

Markup and price dynamics: linking micro to macro



Working Paper Research

by Jan De Loecker, Catherine Fuss and Johannes Van Biesebroeck

October 2018 **No 357**

Abstract

We analyze the aggregate markup of a small-open economy, Belgium, using a firm-level dataset that includes all non-financial, private firms. The dataset covers the period 1980-2016 and merges the annual firm accounts over three periods when firms faced different reporting thresholds for the key variables we use. After harmonizing the data, we find that for the median firm the revenue share of service intermediates doubles, to some extent at the expense of in-house employment. As this general patterns holds true for the vast majority of firms and all sectors of the economy, we need to control for it in the calculation of our firm-level markup estimates.

We document increasing markups in the overall economy throughout the first fifteen years of our sample, 1980-1995, and a continued rise in manufacturing until the early 2000s. In the remaining years, the aggregate markup, although cyclical, remained relatively stable. These patterns are driven by the dynamics in the sales-to-expenditure ratio, with only a small role for changes in the technology parameters. Two decompositions illustrate that the aggregate pattern masks systematic dynamics at the sector and firm level. We find that in periods where the aggregate markup rises—for the full economy or for one of the major sectors—it is almost entirely due to the within component, i.e. firm-level markup growth. In periods where the aggregate markup is stable, the average hides a strong process of reallocation. Firms or sectors with high markups increase their market share, which raises the aggregate markup, but this is dominated by a negative correlation between changes in market share and markups, which depresses the aggregate.

Keywords: *Markups. Market Power. Technological change.*

1 Background

Economists have long understood that market power can negatively affect welfare by limiting output, stifling innovation, and introducing inefficiencies in the allocation of production over firms. On the one hand, there is ample evidence from case-studies, that the presence of market power, in the form of explicit or implicit cartels and other practices of anti-competitive behavior, can lead to substantial damages to producers and consumers in a given market. On the other hand, very little is known, at this point, about the broad cross-sectional and time-series patterns of market power across sectors, regions and countries. In addition, and perhaps more importantly, if market power is present, to what extent does it affect equilibrium outcomes in aggregate product and factor markets? For example, should the analysis of macroeconomic variables, such as productivity growth and investment, take into account the (potential) presence of market power, and does market power play a role in labor market outcomes, such as the recently reported and heavily debated decline in the labor share in many countries?

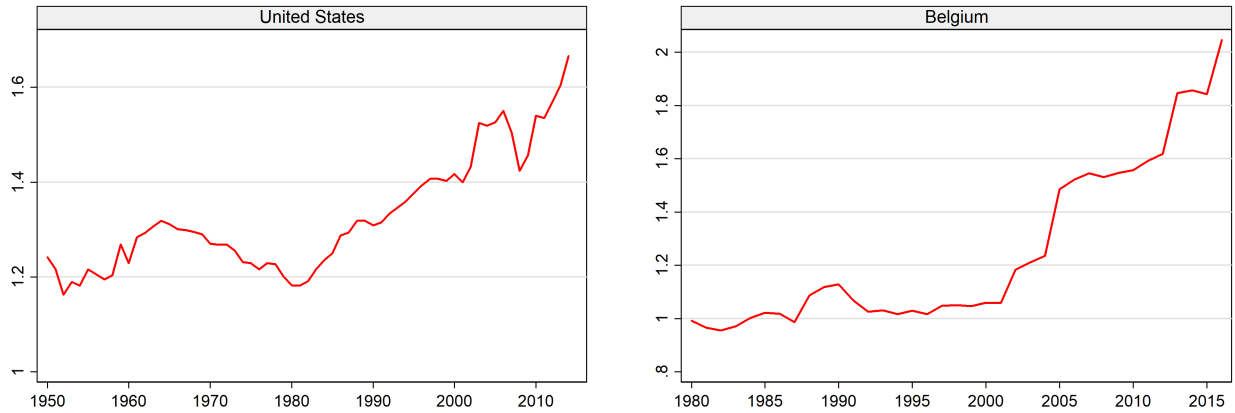
Over the last few years there has been an active debate among economists and policy makers around the globe about the rise in concentration and market power. The evidence so far has mostly been based on data from the United States (e.g. De Loecker and Eeckhout (2017)), but it has increasingly also come from Europe and other regions (e.g. De Loecker and Eeckhout (2018), Calligaris, Criscuolo, and Marcolin (2018), and Weche and Wambach (2018)). The evidence for the United States points to a substantial rise in the price-to-marginal cost ratio, i.e. the markup, which is shown in the left panel of Figure 1. After a temporary rise in the booming years of the 1960s and a subsequent decline during the 1970s recession, the aggregate markup started rising strongly around 1980. The Great Recession of 2009 halted its increase, but this was only temporarily, as the increase resumed during the recovery.

The importance of this pattern for firm-level outcomes, such as profitability and price growth, is obvious. Moreover, it potentially also has wide-ranging implications, both for our understanding of labor market outcomes, innovation and competition policy as well as for broader debates in society related to income inequality and political outcomes. In particular, rising markups have sometimes lead to calls for interventions from various government branches, ranging from competition and antitrust policy, to trade and tax policy. Even central bankers have worried about the implications for

monetary policy.¹

Researchers studying the United States have access to historical data, starting at least in the early seventies, on firms covering the entire U.S. economy, either through the selected set of listed firms in Compustat or through the Census of private firms. Unfortunately, no such comprehensive analysis or evidence exists outside the United States. Very little is known about the situation in other countries.

Figure 1: The Evolution of Markups of Listed Firms



Source: Figure for the United States is taken from De Loecker and Eeckhout (2017) and is based on data from Compustat. Figure for Belgium is constructed using the Worldscope data used in De Loecker and Eeckhout (2018).

In this paper, we study the evolution of the aggregate markup in Belgium, based on a newly-constructed, comprehensive dataset that spans the 1980-2016 period. It includes all private firms that exceed a reporting threshold in the Belgian economy and it covers all sectors.

There are reasons to believe that the situation in Belgium could be very different from that of the United States. First of all, it is a small open economy, centrally located in Europe, with a strong focus on exporting and importing. As a consequence, it forms the hub of activities for many multinationals that operate across Europe. In addition, the economic landscape in Europe changed drastically over the period we consider, from the integration of the EU single market and the signing of the Maastricht Treaty,

¹Recent summits of the European Central Bank (in Sintra 2018) and the annual Federal Reserve Bank of Kansas City Monetary Policy conference (in Jackson Hole 2018, with as title: “Changing market structures and implications for monetary policy”) featured this topic prominently.

to the introduction of the EURO and the accession of a large set of previously centrally-planned economies.

Finally, based on the evidence of the United States, some studies have highlighted the growing importance of large firms, across a variety of sectors, see for example Autor, Dorn, Katz, Patterson, and Van Reenen (2017). This evolution helps explain aggregate patterns of markups, profits and labor market outcomes, such as wages and the declining labor share more specifically. However, large firms are often thought to be less important in Europe. Evidence from a European country would form a useful point of comparison and an opportunity to investigate to what extent the U.S. experience generalizes.

Using information from listed Belgian firm in *Worldscope*, also used in De Loecker and Eeckhout (2018), we show on the right in Figure 1, the comparable evolution of the aggregate markup for Belgium. This shows that the aggregate markup for Belgium started increasing later than in the United States, but once it got underway the increase was even more pronounced. There are, however, several reasons why this pattern should not be trusted at face value. Most importantly, the number of firms used to construct this aggregate is extremely small, in some years fewer than 80 firms are included in the *Worldscope* dataset and due to some missing information they cannot even all be used. In addition, the sample increases over time and this reflects improved coverage, rather than a real underlying economic change. To avoid this data constraints on the sample of listed firms, we turn to information from the universe of firms that submit annual accounts in our own, subsequent analysis.

The remainder of the paper is organized as follows. In Section 2 we present the data and discuss the preliminary analysis of input factor shares over the period 1980-2016. Section 3 introduces the empirical framework through which we will interpret this evidence, and this framework allows us to distinguish technological change from changes in market power. The dynamics of the aggregate and sectoral markups are discussed in Section 4, followed by a decomposition across and within sectors in Section 5. The last section ends with concluding remarks and topics for future research.

2 Data and empirical framework

2.1 Data sources

We construct a firm-level dataset covering all private firms that have to submit their annual accounts to the Belgian authorities, covering the period 1980-2016. The advantage of observing such a long time series of firm-level variables taken from the balance sheet and incomes & loss statement comes at the cost of dealing with changes in reporting standards and requirements over time. Annual accounts are collected for (nearly) all companies located in Belgium, but small firms do not have to report as detailed information as large firms. In particular, only large firms have to provide information on turnover and intermediate inputs consumption and its break down into two components: (i) raw materials and goods, and (ii) services inputs. In the case of Belgium, we have three distinct samples of large firms.

First, the information for the period 1978-1984, for which the firm-level annual accounts have never previously been used in research, is very limited. We only observe total assets, sales, and total input use, which is further broken down into the two types of inputs. Unfortunately, we do not observe labor input, making it impossible to include this period when we estimate production functions. We also do not observe a sectoral classification for these firms, which means that we have to omit these first few years in any analysis conducted within an industry. While the data made available to us already start in 1978, there were too many observations with dubious statistics to include the first two years in the dataset for now.

Second, in the period 1985-1996, we observe firm-level annual accounts for a much broader set of firms thanks to a decrease in employment reporting threshold used to define large firms. Indeed, over 1978-1984, a company was considered as large, either when the yearly average of its workforce is at least 100 or when either turnover (excluding VAT) amounts to at least EUR 2.48 million (BEF 100 million) or total assets exceed EUR 1,24 million (BEF 50 million). While over 1985-1996, large firms are those that exceed at least two of the following criteria: (1) yearly average of workforce of 50, (2) least 3.59 million (BEF 145 million) for turnover (excluding VAT), (3) EUR 1,74 million (BEF 70 million). As before a company employing at least 100 workers is classified as large.

Finally, we observe the annual accounts for the period 1996-2016. This firm-level information for Belgium has been widely used previously in academic research. The coverage has been reduced because, the turnover and total assets thresholds have been raised to, respectively, EUR 9 million and EUR 4,5 million. Given that we want a consistent sample over the entire time period, we limit the sample to firms reporting input use broken down in the two components.

As far we know, we are the first to construct a panel that covers all private Belgian firms over the period 1980-2016. This dataset uses administrative data sources accessed through the National Bank of Belgium (NBB). In terms of variables, we only use the wage bill, employment (in number of full-time equivalent employees), tangible fixed assets at the beginning and end of the year, intermediate input use (total, and also broken down by goods or services), and sales. A small set of corrections concerning dates and years or an apparently erroneous number of months in the annual accounts have been performed. The resulting annual account information was annualised and missing values extrapolated. From 1985 onwards, each firm is allocated to one of ten sector which are defined in a time-consistent manner over the entire sample period using industry concordances. Deflators on value added, investment and intermediate consumption at the 2-digit NACE are based on published data in the National Accounts and sector classification information reported in the annual accounts database.

In Table 1 we report the average yearly number of observations in the sample. These are all firms that report non-missing values for both sales and total input use. In the second column we show the average yearly numbers of firms reporting the breakdown in input use, which will be the sample we work with that has a relatively consistent coverage over time. The increase in this average is the result of firm entry and firms growing enough in sales or total assets to trigger 'large-firm' reporting requirements.²

²In particular, the average of 17,140 for the 1996-2016 period masks an increase from 14,757 firms in 1996 to 21,480 firms in 2015. The total is slightly lower in 2016 as not all annual accounts information had yet been added to the administrative data source we rely on.

Table 1: Summary statistics sample

Period	Nr. Obs.		Reporting Thresholds		
	Total	Input split	Employment	Turnover	Total assets
1978-1984	15,972	11,893	100	2.78	1.24
1985-1995	74,407	12,729	50	3.59	1.74
1996-2016	20,063	17,140	50	9.00	4.50

Note: Averages in the first column are constructed from the underlying administrative data source; in the second column from the sample of firms with non-missing data that we base our analysis on. Turnover and total assets in million EUR. Observations are average number per year. Input split: number of observations reporting split of intermediate inputs into goods and services.

2.2 Empirical Framework

The measurement of markups relies on the framework proposed by De Loecker and Warzynski (2012), based on the insight of Hall (1988). Markups are estimated at the firm level, using firms' production data, i.e. inputs and output, but without any assumptions on demand or the nature of competition between firms. Instead markups are obtained by leveraging cost minimization of a variable input of production. This approach requires an explicit treatment of the production function.

Consider an economy with N firms, indexed by $i = 1, \dots, N$, and firms are heterogeneous in their productivity. In each period t , firm i minimizes the contemporaneous cost of production given the production function that transforms inputs into the quantity of output Q_{it} produced by the technology $Q(\cdot)$:

$$Q_{it} = Q(\mathbf{V}_{it}, K_{it}, \Omega_{it}), \quad (1)$$

where $\mathbf{V} = (V^1, \dots, V^J)$ captures the set of variable inputs of production (including labor, intermediate inputs, materials,...), K_{it} is the capital stock and Ω_{it} is a firm-specific productivity term. In the exposition, the vector \mathbf{V} is treated as a scalar V , both types of inputs can be vectors. Following De Loecker and Warzynski (2012) consider the associated Lagrangian objective function:

$$\mathcal{L}(V_{it}, K_{it}, \lambda_{it}) = P_{it}^V V_{it} + r_{it} K_{it} - \lambda_{it}(Q(\cdot) - Q_{it}),$$

where P^V is the price of the variable input, r is the user cost of capital. $Q(\cdot)$ is the technology (1), Q_{it} is a scalar and λ_{it} is the Lagrange multiplier. Consider the first

order condition with respect to the variable input V , and multiply all terms by V_{it}/Q_{it} . Rearranging terms yields an expression of the output elasticity of input V :

$$\theta_{it}^V \equiv \frac{\partial Q(\cdot)}{\partial V_{it}} \frac{V_{it}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^V V_{it}}{Q_{it}}.$$

The Lagrange parameter λ is a direct measure of marginal cost, i.e. it is the value of the objective function as the output constraint is relaxed. Define the markup as $\mu = \frac{P}{\lambda}$, where P is the price for the output good, which depends on the extent of market power. Substituting marginal cost for the markup to price ratio, a simple expression for the markup is obtained:

$$\mu_{it} = \theta_{it}^V \frac{S_{it}}{E_{it}^V}.$$

S_{it} denotes firm-level sales and E_{it}^V the expenditure on a variable input V . The expression of the markup is derived without specifying conduct or a particular demand system. Note that with this approach to markup estimation, there are in principle multiple first order conditions, one for each variable input in production, that all yield an expression for the markup. Regardless of which variable input of production is used, there are two key ingredients needed in order to measure the markup: the revenue share of the variable input, $\frac{P_{it}^V V_{it}}{P_{it} Q_{it}}$, and the corresponding output elasticity, θ_{it}^V .

While this approach does not restrict the output elasticity, it depends on a specific production function. Assumptions of underlying producer behavior are required in order to consistently estimate this elasticity from the data. One could use different specifications of the underlying production function, but it turns out that the time-series patterns of markups are mainly governed by the revenue share of the variable input. However, it is imperative to correctly capture any technological change that takes place as well as the variation in output elasticity across sectors. This is for the simple reason that we wish to separate markup patterns from pure technology differences, both across producers and time.

2.3 Estimating markups

In the traditional class of Hicks-neutral production functions, such as Cobb-Douglas and Leontief, the output elasticity of an input does not vary across producers within

that specified technology. This implies that the variation in markups is entirely due to the variation in the sales-to-input-expenditure ratio and it is not necessary to identify the exact output elasticity. This is a major advantage as it is often difficult to identify the output elasticity, for example due to unobserved firm-level variation in output prices.

As a result, one can study the cross-sectional dispersion in markups across producers within an industry in this case without requiring any estimation. Similarly, the time series of markups within a sector, is also unaffected by any potential bias in the estimation of the output elasticity; it can only bias the level of the markup.³

Of course, this approach is only valid if one is willing to make the appropriate assumption on production technology. For different functional forms, any bias in the output elasticity estimates will affect both the level and the variation across producers, both in the cross section and over time. For example, in the case of a translog production function, the output elasticity is producer and time-specific, see De Loecker, Goldberg, Khandelwal, and Pavcnik (2016) for a treatment of this case.

Throughout the analysis we consider two distinct specifications. First, we consider a *calibrated* output elasticity which is normalized such that the median markup across the entire time period and relevant group of firms exactly equals 1.1.⁴ This specification serves to highlight the patterns in the *raw data*. Of course, the interpretation of the results based on this specification should keep this assumption in mind. The output elasticity used in this first specification is denoted $\bar{\theta}$.

Second, when we are specifically interested in the importance of reallocation of market shares between sectors, it is important to know the absolute level of the markup in different sectors. Even though the aggregate markup will already differ across sectors in the first specification based on $\bar{\theta}$, because the correlation between markups and market shares will differ across sectors, it is informative to also incorporate information from the production technology. Hence, we estimate separate production functions that include employment (l), capital (k), and intermediate inputs: goods (m_g) and services (m_s). By estimating the production functions on a rolling window of three years $\{t - 1, t, t + 1\}$ we are able to uncover sector-time specific output elasticities θ_{st} .

A well-known challenge in the production function estimation literature is that

³See Brandt, Van Biesebroeck, Wang, and Zhang (2017) for an example of such an approach.

⁴We normalize over all observations when considering the total economy, but for sectoral analyses we normalize over all time-year observations within the sector considered.

physical output and inputs are often not recorded. Even if they are, they are not naturally comparable across producers due to the inherent product differentiation present across products within markets. Therefore researchers rely on deflated sales and input expenditures to measure output and inputs. In the case of homogeneous good producers, the variation in sales is directly informative about the variation in physical quantities. In any other environment where prices vary across producers, the so-called omitted price bias will lead to biased production function coefficients. De Loecker, Goldberg, Khandelwal, and Pavcnik (2016) consider the implementation of production function estimation in the presence of price variation, both output and input, which naturally arises when considering variation in markups across producers.

In light of the discussion of De Loecker and Goldberg (2014), we explicitly acknowledge that all firm-level variables, both output and inputs, are recorded in monetary terms. This implies that even after deflating with the appropriate industry-specific deflator, firm-specific output and input price variation is not accounted for. However, as first noted by De Loecker and Eeckhout (2017), in contrast to the productivity residual (often referred to in the literature as TFPQ), the output elasticities can be identified from relating (deflated) sales to expenditures.

The main estimating equation is obtained by considering a year-industry-specific Cobb-Douglas production function in logs, and by grouping the unobserved prices and productivity shocks into the error term ϵ_{it} as follows:

$$s_{it} = \theta_{st}^L e_{it}^L + \theta_{st}^K e_{it}^K + \theta_{st}^{M_g} e_{it}^{M_g} + \theta_{st}^{M_s} e_{it}^{M_s} + \epsilon_{it},$$

where lower cases denote logs, and $e_{it}^H = \ln E_{it}^H$ with $h \in \{L, K, M_g, M_s\}$. This expression is obtained by noting that for any input H only expenditures are observed: $P^H H$, or in logs $p^H + h$. Substituting this expression for each input yields the estimating equation. We refer to the Appendix for more details and discussion.

We thus consider industry-year specific Cobb-Douglas production functions, and we rely either on OLS or control function techniques as discussed in De Loecker and Eeckhout (2017). In the case of applying OLS, the bias we potentially introduce depends on the correlation one expects, on average, between firm-level expenditures and markups. The main departure from the literature in our implementation is to acknowledge the presence of service-intermediate inputs that are plausible quasi or fully fixed during an annual production cycle, and that the error term of the production function

is in fact the markup itself.⁵

Finally, the main variable of interest is the aggregate markup M_t , and it is computed as follows:

$$M_t = \sum_{i \in A_t} a_{it} \mu_{it}, \quad (2)$$

with a_{it} the relevant share of firm i in the aggregate (A_t), and the exact share depends on the analysis of interest, i.e. whether we consider the total economy or a specific sector.

3 Revenue shares and technological change

3.1 Preliminary evidence

We start by aggregating firm-level markups to the level of the Belgian economy, and we compute a *normalized aggregate markup* (NAM) based on:

$$\bar{\mu}_{it} = \bar{\theta}^M \frac{S_{it}}{E_{it}^M},$$

where M refers to the total bundle of intermediate inputs, including both inputs of goods and services as reported in the annual income and loss statement.⁶ In the left panel of Figure 2, the evolution of $\bar{\theta}^M$ aggregated according to equation (2) is shown for two different samples. The solid red line shows the NAM for all firms consistently reporting the input breakdown, which must be firms that satisfy the most stringent (highest) reporting threshold. We consider this sample to be relatively consistent over the entire period 1980-2016.

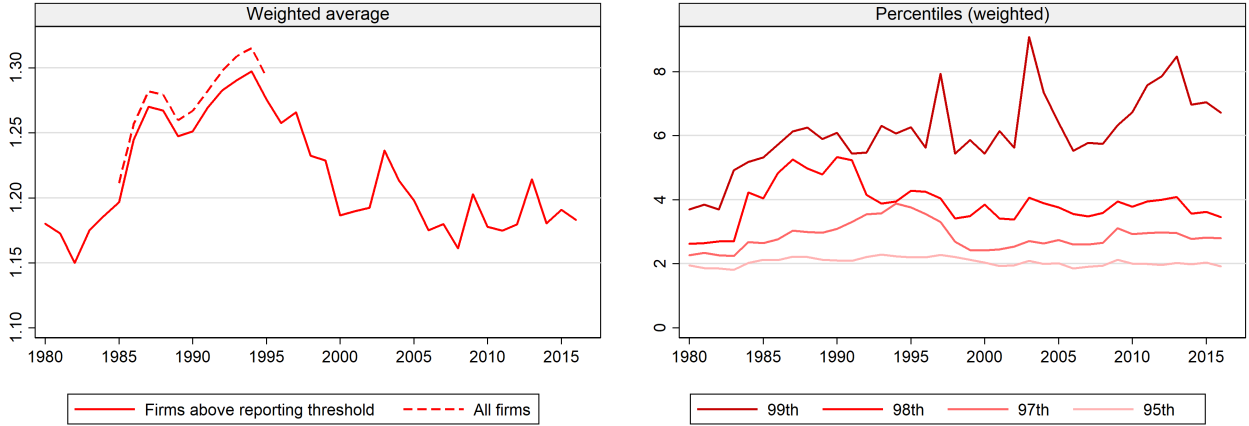
In addition, the dashed red line plots the same series aggregated over all firms in the sample with non-missing data. Only in the period 1985-1995 do the two lines not lie on top of one another and does the dashed-line become visible. The aggregate is slightly higher in the total sample, which suggest that the correlation between markups and market shares is stronger in the full sample. Put differently, the firms that are not included in the aggregate before 1985 and after 1995 tend to be smaller than average,

⁵This would suggest recovering the markup as the residual of the estimating equation. However, this would only yield a correct estimate if all inputs in production were variable.

⁶The output elasticity $\bar{\theta}^M$ is normalized such that the median $\bar{\mu}_{it} = 1.1$.

but also tend to have below average markups. Omitting them reduces the markup-market share correlation and hence reduces the aggregate markup.

Figure 2: Normalized Aggregate Markup Based on Total Intermediate Input Use



We find a rising aggregate markup during the first fifteen years of our sample, 1980-1995, of about 15 percentage points. The increase is apparent in both samples, of large firms and all firms, and even the reversal in 1994 shows up for both lines. As we are mostly interested in the long term evolution of the aggregate, we will only consider the sample of firms above the reporting threshold in subsequent analyses. The patterns in Figure 2 suggests that this will not bias our results, and could be considered a conservative assumption if we expect to find an increase in the aggregate markup.

After 1995, the *NAM* first declines, shedding about two thirds of the previous increase and remains relatively constant thereafter. In the next 15 years it fluctuates around the level of the late nineties, at a level slightly higher than the initial level in 1980. The increasing margins during the 1980-1995 is consistent with the findings for the United States and some European countries, as reported in De Loecker and Eeckhout (2017, 2018).

The overall evolution, however, is at odds with that for the listed Belgian firms that was shown on the right in Figure 1. Both series see a period of rising and a period of stable aggregate markups, but the two periods are reversed. There are several potential explanations. It is, for example, not impossible that the markup dynamics are simply different in the census of Belgian firms. Other possible explanations are technological change or the extent to which reporting of the larger firms changed over time – in

particular the difference between unconsolidated and consolidated accounts.

Before we consider the role of technology we verify whether the trajectory is specific to particular point in the markup distribution that one considers. For the United States and other regions analyzed by De Loecker (2017, 2018), the aggregate markup patterns are mostly governed by the so-called *top firms*, i.e. the firms with high markups. In the right panel of Figure 2, we plot the evolution over time of the sales-weighted top percentiles (99, 98, 97 and 95) of the markup distribution. By construction, the levels of the markup are much higher and the scale of the vertical axis is adjusted accordingly. More importantly, the top 1-percent of Belgian firms seem to have experienced an ever increasing markup throughout the entire period with the largest growth spurts taking place in the second half of the sample period. This pattern is consistent with the pattern of increasing markups of listed Belgian firms (Figure 1). At least if, not implausibly, the ‘top’ firms in the markup distribution also tend to be listed. This comparison is, however, not as straightforward as it may seem, for the simple reason that a firm in our data constitutes a unique tax identifier, which generally does not coincide with the legal entity reported in the stock-listed (consolidated) database of Worldscope.

3.2 Technological change

The main challenge in implementing the above framework over a relatively long panel, here from 1980 to 2016, is to account for technological change. The main approach in the literature on production function estimation is to let this change come uniquely through Hicks-neutral productivity shocks, implying constant output elasticities over time.⁷ While the focus of this literature is to capture the productivity residual, the production-approach to markup estimation requires information on the output elasticity of a variable input in production. Thirty five years of technological progress, changes in shipping cost, increasingly integrated production structures across borders, and many other factors, are expected to affect the input mix used in production. And to affect firms in different sectors differently.

A special feature of our data is that we observe the total use of intermediate inputs (M) broken down into goods-intermediates (M_g) and service-intermediates (M_s), in

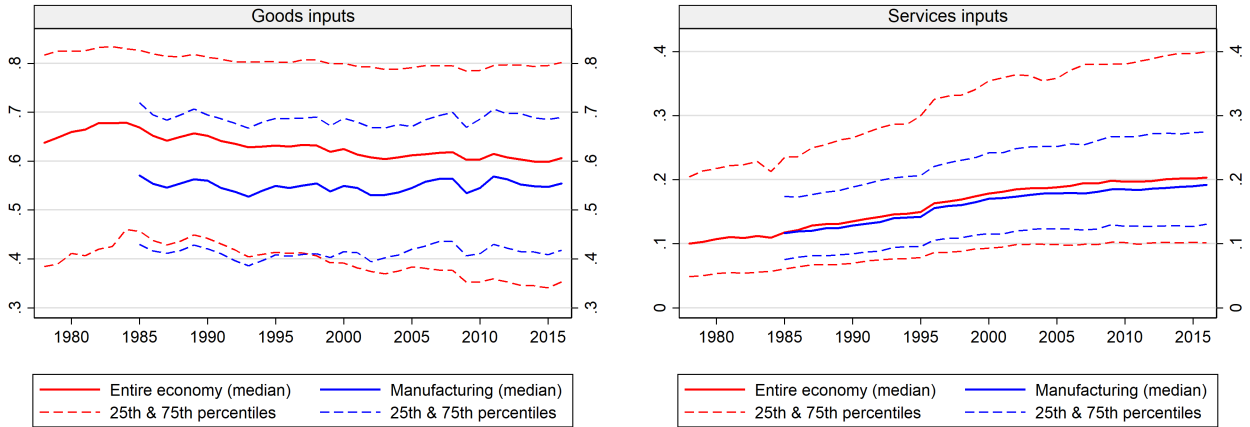
⁷An exception is the translog specification considered in De Loecker and Warzynski (2012) which yields time-varying output elasticities through the change in input intensity.

addition to a measure of the capital stock and employment (or the wage bill). In principle, the markup can be recovered from any variable input in production. Therefore, we can check how the two components of the intermediate input bundle relate to sales (S_{it}), and whether their relationships evolved differently over time or differs between sectors. According to the analytical framework, if both goods and service intermediate inputs are truly variable, the following equality has to hold for each firm-year observation:

$$\theta^{M_g} \frac{S}{M_g} = \theta^{M_s} \frac{S}{M_s}. \quad (3)$$

Before discussing how one can obtain the relevant output elasticities, we simply compare the revenue shares of the two intermediate input components. We are in particular interested in the time-series patterns of both ratios. In Figure 3, we plot the two revenue shares separately in the left and right panels. The lines in red are for the entire Belgian economy, while the blue lines are limited to firms in the manufacturing sector. For each input and each sample, we report the median revenue share (solid line) and the 25th and 75th percentile values (dashed lines).

Figure 3: The Evolution of Revenue shares of Intermediate Inputs



Across the entire economy, the median revenue share of goods inputs declines slightly from about 65 to about 60 percent, while the 75th and 25th percentile fluctuate around 80 and 40 percent, respectively.⁸ This evolution is largely due to differences in the absolute revenue share of goods inputs across sectors and a relative decline of sec-

⁸The decline is a bit more pronounced for the 25th percentile, but almost absent for the 75th percentile.

tors with a higher share. Within almost all sectors the decline is almost imperceptible. This is demonstrated for the manufacturing sector, which comprises approximately 35 percent of total economic activity in the economy, measured by sales. The blue lines in the left panel fluctuate slightly, but no clear trend is apparent.

The pattern is markedly different in the panel on the right, which shows the revenue shares of service inputs. Here, every line trends up notably over time. For the entire economy (in red), the median share grows from about 10 percent in 1980 to 20 percent in 2016. Perhaps somewhat surprisingly, the evolution and even the absolute levels are almost identical for the manufacturing sector (in blue). The 25th and 75th percentiles also approximately double. In the case of firms at the 75th percentile level, this means that service inputs make up 40 percent of revenue at the end of the period. Naturally, there is a lot of sectoral heterogeneity. Within the manufacturing sectors the quartile bands are naturally a lot closer to the median, but importantly, the increase in revenue shares shows up across the entire distribution.

These patterns suggest that the production technology has fundamentally changed, and firms nowadays use a different mix of intermediate inputs from thirty five years ago. Two confounding factors in interpreting these changes as changes in technology, is that markups changed over time and that service inputs are likely to capture more (quasi-)fixed factors of production as well. In light of the equality in (3), even if the relatively output elasticities do not change over time, revenue shares can diverge simply because service inputs contain more fixed factors than goods inputs.

This latter interpretation seems plausible based on the accounting categories in services inputs. These include expenditures on human resources, IT, and other service contracts such as catering, security, etc.

This latter interpretation seems plausible based on the accounting categories in services inputs. These include expenditures on human resources, IT, and other service contracts such as catering, security, etc.⁹

⁹More specifically, in the Belgian accounts the following items are listed: 1) Insurances; 2) Transportation, Travel and Catering; 3) Deliveries to the firm; 4) Availability fees; 5) Rent; 6) Maintenances and repairs; 7) Temporary and external work; and 8) Wages, bonuses, pensions of CEO, partners and active owners.

4 Markup dynamics

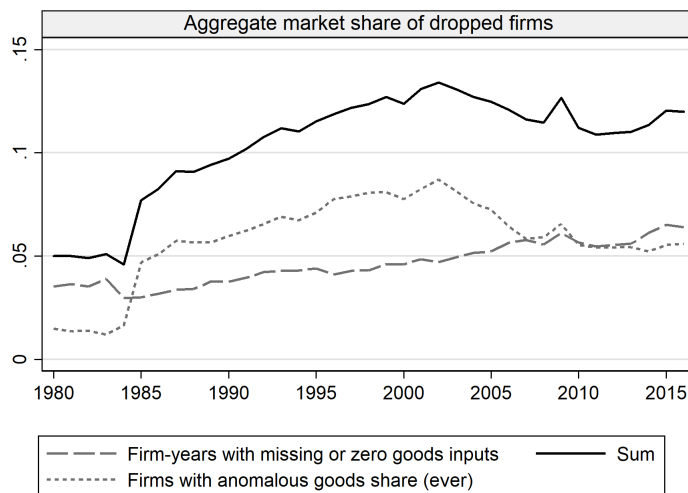
The different evolution over time in the revenue shares of goods and services inputs, is not unexpected in the light of the widespread phenomenon of service outsourcing, see for example Amiti and Wei (2005). Important for our analysis, is that a substantial component of purchased service inputs are likely to be rather fixed in nature. As such, including the bundle of fixed inputs, like catering, maintenances, insurance, etc., in the bundle of variable inputs invalidates the first-order condition approach of the production-approach to measuring markups.

Given that we observe goods intermediates (M_g) separately, we can simply use only this component to compute markups. While this is straightforward in principle, decomposing the total intermediate input variable into a goods and service component gives rise to two thorny measurement problems.

First, a significant share of firms reports zero or missing goods inputs. The long-dashed line in Figure 4 plots the share of total sales in the economy that is accounted for by these firms. For some of them, in particular firms in service sectors, actual use of goods inputs might indeed be zero or too small to report separately. But even when the zeros correctly reflect reality and are not a reporting problem, it still means that we cannot calculate a markup for these firms. Moreover, as the fraction of firms in the economy that display this problem increases over time, from approximately 4 percent of aggregate sales in 1980 to more than 6 percent in 2016, it introduces a compositional change in the aggregate as the sample over which we calculate the aggregate markup changes over time.

A second problem is that for many more firm-observations the revenue share of goods input leads to an implausible value, than is the case for the revenue share of total inputs. This might reflect year-on-year changes in accounting, but might also reflect changes in the organization of economic activity over subsidiaries. Recall that the unit of observation in our dataset are legal entities identified by a unique company registration number, but many of these entities will be under common ownership. The reason we suspect that part of the problem might be due to our use of unconsolidated accounts is that anomalous revenue shares are more likely to appear for larger firms than straightforward data errors, e.g. reporting numbers in thousands of euros rather than euros. To avoid having larger firms sporadically entering and exiting our dataset,

Figure 4: Aggregate Market Share of Firms which are Dropped



we omit firms in all years if we ever see them reporting a revenue share of goods inputs that implies a markup that exceeds 40. The dotted line in Figure 4 indicates that the aggregate sales share of these omitted firms is quite large, but is not trending up over the entire sample period.

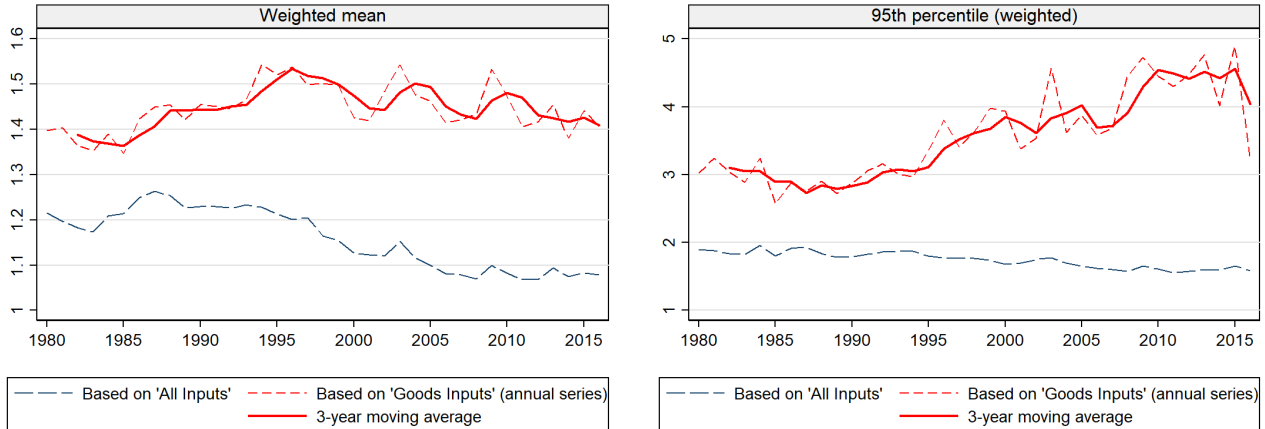
Without access to consolidated accounts or limiting the sample only to sectors where firms rarely report zero goods inputs, there is not much we can do about it. It just bears remembering that in the subsequent analysis approximately 10 percent of aggregate sales for the Belgian economy had to be omitted.

As discussed above, if both types of intermediate inputs are truly *variable* in production, we should obtain identical markup series using either variable, both at the firm level and averaged to the aggregate. In Figure 5, the blue-dashed lines repeat the earlier results for the share-weighted aggregate markup and the 95th percentile using the total intermediate input bundle ($M_g + M_s$). One difference is that these series are now constructed on the more limited sample eliminating the problem observations shown in Figure 4. A second difference is that we now show a three year weighted average (from 1982 onwards) to smooth out some of the cyclical fluctuations that are not of immediate interest.

The two lines in red show the comparable statistics using instead a markup calculated using solely goods inputs (M_g) in the variable input share. Naturally we also use

a lower value for $\bar{\theta}$ in these calculations. As before, we have normalized the firm-level markup to have a value of 1.1 for the median firm over the entire sample period. The dashed line represents the annual series, while the solid line is also a three year moving average.

Figure 5: Variable versus Fixed Intermediate Inputs



Both the share-weighted average or aggregate markup (on the left) and the share-weighted 95th percentile patterns show patterns that are drastically different using the total intermediate input bundle ('All inputs') or the goods intermediates only ('Goods inputs'). In particular, while the total intermediate input bundle implies flat and even moderately declining markups, the markups calculated based on the goods-intermediate component suggests increasing markups for some of the period. Moreover, while in Figure 2 markups stagnated around 1994, we now find continued growth almost to the year 2000 and less of a decline thereafter. The difference in the pattern for the top 5 percent firms is even more pronounced. In Figure 2 there was an increase for the top 1 percent firms, but not for other percentiles. In contrast, the results in Figure 5 show a continued increase and even some acceleration towards the end of the sample. This latter pattern is much more in line with the evidence for listed Belgian firms in Figure 1.

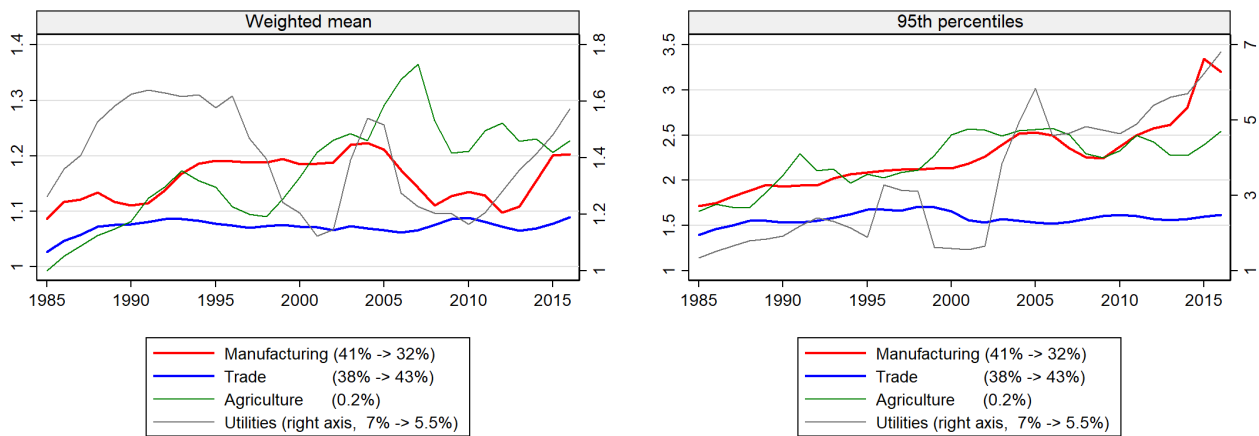
4.1 Sectoral analysis

Next we compute aggregate markups at the sectoral level, hereby freeing up the technology to be sector-specific, but for now still time-invariant. The normalization of the

median markup to 1.1 is now done separately for each sector. We show results for four sectors: Manufacturing, Trade, Utilities and Agriculture. Together they account for approximately 82 percent of total revenue in the Belgian economy.¹⁰ The only large sector we omit is Private Services, but goods inputs is not a relevant variable input for many firms in that sector.¹¹

In Figure 6 we again show the aggregate and 95th percentile for the four sectors considered. With a single exception the aggregate markup for the Utilities sector, all lines are now trending up to various degrees. In the Trade sector (shown in blue), the goods-intermediate share is very high and it is hard to reduce it a lot. As a result, the implied markups do not change very much, but they do trend up slightly, but consistently over the entire period. For manufacturing (in red) the aggregate markup shows an increase up to 2004 and some cyclicity afterwards. The evolution of the 95th percentile for the Manufacturing sector shows a very pronounced and sustained increase.

Figure 6: Evolution of Markups by Sector



So far we have restricted the output elasticities to be time invariant. Estimating these coefficients in the presence of market power, and thus potential price bias, is a challenging task. In the Appendix we document how we have performed this estima-

¹⁰We omit two sectors that show erratic markup patterns and would make the figure hard to read. Mining is ignored as it represents an extremely small share of the Belgian economy. Construction is a larger sector, but its aggregate markup is extremely cyclical, with the 95th percentile easily doubling from the cyclical low to high.

¹¹For the same reason we also omit results for the three smaller service sectors of Hotels and Restaurants, Transportation, Post and Telecommunication, and Personal and Public Services.

tion. Using estimated output elasticities that vary across time and sector to construct the sectoral markup evolutions we find similar patterns, although the upward trend in the markups is slightly reduced.

We have aggregated sectoral markups that are constructed both ways to an aggregate for the economy (using time-varying sector weights). Figure B.1 in the Appendix compares the two resulting series. The red-dashed line uses the normalized markups and the solid-blue line uses the estimated output elasticities. As could be expected from the slightly downward trend in the goods-intermediate revenue shares in Figure 3, the blue line is slightly below the red line, but the overall patterns are comparable.

5 Markup growth or reallocation

There is a vibrant debate in the macro-labor-IO literature related to the factors governing the markup and increased concentration patterns in the US.¹² An intermediate step to identifying causal drivers of aggregate markup patterns is to first decompose the aggregate markup M_t into a so-called *within* and *reallocation* component. This separates the forces behind a pure markup-growth effect at existing firms, from those responsible for shifting market shares towards say high markup firm. In addition, the process of entry and exit, both entering and leaving the economy or entering and leaving specific sectors, can further impact the aggregate markup and we also isolate the impact of these two processes.

We consider the following decomposition, taken from Haltiwanger (1997):

$$\Delta M_t = \sum_{i \in \mathcal{I}} a_{it} \Delta \mu_{it} + \sum_{i \in \mathcal{I}} \tilde{\mu}_{it-1} \Delta a_{it} + \sum_{i \in \mathcal{I}} \Delta \mu_{it} \Delta a_{it} + \sum_{i \in \text{Entry}} \tilde{\mu}_{it} a_{it} - \sum_{i \in \text{Exit}} \tilde{\mu}_{it-1} a_{it-1}, \quad (4)$$

where \mathcal{I} denotes the set of firms active in two adjacent periods, and *Entry* and *Exit*, the set of entering and exiting firms. We take care to normalize the firm-level markups that enter the decomposition for year t , by the lagged aggregate markup, and this is denoted with $\tilde{\mu}_{it-1} = \mu_{it-1} - M_{t-1}$.¹³ The first term captures the within-firm markup

¹²Most notably Autor, Dorn, Katz, Patterson, and Van Reenen (2017) document that a substantial share of the increase in industry concentration levels is due to a reallocation of activity towards what they refer to as superstar firms. De Loecker and Eeckhout (2017) decompose the aggregate markup at the industry and firm level, and find a large within-industry and within firm component during the period 1980-1990, followed by a period of reallocation.

¹³Note the slight abuse of notation, but the markup for entering firms $\tilde{\mu}_{it}$ is really equal to $\mu_{it} - M_{t-1}$.

growth, while the remainder parts taken together represent a reallocation term, in the sense that it is a market-based allocation of market shares that affects the aggregate markup in the economy.

We perform this decomposition for the full economy, both across sectors and across all firms, and subsequently for the major sectors. In particular, we rely on the fact that we can always rewrite the aggregate markup as sector-share weighted mean of sector-specific aggregate markups.¹⁴ Performing the decomposition for the full economy across all firms, or across the (share-weighted) sectors helps to discriminate the forces that operate at the sectoral level from those that combine the sectoral and individual ones.¹⁵

It is well-known that the interpretation of this decomposition is somewhat sensitive to the weights used in the different terms to aggregate the changes. We consider two alternative specifications.

First, we modify the decomposition in (4) as in Griliches and Regev (1995), and use the weight $\bar{a}_{it} = (a_{it-1} + a_{it})/2$ to aggregate the $\Delta\mu_{it}$ changes in the first ‘within’ term. Similarly, it uses a weight $\bar{\mu}_{it} = (\tilde{\mu}_{it-1} + \tilde{\mu}_{it})/2$ to aggregate the Δa_{it} changes in the second ‘between firms’ term. Using these weights amounts to dividing the third ‘covariance’ term equally over the first two terms. This covariance term has both a within firm and a between firms interpretation as it contains both the change in firm-level markups and the change in firm-level market shares.

This decomposition has the flavor of an empirical decomposition. The weights to aggregate the changes in the first two terms are, respectively, the average market share and the average markup over the two periods. The decomposition uses average, observed weights over the period considered to split changes in within-firm and between-firms components.

Second, we use the exact decomposition (4), which has the interpretation of a theoretical counterfactual. It allows to ascertain how much both the within and between components, individually, would affect the aggregate markup if only the changes mattered and weights were held constant. If one uses constant weights in the first two terms, the exact decomposition requires the third covariance term, which indicates to

¹⁴Denoting sectors by s , $M_t = \sum_s a_{st}M_{st}$, with $M_{st} = \sum_{i \in s} a_{it}\mu_{it}$.

¹⁵When we perform the decomposition at sectoral level, the last term in equation (4) drops out of course.

what extent the constant weight assumption is violated in the data and changes are correlated.

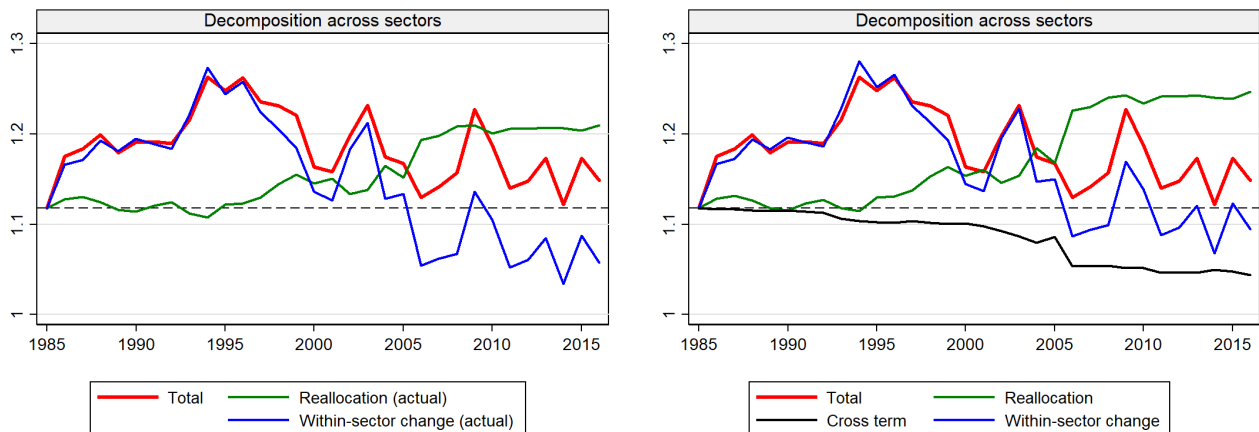
In both of these decompositions, we first calculate the different terms in (4). They each represent a change in markup which we then turn into an index. We normalize the first year to the actual aggregate markup in the year 1985 for the economy (or sector) and by adding the annual changes we roll the index forward for each term. The resulting indices each represent the cumulative change that is due solely to each individual term, which can exceed or fall short of the aggregate change.

In all the analyses that follows, we calculate the markups using the sector-time specific output elasticities. Each figure that shows results follows the same structure. We present the *actual* Griliches-Regev decomposition in the left panel, where we only distinguish between the within and the reallocation (between) component. In the right panel we present the *counterfactual* Haltiwanger decomposition, that introduces the third ‘covariance’ term, and now the indices represent the hypothetical contribution of each component.

5.1 Decomposition: Full Economy

Figure 7 presents the decomposition for the full economy across sectors as discussed above. A within change now represent a change in the sector-level markup and a between share means changes weights across sectors.

Figure 7: Decomposition Full Economy: Across Sectors



The actual decomposition (on the left) indicates that until the year 1996, the increasing aggregate markup was almost uniquely driven by the within-sector markup growth. Interestingly enough, the moment that the aggregate markup started fluctuating around the level of the late-nineties, marks the point that the within-markup growth term declined and even became a negative contributor. Consequently, the offsetting factor was a take-up in the importance of the reallocation term between sectors of the economy. This process only kicked in after the year 2000, but was almost as important from 2000 to 2010 as the within-firm was from 1985 to 1995.

The panel on the right considers the thought experiment by how much the aggregate markup would evolve if weights on the changes would remain constant at their value in $t - 1$. The sharp increase in aggregate markups during the first ten years of our sample can be solely generated by the process whereby sectoral markups grew with about 18 percentage points. Again, we find that reallocation process slowly picked up around the late nineties. By 2006 the contribution of reallocation to aggregate change also ceased and the cyclical nature of the sectoral markups shows up directly in the aggregate. The important contribution of reallocation between sectors is not surprising given that the manufacturing sector once responsible for 41 percent of total output, only represents 32 percent of total output by the end of the sample period.

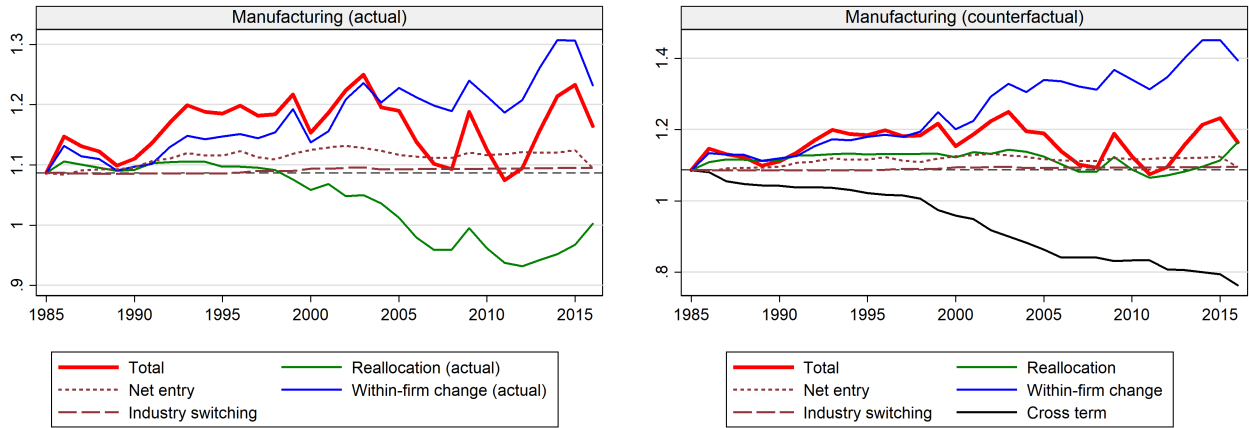
Finally, the black line for the 'correlation' term is negative over the entire sample period. It implies that sectors with rising markups systematically saw their share of economic activity decline. The blue and green lines on the right show what the contribution of the within and between forces on the aggregate would have been if weights had been constant. The black line shows that, in practice, weights have not been constant in the face of growth. In reality changes in markups and market shares are negatively correlated and the actual contribution of the blue and green lines, shown on the left, is lower because of the drag represented by the black line. At the sectoral level this factor does not change the overall picture, but that will be different once we turn to the within-sector decompositions.

5.2 Decomposition of Major Sectors

We now perform the decompositions across firms within two major sectors, manufacturing and trade (retail and wholesale). Figure 8 presents the evolution of the aggregate

markup, and its underlying components, for the manufacturing sector. Again, in the actual decomposition, the pure growth of markups tracks the aggregate (red line) quite closely until the early 2000s. As the aggregate markup reaches a plateau, the reallocation component kicks in. In this case, however, it is negative factor and it offsets the continued growth in the markup at continuing firms (evaluated at the average weight across two periods).

Figure 8: Sectoral Decomposition: Manufacturing

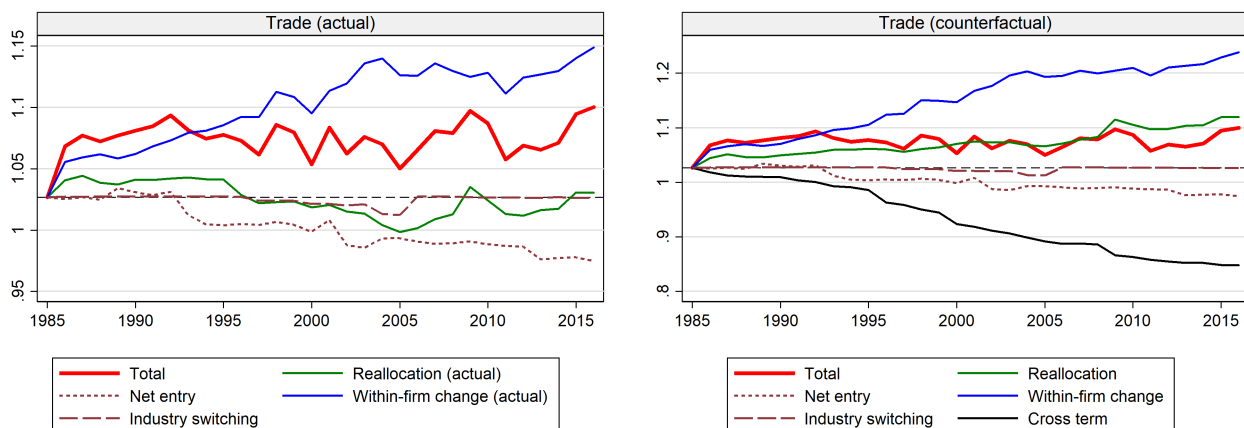


The contribution of firms switching in and out of manufacturing is truly negligible, while the contribution of net entry is positive, but limited. The exit of low markup firms and entry of higher markup firms boosts the aggregate, but the small market shares of entrants and exiting firms mean that this force does not move the aggregate by much.

Turning to the counterfactual analysis, we find an even stronger markup growth (within) component, which is reflected by the blue line overshooting the aggregate (in red) throughout the last 16 years (2000-2016) of our sample. Had firms with growing markets been able to maintain their market shares (at their initial levels), the aggregate markup would have been 40 percentage points higher. The large negative component is the cross-term, indicating a strong negative correlation between market share changes and markup growth, i.e. growing firms tend to experience declining markups. The net-entry process contributed positively to the aggregate markup, but only at a very moderate rate.

The analysis is qualitatively similar for the trade sector, which includes both firms

Figure 9: Sectoral Decomposition: Trade



in retailing and wholesale trade. This sector accounts for 43 percent of total output in the last year of our sample, 2016, and has experienced a gradual increase from its initial share of 38 percent. The patterns are similar to manufacturing, but the absolute changes are smaller and also less cyclical. Again the rise in the sectoral aggregate markup is largely due to firm-level markup growth. The aggregate markup stops growing—around the year 1993, and thus earlier than in manufacturing—when reallocation kicks in, which is also here a negative force.

Different from manufacturing, net entry also makes an ever increasing negative contribution. It seems that trading firms that exit the economy tended to have relatively high markups. This process is reminiscent of the impact of e-commerce on high street that has generated some literature in economics. For example, Goldmanis, Hortaçsu, Syverson, and Emre (2010) document that growth in e-commerce is often followed by pronounced exit process of high-cost retail firms. These niche firms are often high-markup firms as well, and they are replaced by more efficient, but also more price-competitive e-commerce firms.

The counterfactual analysis again indicates a big role for the markup growth (within) component, and similar as in the manufacturing sector the aggregate markup would have continued to rise until the very end of the sample period if market shares had held constant. Somewhat more pronounced than in the manufacturing sector, the reallocation component capturing the pure market share reshuffling—now holding markups constant at their lagged values—is also a substantial force. It even tracks the aggregate

pattern quiet closely. The much higher green line in the right panel compared to the left indicates that the reallocation of market shares was going to firms with initially high markups and this could have contributed strongly to the aggregate market growth, had it not been that this reallocation process tended to depress markups.

In practice, both the positive (counterfactual) within and between forces are compensated by a very strongly negative contribution, and increasingly so, of the cross-term. It confirms that the increasing negative covariance of markup growth and sales growth impacted the aggregate markups very substantially. Put differently, had it not been for this process, this hypothetical decomposition suggests a potentially much more pronounced markup increase for this sector.

5.3 Linking the decomposition to other secular trends

At the point where the aggregate markup started to stagnate (around the late nineties in the overall economy, and the early 2000s for the manufacturing sector), the international competitiveness of Belgian producers also changed dramatically. First of all, imports from Central and Eastern Europe increased substantially, thereby affecting the demand for Belgian products domestically and abroad. In addition, Belgian productivity and wages evolved negatively relative to its neighboring competitors, Germany and France. This process of increased international competition is reflected in the declining trade balance, ultimately leading to a current account deficit with the largest partner, the intra-EU trade. This evolution is clearly visible in the onset of a decade-long decline in the Belgian trade balance in the late nineties, as depicted in Figure 1 of De Loecker, Fuss, and Van Biesebroeck (2014). It reflects, among many factors, a weakening of the competitive position of Belgium in the overall EU market. This process is, however, only the case of trade in goods, whereas trade in services has strengthened, leading to a surplus of 5 billion EUR. It seems a fruitful path to explore in future work, whether the reversal in the external competitiveness of Belgian firm is related in a structural way to the end of the secular increase in the aggregate markup that we have documented here.

6 Concluding remarks

In this paper we analyze markups of a small-open economy, Belgium. We first constructed a novel firm-level dataset covering the period 1978-2016. This is an unusual long panel of all private firms with detailed balance sheet, income/loss statements, and entry and exit information. Compared to other studies documenting patterns of markups, we can track the markup, and the underlying components at the sectoral and firm level, over more than thirty years. With the exception of the recent work on US firms, this is the first analysis of aggregate markups of a European country covering such a long time period. This provides a rich setting to study the underlying drivers and correlates of firm-level and aggregate markups.

We uncover a significant change in the ratio of goods- and service intermediate inputs, indicating a fundamental change whereby Belgian firms started to organize production and generate sales over the last thirty years. We present evidence that the service component of intermediate inputs is highly fixed in nature, and therefore needs to be separated from the arguably more variable in nature goods intermediate input, when implementing the production-approach to markup estimation.

Once we split the input bundle along this dimension, we document increasing markups throughout the first ten years of our sample, 1985-1995, in the overall economy, but a continuing rise of markups in manufacturing until the early 2000s. In the remaining years, the aggregate markup, although cyclical, remained rather stable. We show that the results are uniquely driven by the dynamics in the sales-to-expenditure ratio, and not so much in the changing technology parameters – once of course we take into account the split between service and goods intermediates.

The aggregate patterns mask the underlying dynamics as the sector and firm level. Performing various decompositions, we find that the period where the aggregate markup (be it for the full economy or for one of the major sectors such as manufacturing or trade) rises, this is almost entirely due to the within component – i.e. markup growth. The period where the aggregate markup cycles around a stable average hides a strong process of reallocation, either at the sectoral or firm level: a growing negative correlation between sectoral market share and markup growth.

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Appendix A Estimating output elasticities

An obvious approach is to not observing output and input prices, might be to want to add price data to directly measure the unobserved price term. This strategy has been used in the literature, see e.g. Foster, Haltiwanger, and Syverson (2008), and can be employed when first of all price information is available. This might seem rather obvious, but the point is that there is, at this point, no systematic collection of price data at the level of producers, matched into production data. In addition, even when price data is recorded, the issue of how to compare quantities across products remains. This is precisely the strategy behind Foster, Haltiwanger, and Syverson (2008) in selecting very specific industries in US manufacturing for which first, there is price data recorded, and second, quantities are directly comparable across producers and time. Adding to this the requirement to not only observe output, but also input prices. Given the focus on the aggregation to an entire economy, or at least a sizable part of it, the addition of price data (output or input) is at best only going to be helpful for robustness checks of the markup estimates whenever this data is available.

Special attention needs to be given to the error term which not only consists of the traditional unobserved productivity shock, but also contains the unobserved prices:

$$\omega_{it} + p_{it} - \sum_H \theta_{st}^H p_{it}^H. \quad (\text{A.1})$$

Under constant returns to scale, this error term collapses to the (log) markup μ_{it} .

In the most general case, given the production structure assumed throughout, we are left with (deflated) revenue and (deflated) expenditures. Conditional on productivity shocks, the error terms cancels out if variation in input prices (scaled by their relevant output elasticity) are perfectly absorbed by the variation in output prices. This is the case if pass-through is complete, i.e., changes to input prices are fully passed on to prices, scaled by the relevant cost share of that input (i.e. the output elasticity). This can be thought of as operating both within a producer over time, or across producers in any given year.

In the case of incomplete pass-through, the variable markup creates a wedge between the output price and the input price bundle. This implies that the output elasticity is in general biased. However, an alternative strategy presents itself by recognizing how the total error term in (A.2) relates to marginal cost. Under a constant returns to scale production function:

$$\ln \lambda_{it} = \sum_h \theta_H P_{it}^H - \omega_{it}. \quad (\text{A.2})$$

Using the fact that $p_{it} = \ln \mu_{it} + \ln \lambda_{it}$, and plugging in the expression for the price in equation (A.2) yields

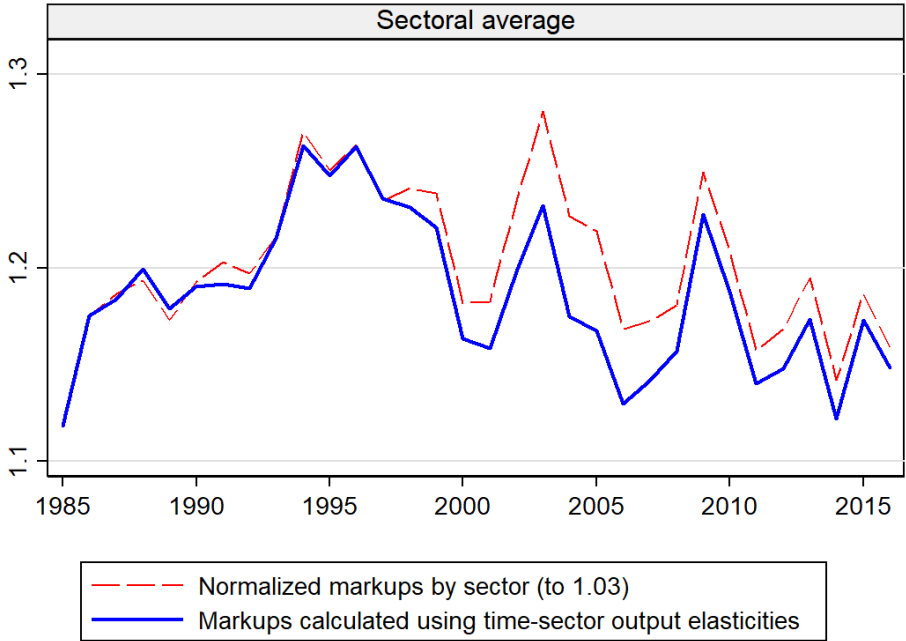
$$s_{it} = \sum_H \theta^H e_{it}^H + \ln \mu_{it} + \epsilon_{it}. \quad (\text{A.3})$$

This expression highlights that output elasticities can be consistently estimated using data on sales and expenditures as long as one can control for markups. If in fact the variation in markups is uniquely determined by cost-side heterogeneity, say productivity, then the approach of Akerberg, Caves, and Frazer (2015) applies.¹⁶ More generally, the variation in markups can be controlled for by a function that contains relevant determinants of markups. See De Loecker and Eeckhout (2017) for more discussion. The output elasticities are identified, and estimated, using additional parameters – i.e., the parameters associated with the markup control function $\mu_{it} = \mathcal{M}(\cdot)$. An important element in this control function is the market share, in addition to the standard productivity term ω_{it} .

¹⁶Under arbitrary returns to scale the relationship between sales and the input bundle expenditure depends on the *scale* of production.

Appendix B Additional figures

Figure B.1: Sector and Time Varying Output Elasticities: Robustness



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National Bank of Belgium
Limited liability company
RLP Brussels – Company's number: 0203.201.340
Registered office: boulevard de Berlaimont 14 – BE-1000 Brussels
www.nbb.be

Editor

Jan Smets

Governor of the National Bank of Belgium

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Layout: Analysis and Research Group
Cover: NBB AG – Prepress & Image

Published in October 2018