ratio (C4) on the labor share



Notes: This figure plots the regression coefficients from equatation (2). Each coefficient follows from a seperate 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 **Figure A2** allows us to delve deeper into possible time trends. Considering only the last eight years, the coefficient for Transportation & Storage is negative and significant.[12] The regression coefficients for Manufacturing, Construction and Wholesale & Retail become are becoming more negative. By contrast, the regression coefficients for Information & Communication, Financial & Insurance activities, Professional, Scientific & Technic activities and Supportive and Administrative Services do not reveal any trend towards (more) negative regression coefficients.

Overall, we confirm the second hypothesis for Manufacturing, Construction, Wholesale & Retail and Financial & Insurance activities. The negative relationship between the concentration ratio and the labor share evolution turns out to be a rather recent phenomenon in Transportation & Storage.

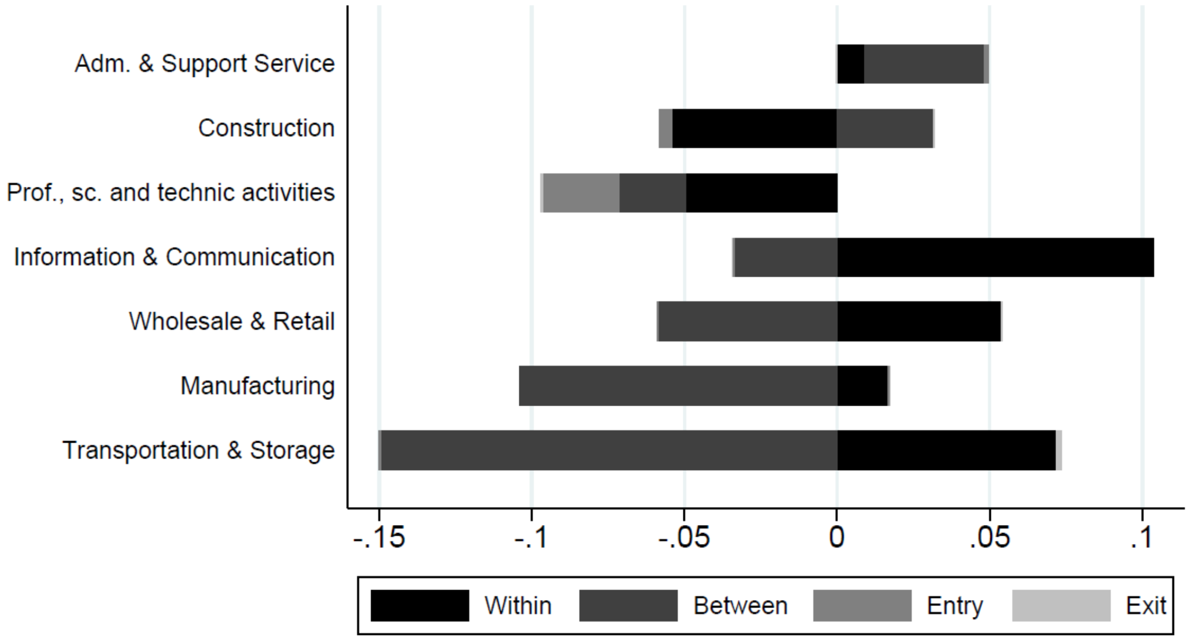
<u>Prediction 3:</u> The reallocation effect drives the fall of the labor share

The results of the decomposition are shown in **Figure 6**. The corresponding standard errors and significance levels are shown in **Table A1**.

[12] During a more recent period (2007-2014), the coefficient β_s for Transportation & Storage is -.353 (p = 0.024).

The between-firm component drives the fall of the labor share in Manufacturing, Wholesale & Retail, Transportation & Storage and Financial & Insurance activities[13]. This means that the between-firm component is significantly negative and larger in magnitude than the within-firm component in absolute value[14] and that the difference between the two components is also significant. For example, the between-firm component equals -10.40% and easily offsets the within-firm component which equals 1.65% in Manufacturing. The difference between the within-firm and the between-firm component is shown in the last column of **Table A1** and demonstrates that the difference is significantly negative. Combining these findings, we conclude that the reallocation effect drives the fall of the labor share in Transportation & Storage, Manufacturing, Wholesale & Retail and Financial & Insurance activities. The third prediction does not hold in Construction, Information & Communication, Prof., Sc. And Technic activities and Administrative and Support Services.

Figure 6: Melitz-Polanec decomposition of the change in labor share



Notes: Each bar shows the cumulated sum over 30 years for each labor share component of the Melitz-Polanec decomposition. The Financial & Insurance activities sector is excluded in this figure as it would confound the readability due to its high between-firm component.

[13] We refer to **Figure A3** for the decomposition in Financial & Insurance activities. We did not include it in **Figure 6** because its large between-firm component confounds readability.

[14] 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.

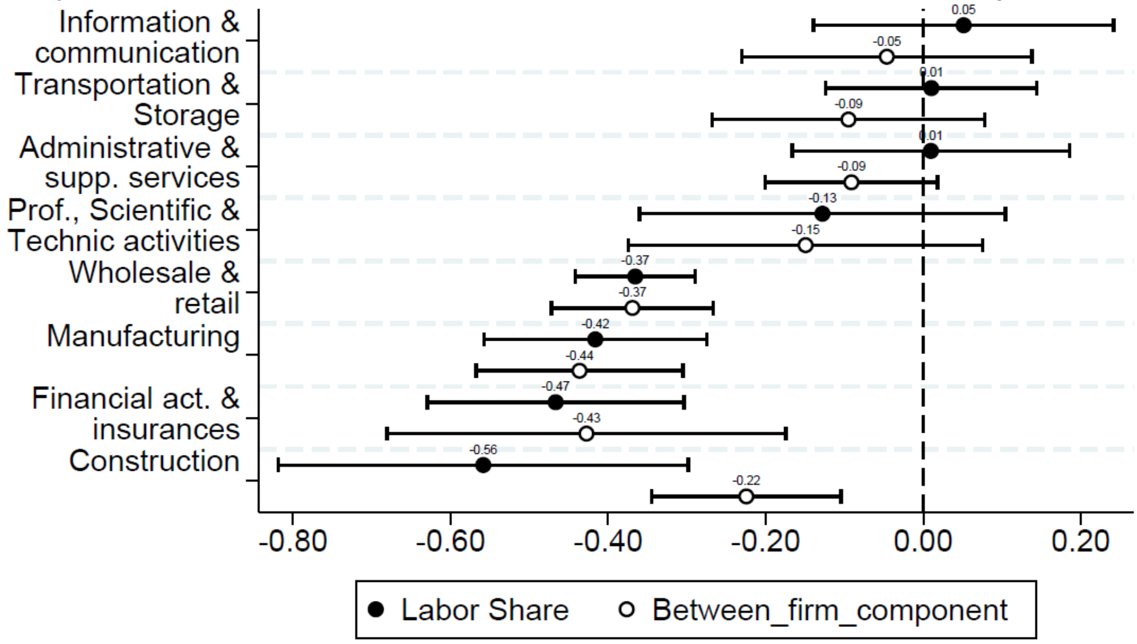
Our results in **Table A1** also indicate that the within-firm component is significant in all sectors but there is no pronounced common trend apparent. At last, the firm entry and firm exit components play a negligible role as both are nearly always insignificant and very small.

> <u>Prediction 4:</u> An increase in the concentration ratio leads to a decrease in the between-firm component

We extend **Figure 5** with a second regression coefficient which comes from equation (6) and show this in **Figure 7**. The second regression coefficient displays the effect from the change in market concentration on the between-firm component.

The regression coefficient is significant and negative in Manufacturing, Financial & Insurance activities, Wholesale & Retail, and Construction. We thus observe a reallocation effect which lowers the labor share in these four sectors. An increase of one percentage point in the market concentration ratio in Manufacturing lowers the labor share by .44 percentage point through the between-firm component. The regression coefficients are also negative in the four other sectors but insignificant.

Figure 7: The effect of the change in the concentration ratio (C4) on the labor share and on the between-firm component



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

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

Disaggregating the regression coefficients into yearly coefficients, displayed in **Figure A4**, reveals that the regression coefficients in Transportation & Storage experience a decrease during the past years. The negative relation between an increase in the concentration ratio and the decrease in the between-firm component is thus a rather recent phenomenon in this sector.[15] Further, the regression coefficients in Manufacturing and Wholesale & Retail display a downward trend over time. This means that the increasing market shares led to a strong negative reallocation effect on the labor share, but this trend reversed after the financial crisis. Coefficients are becoming less negative again during recent years, although they are still negative.

We summarize the results of the four predictions in **Table 3** for both the United States and Belgium. Recall that Autor et al. (2017) provided evidence for the superstar firm hypothesis across a variety of sectors in the United States. They confirmed their hypothesis in all examined sectors.

Table 3: *Summary of predictions of the superstar firm model*

Predictions	United States	Belgium
<u>P1:</u>Concentration is rising.	All Sectors	Depends upon sector. **M** **WR** **TS** C IC <u>PST</u> AS FI
<u>P2:</u> ΔConcentration $\overset{-}{\Rightarrow}$ *ΔLS*	All Sectors	Depends upon sector. **M** **WR** <u>TS</u> **C** IC PST AS **FI**
<u>P3:</u> Between-firm > Within-firm & drives the fall of the LS	All Sectors	Depends upon sector. **M** **WR** **TS** C IC PST AS **FI**
<u>P4:</u> ΔConcentration $\overset{-}{\Rightarrow}$ *ΔBetween-firm component*	All Sectors	Depends upon sector. **M** **WR** <u>TS</u> **C** IC PST AS **FI**
Conclusion: *Superstar Firm Model or not?*	All Sectors	Three sectors **M** **WR** <u>TS</u> C IC PST AS FI

Notes: *The eight Belgian sectors are abbreviated by their first letter(s). These sectors are shown in bold (regular) if we can(not) confirm the hypothesis. An underlined letter means that we can only confirm the hypothesis for a more recent time period than '85-'14.*

Our Belgian analysis shows that the superstar firm hypothesis is indeed present in multiple sectors, but not in each sector. It is thus a sector-specific phenomenon in Belgium. We show that the four predictions hold in Manufacturing and in Wholesale & Retail. It also holds in Transportation & Storage although two hypotheses hold only in a more recent time period. The other sectors do not have the characteristics, not even in recent years, to confirm the superstar firm hypothesis. Manufacturing,

[15] During a more recent period (2007-2014), the coefficient for Transportation & Storage is -1.10 (p = 0.007).

Wholesale & Retail and Transportation & Storage are the three largest sectors and account for 62% of the Belgian economy.

5. Robustness tests

We elaborate on three robustness tests. First, we use alternative specifications for the concentration ratio measure. Subsequently, we take into account that a firm might belong to a parent company. Lastly, we treat labor share outliers in multiple ways. We show that our results are robust to all adjustments.

We consider C10 and C20 as alternative concentration measures. **Figure 4** already introduced these concentration measures. We observe that C10 and C20 closely follow the evolution of C4. **Figure A5** and **Figure A6** show the results of the second 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. **Figure A5** and **Figure A6** also display the results of the fourth prediction with respectively C10 and C20 as concentration measure. The second regression coefficient is again significantly negative in the four abovementioned sectors. This corresponds with our basic findings. Therefore, our results are robust to alternative specifications of the concentration measure.

Next, our firm-level data structure does not take into account that firms might belong to a parent company. Each firm has its own unique VAT number but multiple firms can belong to the same parent company. The holding then combines the market shares of these firms. How does this impact our analysis? We illustrate this with an example. Suppose an industry with ten supermarkets. The four largest firms produce an output €50, €40, €30 and €20. Suppose now that the six other supermarkets produce an output of €10 each. Our concentration measure C4 would be .70 (= 140/200) in this case. However, if the six other supermarkets belong to the same parent company, then this holding produces €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. It will also have more market power than each of its subsidiaries separately. We use the method of Goutsmet, Lecocq & Volckaert (2017) in order to match firms with their corresponding parent company. We refer to their paper for technical details. We aggregate subsidiaries belonging to the same parent company up until the level of an industry. This is our aggregation level of interest for the regression analysis. Our new results turn out to be robust to this adjustment. The outcomes of the predictions remain very similar.

Finally, recall that the labor share is defined as the ratio of remuneration and value added on the firm-level. We replace very high labor share observations by a value of 2. We check whether this definition is robust to alternative specifications. We consider replacing it by 2.5 or 3 instead. We also winsorize the labor share at the 95th percentile. Our results are robust to these alternative treatments of the high labor share values.

6. Conclusion

The labor share, defined as the part of GDP going to labor, is declining in the vast majority of the countries worldwide. The labor share has always fluctuated, but the decrease occurring during the past decades is unprecedented. A dominant strand in the literature relates this to the rapid advancement of technology as well as to the globalization of trade and capital (Chi Dao et al., 2017).

Recently, a novel strand in the literature focusses on its granular origins. Autor et al. (2017) link the rise of superstar firms to the fall of the labor share across a variety of U.S. sectors. Superstar firms are large firms with a dominant market share in their industry – like Apple, Walmart and so on. These firms are characterized by a lower labor share. Besides, the authors show that market concentration is rising as these large firms are acquiring more market share. The combination of superstar firms with a lower labor share and rising market concentration causes the aggregate labor share to decline over time.

We investigate to what extent the U.S. findings generalize to a European setting as evidence is lacking in this field and consider the Belgian economy. The Belgian labor share follows the global secular trend of declining labor shares. It drops from 65.6% in 1985 to 60.4% in 2014. This drop is comparable to the one observed in the United States. The labor share evolution depends on the real wage and productivity evolution. On the one hand, we show that the average real wage increased by roughly 25% in Belgium. Workers acquire more purchasing power over time. On the other hand, real productivity increased by approximately 35% in Belgium. Therefore, workers are benefitting relatively less from productivity increases whereas capital owners are benefitting relatively more. Workers might perceive this growing wedge between wages and productivity as an unfair evolution.

We show that the superstar firm hypothesis holds in the three largest Belgian sectors: Manufacturing, Wholesale & Retail and Transportation & Storage. These three sectors represent approximately two-thirds of the Belgian economy. The growing dominance of large firms can thus be linked to the fact that workers are getting a smaller part of a growing economic pie.

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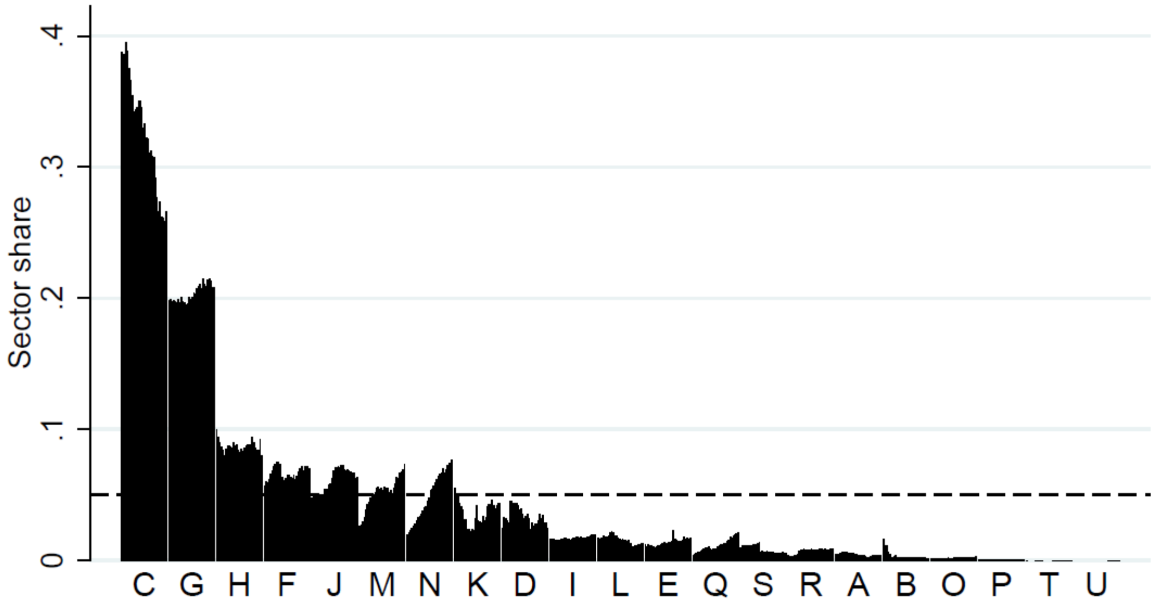
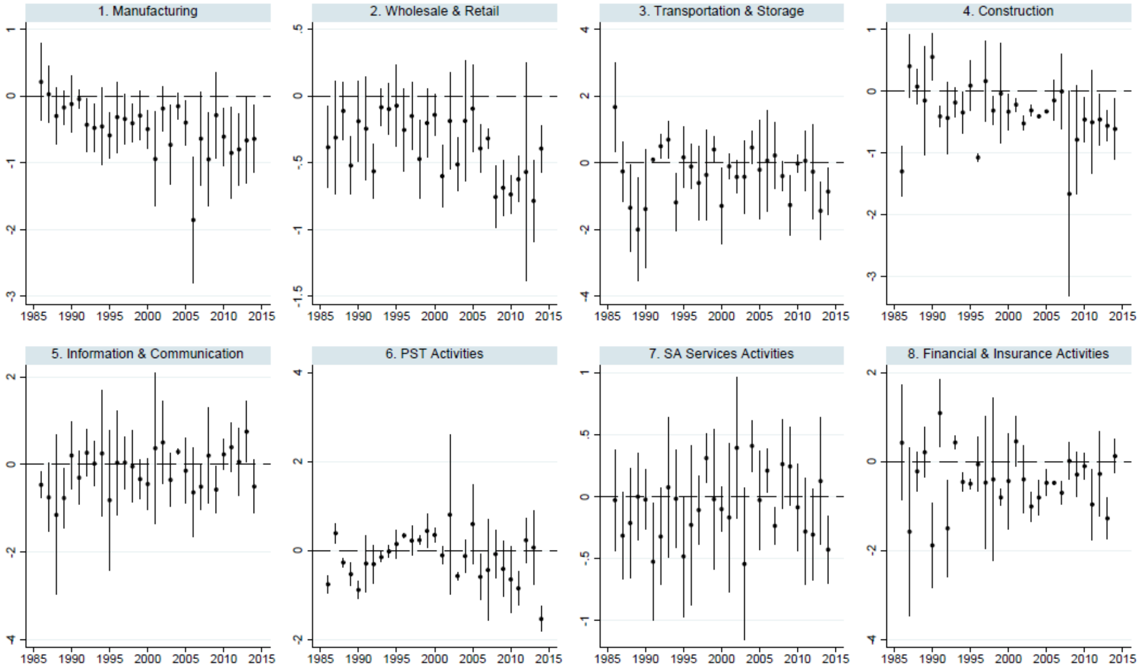
Appendix Figures

Figure A1: Sectoral market share in total value added



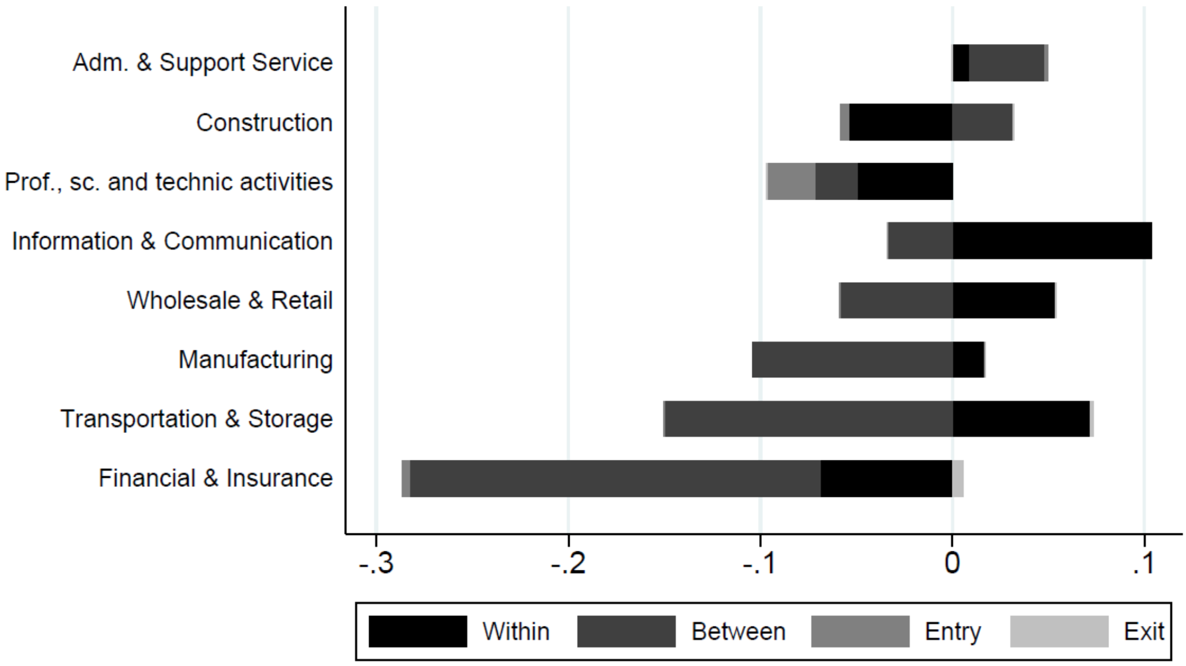
Notes: The market share evolution is plotted from 1985-2014 for each sector. Each sector is represented by its section code as used in NACE Rev. 2. The horizontal line represents the cut-off value of five percentage market share. The market share is calculated within a year. The eight largest sectors 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 A2: Yearly impact from a change in C4 on change in labor share



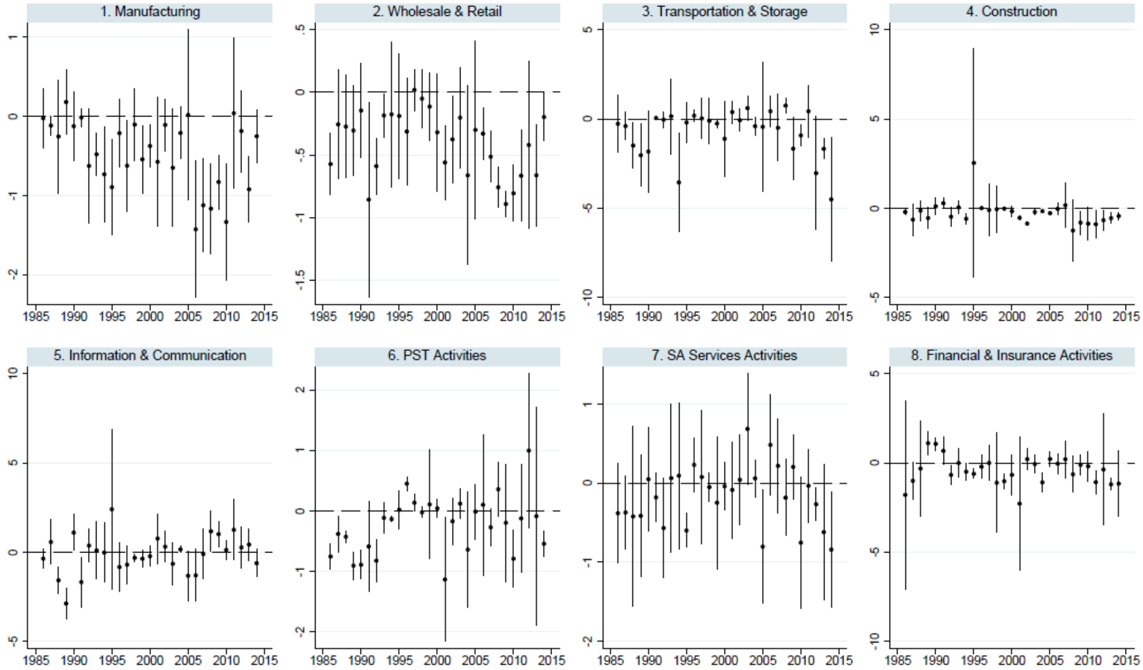
Notes: Each panel shows the yearly coefficient from equation (2)

Figure A3: Melitz-Polanec decomposition of the change in labor share



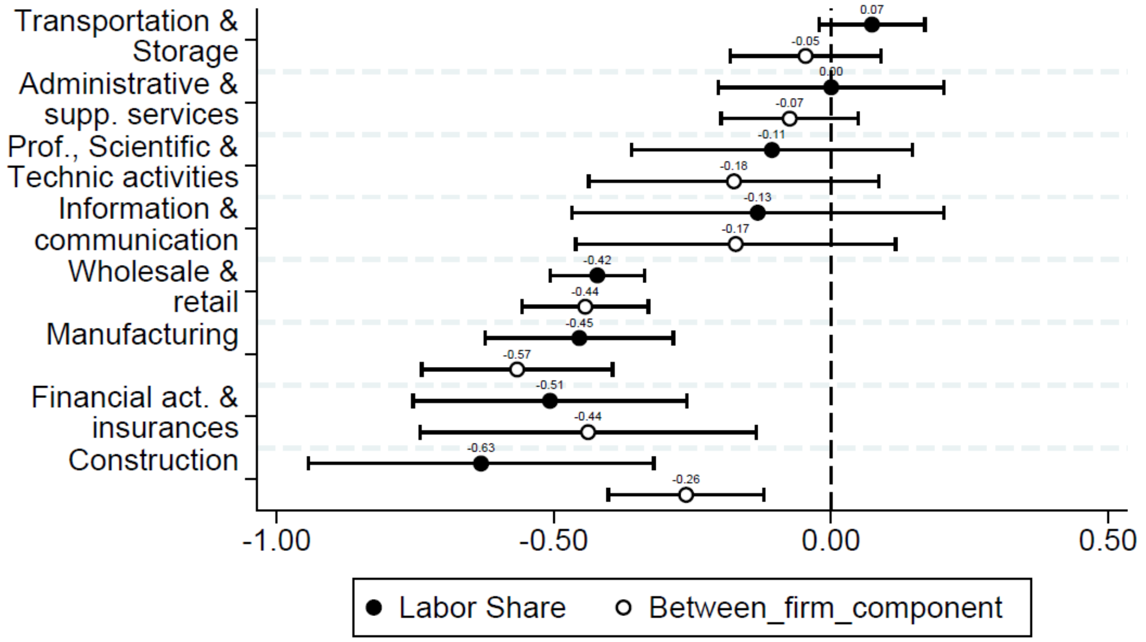
Notes: Each bar shows the cumulated sum over 30 years for each labor share component of the Melitz-Polanec decomposition. All eight sectors are included in this figure.

Figure A4: Yearly impact from a change in C4 on change in the between component



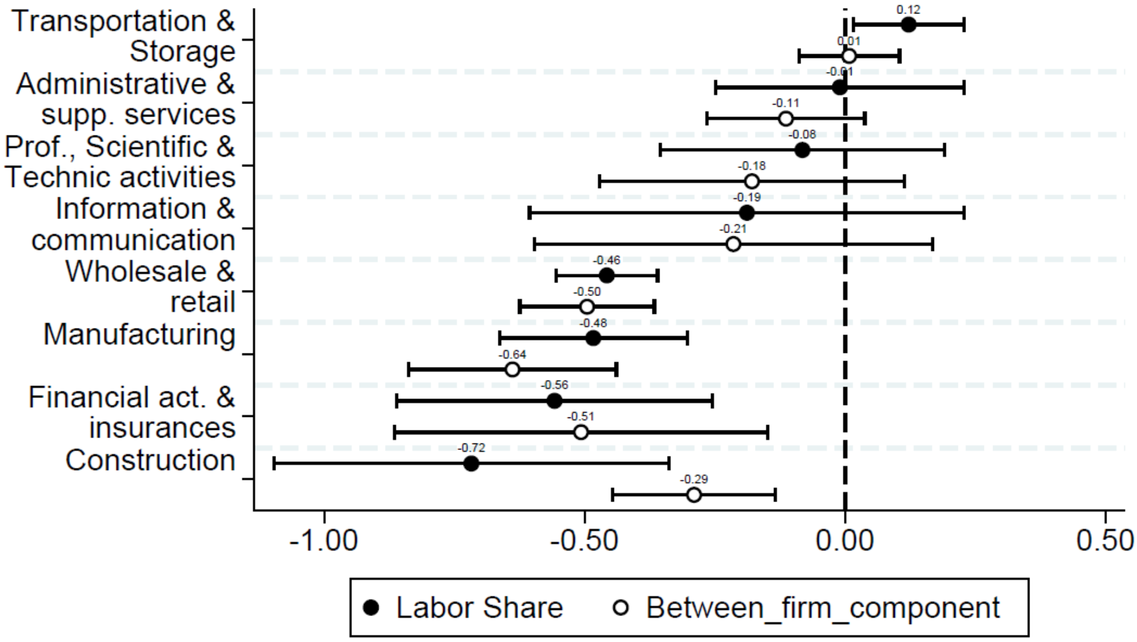
Notes: Each panel shows the yearly coefficient from equation (6)

Figure A5: The effect of the change in the concentration ratio (C10) on the labor share and on the between-firm component



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

Figure A6: The effect of the change in the concentration ratio (C20) on the labor share and on the between-firm component



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

Appendix Table

Table A1: *Melitz & Polanec decomposition*

Sector	Within		Between		Entry		Exit	Prediction 3	
Manufacturing	1.65% (0.35)	***	-10.40% (2.72)	***	0.09% (1.68)		0.01% (1.13)	-12.05% (2.74)	***
Construction	-5.39% (0.28)	***	3.14% (2.51)		-0.43% (1.25)		0.06% (1.01)	8.53% (2.53)	***
Wholesale & Retail	5.36% (0.23)	***	-5.85% (3.13)	*	-0.04% (1.01)		0.03% (0.75)	-11.21% (3.14)	***
Transportation & Storage	7.17% (0.50)	***	-14.96% (3.28)	***	-0.07% (2.68)		0.20% (2.07)	-22.12% (3.32)	***
Information & Communication	10.36% (1.12)	***	-3.37% (10.17)		-0.05% (2.47)		-0.01% (3.99)	-13.73% (10.23)	
Financial & Insurance	-6.86% (0.91)	***	-21.40% (5.31)	***	-0.37% (2.07)		0.57% (2.25)	-14.54% (5.39)	***
Prof.. sc. and technic activities	-4.95% (0.48)	***	-2.21% (3.55)		-2.50% (0.95)	***	-0.06% (1.44)	2.75% (3.58)	
Adm. & Support Service	0.92% (1.17)		3.92% (3.56)		0.14% (1.91)		-0.03% (3.58)	3.00% (3.74)	

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 ***. Column (6) calculates the difference between the within and between component. It also tests the significance of this difference.*

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