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Empirical investigation into market power, markups and employment

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In this paper I use the production function approach popularized by De Loecker et al. (2020) to analyze the evolution of market power in Slovakia and some of its micro and macro implications. In contrast to other studies, I calculate markups from both value added and sales and empirically test whether some of the global trends in market power can be seen in Slovak firm level data as well. I find that the markups in Slovakia in fact declined since 2010, both in terms of value added and sales. Although the decrease in sales markups is negligible, the value added aggregate markup declined by 25 % from 2.35 in 2012 to 1.78 in 2018. Value added markups tend to be higher for relatively value-added larger firms and they are also higher in larger sectors. Smaller firms (size indicated by number of employees) tend to have higher markups. It seems that a typical high markup firm is relatively small (in terms of number of employees) but produces relatively larger output. Correlations between markups and various measures of profitabality show that there is indeed a relationship between markups and market power. Markups strongly correlate with profits and they do not significantly react to changes in costs. Markups in Slovakia evolve in excess of marginal costs. Slovak firm data shows that markups are also inversely associated to labor shares. Correlation is statistically strong and empirically well established.

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In this paper I use the production function approach popularized by De Loecker et al. (2020) to analyze the evolution of market power in Slovakia and some of its micro and macro implications. In contrast to other studies, I calculate markups from both value added and sales and empirically test whether some of the global trends in market power can be seen in Slovak firm level data as well. I find the that markups in Slovakia in fact declined since 2010, both in terms of value added and sales. Although the decrease in sales markups is negligible, the value added aggregate markup declined by 25% from 2.35 in 2012 to 1.78 in 2018. Value added markups tend to be higher for relatively value-added larger firms and they are also higher in larger sectors. Smaller firms (size indicated by number of employees) tend to have higher markups. It seems that a typical high markup firm is relatively small (in terms of number of employees) but produces relatively larger output. Correlations between markups and various measures of profitability show that there is indeed a relationship between markups and market power. Markups strongly correlate with profits and they do not significantly react to changes in costs. Markups in Slovakia evolve in excess of marginal costs. Slovak firm data shows that markups are also inversely associated to labor shares. Correlation is statistically strong and empirically well established.

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1 Introduction

Studying market power and its economic implications has become a fruitful area for contemporary economic research. Healthy competition among firms is an essential determinant of a well-functioning economy. It ensures that prices reflect costs and motivates firms to constantly innovate which in turn improves consumer welfare and drives economic growth. On the other hand, barriers to entry, various market distortions and monopoly power allow firms to charge higher than optimal prices thus reducing welfare which is harmful to economic development.

In this paper I follow the most up-to-date literature on markups and market power and apply the production function markup estimation to Slovak firm level data. I empirically verify some of the trends seen mainly in the U.S. and discuss the evolution of market power in a small open economy. I also empirically investigate whether the claims of inverse size-markup and positive profit-markup relation can be found in data. So far the studies analyzing trends in market power came from the U.S. and little is known about this issue in other countries. There are some studies using international data and/or cross-country comparison but none provides comprehensive understanding of a country specific evolution of market power from firm level data.. I focus on Slovakia because the firm data availability is excellent, and to my knowledge, there is no other study that applies the methodology from De Loecker et al. (2020) to a European economy in such detail. Also, this is a first comprehensive study analyzing market power in Slovakia and in the CEE region from firm level data. Firstly, I study the evolution of firm markups in the last decade and discuss their distribution. I then analyze their relation to various firm characteristics, mainly firm size, profitability and labor share. I also discuss how the results depend on the choice of variable inputs and production function specification.

Looking at the markup evolution I find the that markups in Slovakia in fact declined since 2010, both in terms of value added and sales. Although the decrease in sales markups is negligible, the value added aggregate markup declined by 25% from 2.35 in 2012 to 1.78 in 2018. Value added markups tend to be higher for relatively value-added larger firms and they are also higher in larger sectors. Smaller firms (size indicated by number of employees) tend to have higher markups, but there are some large firms with higher markups that drive the evolution of aggregate markup. Markup decomposition shows (both for sales and value added markups) that at the firm level the within effect is the main driver of the aggregate markup movements and the change in markups occurs within and between sectors at the same time. It seems that a typical high markup firm is relatively small (in terms of number of employees) but produces relatively larger output.

Correlations between markups and various various measures of profitability show that there is indeed a relationship between markups and market power. Markups strongly correlate with profits and they do not react significantly to changes in costs. Markups in Slovakia evolve in excess of marginal costs. Firm data shows that markups are also inversely associated to labor shares. Correlation is statistically strong and empirically well established. These finding are well in line with De Loecker et al. (2020). On the other hand, market power measured through firms' market shares does not systematically correlate with markups. The results using market shares as explanatory variable are statistically inconsistent and require further understanding. Decreasing aggregate markup crudely correlates with increasing share of labor's income in GDP thus giving merit to certain macroeconomic implications of market power.

The rest of the paper is structured as follows: next section reviews the literature on market power and its economic implications, in Section 3 I introduce markup derivation via the production function approach and in Section 4 I briefly discuss data quality and present some summary statistics. Section 5 deals with the baseline results and presents the evolution of market power from the value added specification of markups. In Robustness checks I calculate markups from sales and analyze the relation between markups and labor shares at the firm level. In section 7 I conclude the paper and emphasise the main findings.

2 Literature review

Recent period has seen a growing number of studies dedicated to analyzing market power and its various macroeconomic impacts. Together with a diffusion of high quality firm-level data many studies focused on estimating firm-level markups and concentration indices, their evolution and their effect on aggregate employment, wages and labor share.

De Loecker et al. (2020), using Compustat and Census data, analyze in great detail the evolution of aggregate and firm markups and document the presence of rising market power in the U.S. starting from 1980s. Similarly as Autor et al. (2020)) they find the increase in markups is driven mainly by the upper tail of the markup distribution while median markups remain unchanged. In addition to the fattening upper tail of the markup distribution, there is reallocation of market share from low to high markup firms. They also discuss some macroeconomic implications of rising mark ups and relate the results to declining labor and capital shares as well as to the decrease in labor market dynamism.

Autor et al. (2020) link the fall of labor's share of GDP in the United States to the phenomenon of the so called *superstar firms*. According to the authors, globalization and technological changes push sales towards the most productive firms in each industry thus product market concentration will rise as industries become increasingly dominated by superstar firms. Since these firms have high markups and a low labor shares of value added and sales, a reallocation of output toward superstar firms depresses the aggregate labor share. They find that in industries where concentration has risen the most, labor shares declined significantly. This effect is mainly driven by reallocation of economic to high productive firms. Overall they document that in past decades U.S. sectors have become much more concentrated and some of the decline in labor share through rising concentration might be seen in Europe as well.

From the European perspective, McAdam et al. (2019) finds that concentration and markups are largely stable in the Euro Area. In the study the authors find that the aggregate euro area markup has been fairly stable, varying around the value of 10-15% and has even declined marginally since late 1990s. According to the results, these developments are driven largely by manufacturing and may be attributed to the stability of market power and to the impact of trade and monetary integration in the Euro Area. Contrary to the U.S. case, there are industries and firms that have high (and rising) markups but such firms are not those with particularly high market shares; thus they do not impart a trend in the aggregate markup in the Euro Area.

Other papers document negative impact of rise in market power on employment and wages. Benmelech et al. (2018) using US Census data of American manufacturing firms in the period of 1977-2009 show that local-level employer concentration increased over time and is negatively related to wages. According to their estimates the negative relation between labor market concentration and wages is stronger when unionization rates are low and the link between productivity growth and wage growth is stronger when labor markets are less concentrated. Their results emphasize the role of local-level labor market monopsonies in influencing firm wage-setting behavior and state that the results can explain some of the stagnation of wages in the United States over the past several decades. Qiu & Sojourner (2019) find also similar results.

Jarosch et al. (2019) build a model where firm size is a source labor market power. In Austrian micro-data, the authors find that granular market power depresses wages by about ten percent and can explain 40 percent of the observed decline in the labor share from 1997 to 2015. According to the authors, mergers decrease competition for workers and reduce wages even at non-merging firms.

Bridging both product and labor marker imperfection Dobbelaere et al. (2013) show that both product and labor market imperfections generate a wedge between factor elasticities in the production function and their corresponding shares in revenue. The authors then classify industries into different regimes based on product market (markup) and labor market imperfections that can be characterized by a so called joint market imperfections parameter. For each of the predominant regimes in each country, they then investigate industry differences in the estimated product and labor market imperfections and scale economies.

Another branch of literature focuses on the relationship between markups and firm size. Although the literature is scarcer, Atkin et al. (2015) show that firm size is positively related do mark ups. Using firm level data of 135 soccer-ball manufacturers in Pakistan they show that elasticity of firm size to markups increases with higher quality products, where in turn larger firm size is associated with higher quality production. According to the authors, average markups increase with firm size because larger firms produce disproportionately more high-quality balls, and within each type of ball obtain higher markups. On the other hand, in the Appendix 6 of De Loecker et al. (2020) the authors document that there is a negative relationship between markups and firm size (in terms of employment). These contradicting results suggest non-monotonicity in markup-size relationship. In fact, Diéz et al. (2019) using international ORBIS firm level data find non-monotonicity, but positive relationship between firm size and markups is found only for the highest percentile of firms in firm sales distribution. Although non-monotonicity is found for industry firm sales share, the additional results indicate that there is indeed negative correlation between between firm size measured in number of employees and markups.

3 Markup derivation

To precisely estimate markups one would need to exactly know firm level or even product level individual prices and marginal costs. Since firm or product level prices are a feature of very few databases and marginal costs are not trivial to estimate, researchers rely on various assumptions on economic behaviour of firms in order to produce plausible estimates of firm level markups. In general, there exists three distinct approaches to calculate markups. First approach relies on accounting standards, where in the case of Slovak accounting legal framework, commercial markups are calculated as a difference between sales and intermediate inputs, specifically, between sold and purchased merchandise. Although this approach is straightforward and very easy to implement, it abstracts from other types of variable costs and sales items and does not provide economically meaningful insights into firm pricing behaviour.

The second approach draws from the Industrial Organization literature and builds on the specification of a demand system. It uses information and assumptions on how firms compete which then under first order conditions delivers optimal firm pricing and desired demand elasticities. Similarly as in De Loecker et al. (2020) this approach does not fit this study since the data does not include information on product prices and quantities and I do not consider appropriate to impose one demand system for all the products under consideration or for all sectors.

The third approach, used in this paper, stems from cost minimizing behaviour. In order to estimate firm level markups I rely on approach developed by Hall (1988) and recently applied by De Loecker & Warzynski (2012) or De Loecker et al. (2020). This method uses information from firm's financial statements, and does not require any assumptions on demand and how firms compete. Instead, markups are obtained by exploiting cost minimization of variable inputs in production. This approach requires, however, an explicit treatment of the production function to obtain the output elasticity of at least one variable input of production.[1]

3.1 Production function approach

Markup is defined as a wedge between price and marginal cost and can be interpreted as as measure of market power. Mathematically markups are defined as the ratio of price to marginal cost:

$$\mu \equiv \frac{P}{c} \tag{1}$$

Since prices and marginal costs are not observable in the firm level data I use value added, sales, expenditure on variable inputs and output elasticities to recover the measure of markups. For this purpose I follow De Loecker et al. (2020) and calculate markups from static first order conditions of cost minimization. Consider and economy with N firms, indexed by $i = 1,..., N$. Firms are heterogeneous in terms of productivity A_{it} and technology F_{it} is sector specific. In each period t firms minimize the contemporaneous cost of production given the production function:

$$Q_{it} = F_{it}(A_{it}, K_{i,t-1}, L_{it}), \tag{2}$$

where $K_{i,t-1}, L_{it}$ denote net capital stock and labor, respectively. Variable input L_{it} adjust perfectly while capital stock K_{it} faces adjustment frictions. In terms of cost minimization I consider the Lagrangian objective function:

$$\Lambda(K_{it}, L_{it}, \lambda_{it}) = w_{it}L_{it} + r_{it}K_{i,t-1} - \lambda_{it}(F(\cdot) - \overline{Q_{it}}), \tag{3}$$

[1] De Loecker et al. (2020)

where w_{it}, r_{it} denote input factor prices, $F(\cdot)$ is the technology specified in equation (2), $\overline{Q_{it}}$ is a scalar and λ_{it} is the Lagrange multiplier. I assume that firms are price takers on input factor market. The first order condition with respect to the variable input L_{it} is:

$$FOC_{L_{it}} := w_{it} - \lambda_{it} \frac{\partial(F(\cdot))}{\partial L_{it}} = 0, \tag{4}$$

Multiplying all terms in equation (4) by $\frac{L_{it}}{Q_{it}}$ and rearranging terms yields an expression for the output elasticity of the variable input:

$$\theta_{it}^{L} \equiv \frac{\partial(F(\cdot))}{\partial L_{it}} \frac{L_{it}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{w_{it} L_{it}}{Q_{it}}, \tag{5}$$

Since the Lagrangian multiplier can be interpreted as a measure of marginal cost and therefore from definition (1) we have $\mu = \frac{P}{\lambda}$, where P is the output price. Substituting marginal cost for the markup to price ratio, I obtain a simple expression for the markup:

$$\mu_{it}^{L} = \theta_{it}^{L} \frac{P_{it} Q_{it}}{w_{it} L_{it}}, \tag{6}$$

Therefore in order to estimate the firm markup one needs to know the output elasticity θ_{it} and the share of the variable input in total sales. An important feature of the markup derivation is to correctly estimate the output elasticities. Value added and personnel costs are available from the data. Therefore in order to estimate output elasticities I use control function approach developed by Levinsohn & Petrin (2003).

3.2 Production function estimation

In production function literature the major obstacle for consistent estimation is correlation between unobserved productivity shocks and input levels. As Petrin et al. (2004) state, profit-maximizing firms respond to positive productivity shocks by expanding output, which requires additional inputs. Negative shocks lead firms to pare back output, decreasing their input usage. When true, ordinary least squares (OLS) estimates of production functions are biased and, by implication, lead to biased estimates of productivity and output elasticities. Various methods have been proposed to tackle such simultaneity issue and, according to these approaches, it is possible to group them in three families: Fixed Effects (FE), Instrumental Variables (IV) and Control Function (CF).[2] In this paper I use the CF approach and rely on intermediate inputs as a proxy for unobserved productivity shocks.[3]

Similarly as in the section above, I work with two-factor, but log-linear Cobb-Douglass production function specification (capital and labor). I apply the Levinsohn-Petrin approach to a robust panel of more than 380 thousand firm-year observations covering the period of 2014–2018 and estimate output elasticities for each firm. To overcome the productivity shock endogeneity problem in CF estimations I use intermediate inputs as the proxy variable. To capture differences in sectoral technologies, CF regressions are performed for each 3-digit sector separately and the production function is given by:[4]

$$(P_{sit} Q_{sit}) = \theta_1 Capital_{si,t-1} + \theta_2 Labor_{sit} + \tau_{st} + \omega_{sit} + \epsilon_{sit} \tag{7}$$

[2] Mollisi & Rovigatti (2017)

[3] The benefits of using Levinsohn-Petrin approach are described in Petrin et al. (2004).

[4] Performing production function estimation sector by sector allows me to estimate sector specific output elasticities and distinguish among different technologies used by firms in different sectors.

where $P_{sit}Q_{sit}$ represents log of firm value added, $Capital_{si,t-1}$ stands for log of sum of net fixed and intangible assets from the previous year and $labor_{sit}$ stands for log of number of employees.[5] I also incorporate year fixed effects τ_{st}. By incorporating year fixed effects I capture any common trends that may affect firms in a given sector. If these common trends are variations in input and output prices, it is possible to, at least partly, alleviate the concerns that price level movements confounds the estimates of θ_{it}. In general, year fixed effects could capture some evolution in prices, thus partly (but not fully) alleviate the problem of price bias in productivity estimation. Term ϵ_{sit} is the idiosyncratic error and the term ω_{sit} represents the unobserved productivity. Subscripts s, i, t stand for sector, firm and year, respectively. Three remarks must be made here. Firstly, for capital I use the sum of net fixed and intangible assets. Secondly, simple metric of number of employees does not have to properly differentiate between quality of human capital. Some studies, e.g. Hsieh & Klenow (2009), use personnel costs rather than number of employees. By doing so they crudely control for differences in worker skills and education. Firms operating with higher share of highly educated individuals should be more productive and this fact is usually reflected in more expensive labor input. Although these concerns are valid, using personnel costs instead of number of employees would provide implausible low levels of labor output elasticities. To stay in line with the literature and common approaches I use the number of employees as a baseline labor indicator. Intermediate inputs are calculated as the sum of purchased merchandise, goods and services, materials and energy costs. Output elasticities estimated from the CF regressions are then applied to all firms in their respective 3-digit sector for the period of 2010-2018.

4 Data description

In order to evaluate the evolution of markups and market power in Slovakia I use a detailed firm level database compiled from four key sources which are the Registry of Financial Statements,[6] the Statistical Office of the Slovak Republic, and a private company, Finstat s.r.o..[7] The fourth source is the Social Insurance Company from which I draw firm level data on employment (full time and part-time employees) and average firm wages. Employment and wage data is available for the years 2014 to 2018. I match firms from all databases based on a unique firm identifier.

Although the data starts in 2010, it was only compulsory for firms to publish data in the Registry from 2013 onward. Therefore the data for the period between 2010 and 2012 is to be considered as a subsample of the Slovak firm population. On average, the unbalanced panel of firms consists of of 182 thousands observations per year (1.6 million in total) over the period of 2010 to 2018 and covers all sectors of the economy.

For the purpose of markup calculation I use data on sales, value added, intermediate consumption, capital (net fixed and intangible assets), personnel costs and number of employees in order estimate firm production function and output elasticities of variable inputs. As will be reported later in the following sections I then use these elasticities to calculate firm markups stemming from the first order minimization conditions.

To proceed with the analysis further, I start by cleaning the database. I drop missing and negative observations from the data. Public sector, finance and real estate companies are also excluded. In order to not have the analysis sensitive to outliers I trim the top and bottom 1 percent of a ratio of value added to personnel costs and drop firms with less than 2 employees.[8] To estimate the production function I drop sectors with less than 100 observations, where sectors are defined at 3-digit NACE Rev. 2 level. I also drop firms that uploaded their financial statements for the period covering more than 457 days and less than 273 days, respectively. In the end I am left with total number of 380 thousand observations distributed across all main sectors of the Slovak economy for the period of 2010 to 2018.

Table 1 presents some elementary summary statistics which are divided in three 4-year windows. As it

[5] Aggregate firm employment is a sum of full-time and part-time employees, where part-time employees are assigned 50% weight. Since capital stock is reported in the financial statement as of end-of-the-period, I use its lag to properly estimate the effect of capital on production taking into account capital stock adjustment frictions.

[6] The Registry is administered by the Financial Administration of the Slovak Republic where firms upload entire balance sheets and income statements for public disclosure.

[7] However, not all firms have their data freely accessible. Some firms and mainly the self-employed do not have their balance sheets and income statements publicly available. Since the self-employed are not of interest and only a minimum of firms have their data unavailable, I do not consider this to be an issue of great importance.

[8] In the Robustness check section I follow the same data cleaning procedures but instead of the value added to personnel costs ratio I drop top and bottom 1 percent of a ratio of sales to variables costs (sum of personnel costs and intermediate consumption).

can be seen, unweighted average of firm value added markups oscillates around 1.4 - 1.5 and increased since 2010. Even after dropping outliers, markups among Slovak firms are very heterogeneous indicated by large dispersion between the minimum and maximal values. The unweighted mean of around 1.5 is in line with other studies such as Diéz et al. (2019) or De Loecker et al. (2020). The median markup reaches 1.12 in 2018. I also report labor shares in relation to sales and value added. In the post-crisis period average labor share in relation to sales (personnel costs divided by sales) increased from 25% to 30% but average labor share in value added decreased from 97% to 86% in 2018. Slovak firms are on average very small with around 20 employees but are characterized by a substantial size heterogeneity. I believe that these data features will provide valuable insights into relationships between market power, employment and labor shares.

Table 1: Selected summary statistics

VARIABLES	N	mean	sd	min	max
2010					
Markup	27,120	1.422	1.463	0.00400	25.97
Labor share (output)	27,090	0.246	0.725	0.000156	79.86
Labor share (VA)	27,120	0.974	1.678	0.0390	107.5
2014					
Employment	46,195	22.11	152.6	2	14,259
Markup	46,195	1.511	1.483	0.0149	25.93
Labor share (output)	46,171	0.235	1.022	0.000295	153.0
Labor share (VA)	46,195	0.905	1.129	0.0205	23.59
VA per worker	46,195	17,813	26,855	3	1.484e+06
Output per worker	46,195	116,348	513,959	0	5.648e+07
Capital intensity	46,195	24,868	169,417	0	2.568e+07
2018					
Employment	57,372	19.81	132.5	2	14,583
Markup	57,372	1.536	1.546	0.0125	23.69
Labor share (output)	57,355	0.300	13.29	0.000436	3,180
Labor share (VA)	57,372	0.862	0.968	0.0200	29.27
VA per worker	57,372	19,873	27,799	16.25	1.334e+06
Output per worker	57,372	116,488	489,525	0	4.833e+07
Capital intensity	57,372	25,061	152,560	0	1.972e+07

5 Results

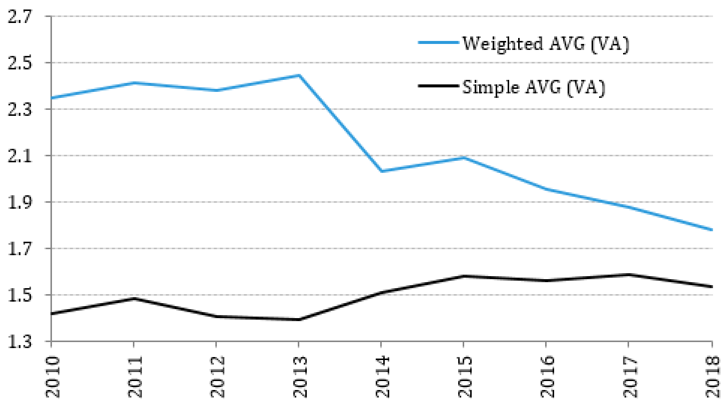
In this section I report the baseline results regarding the evolution of markups and market power in Slovakia. I start by computing aggregate markup for the whole economy and analyze its evolution.[9] Later in the paper I will provide decomposition of the aggregate markup change to show what are the main forces behind its evolution. Distribution of markups will also be of interest. In the second part I use estimated markups and relate them to various firm characteristics and investigate whether movements in markups affect market power. Since the main results deal with markups calculated only from value added, in the Robustness checks section I replace value added with sales and add intermediate consumption as a third factor into the production function. I will then discuss the effect of markups on firm labor shares.

[9] I start by analyzing markups calculated from the value added specification. Later in the Robustness check section I evaluate the evolution of markups from the standard gross output (sales) specification.

5.1 Evolution of the aggregate markup

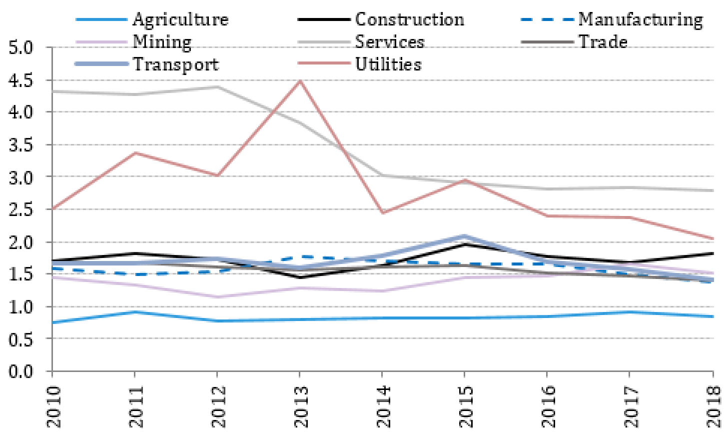
To present the results for the evolution of the aggregate (weighted) markup I calculate firm markups according to the equation (6) for every year in the dataset and weight them by their respective value added share in total economy. Results are presented in Figure 1. After the Great Financial Crisis and austerity induced GDP growth slowdown from 2009 to 2012 the aggregate markup declined by 25% from 2.35 in 2012 to 1.78 in 2018. What is very interesting is that the decrease in the aggregate markup is driven solely by the decline of markups in services and utilities while in all other sectors markups are largely stable (Figure 2).[10] Between 2010 and 2018 markups in services declined by 35% and in utilities by 18% and the decrease was driven mainly by telecommunication, casinos and IT services. Since 2016 markups in services stabilized and are the highest within the whole economy. In 2018, out of top 10 NACE 2-digit sub-sectors in markup distribution, were 8 from services (mainly ICT sectors, casinos and legal and administrative services).

Figure 1: Aggregate economy-wide markup



Note: Weighted average markup equals the value-added-share-weighted average of firm level markups. Simple average is calculated as an arithmetic mean of individual firm markups.

Figure 2: Sectoral markups



Note: Sectoral markup equals the value-added-share-weighted average of firm level markups. Weights are calculated as a ratio of firm value added in total sector value added.

The difference between the weighted and unweighted markup in the Figure 1 indicates that, on aggregate, larger firms (in terms of value added) have higher markups. Empirically, these results are well in line with

[10] Sectoral markups are calculated analogically to aggregate markup but firm value added shares are computed for each sector separately.

De Loecker et al. (2020) but contradict the results found in Diéz et al. (2019). The fact that the blue line (weighted markup) is always above the black line (unweighted average) indicates that relatively larger firms do have higher markups. Diéz et al. (2019) using the Orbis database find opposite results. In their case the explanation is that small firms operate in niche markets facing demands that allow them to charge high markups.[11] According to my results, this in not the case for Slovak firm level data. If markups are allowed to be treated as distortions similarly to Hsieh & Klenow (2009) then they might distort firm size but not necessarily from the output side. Later in the paper I investigate whether markups are inversely related to firm size from the input size (employment) and discuss their exogeneity. Mathematically the relationship between relative firm size (in terms of valued added) and markups can be shown using the following decomposition by Olley & Pakes (1996):

$$\mu_t = \sum_i s_{it}\mu_{it} = \overline{\mu_t} + \sum_i (s_{it} - \overline{s_t})(\mu_{it} - \overline{\mu_t}), \quad (8)$$

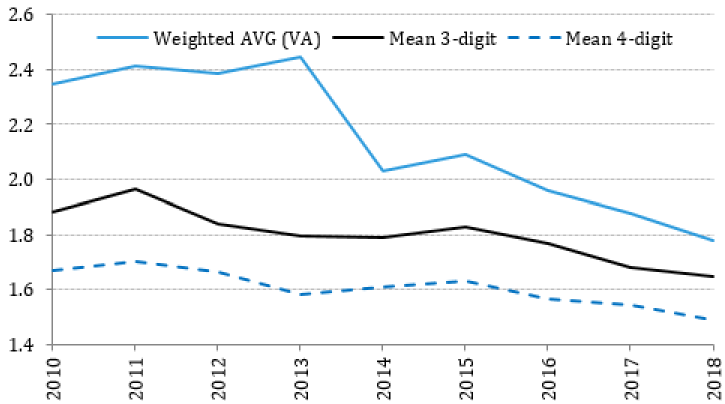
where μ_t is the value-added-weighted average markup; s_{it} is the share of firm i's value added ($P_{it}Q_{it}$) in total value added in the economy ($V_t = \sum_i P_{it}Q_{it}$); $\overline{\mu_t}$ is the unweighted average of markups and the second term shows the covariance between relative firm size s_{it} and firm markup μ_{it}. Since in the Figure 1 the unweighted markup (black line) is always below the weighted markup (blue line) then the covariance is positive implying that on aggregate level there is a positive relationship between a firm's value added share and its markup.

Similar decomposition can be done at the sectoral level as well. Following De Loecker and Eeckhout (2017) I can decompose the evolution of the aggregate markup as follows:

$$\mu_t = \overline{\mu_{st}} + \sum_s (s_{st} - \overline{s_{st}})(\mu_{st} - \overline{\mu_{st}}), \quad (9)$$

where $\overline{\mu_{st}}$ is the unweighted average of (weighted) markup across industries, and the last term is the covariance between market share and markups at the industry (sectoral) level. Variables s_{st} and μ_{st} represent the sector's value added weight in the total economy and the sectoral weighted markup, respectively.[12]

Figure 3: Evolution of markups: Aggregate weighted vs. mean sectoral markups



Note: Mean sectoral markups calculated as a simple unweighted average of sectoral markups.

Figure 3 documents the decomposition from the equation (9). The difference between the average of 3-digit sectoral markups (black line) and the aggregate weighted markup (blue line) is proportional to the covariance between the industry share of sales in the entire economy and the average weighted markup in that

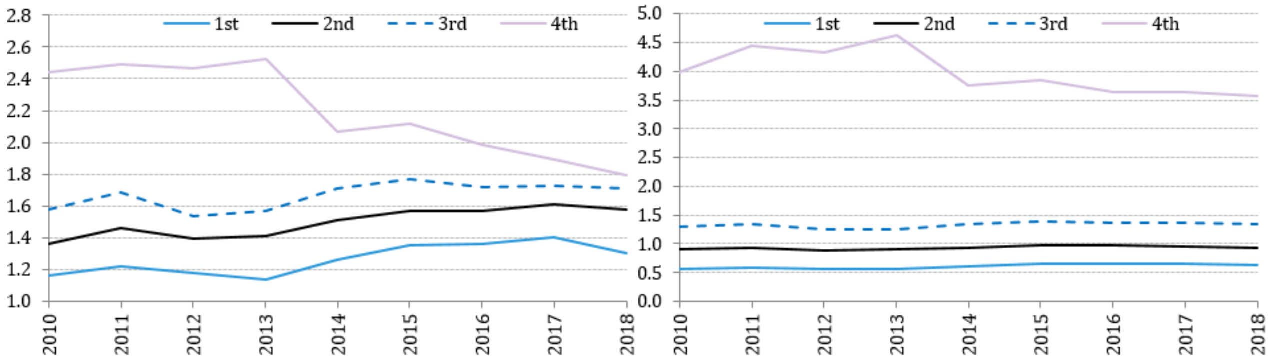
[11] Diéz et al. (2019) and Holmes & Stevens (2014)

[12] See De Loecker & Eeckhout (2017) equations (11) and (12).

industry. During the whole period from 2010 to 2018 mean sectoral markups are always below the weighted aggregate markup indicating that not only relatively larger firms but also larger sectors have higher markups. Although markups have markedly declined in the last decade, they are consistently larger for large firms and large industries.

Diéz et al. (2019) made an important point regarding the evolution of the aggregate markup. In their paper they showed that large firms are the main drivers of markup evolution.[13] Similarly as in their Orbis database, Slovak firms are very heterogeneous both in terms of markups and other firm characteristics. Taking the substantial heterogeneity of Slovak firm characteristics into account, it is clear to see that the markup time series variation is driven mainly by firms with relatively large value added (Figure 4, left panel). Surprisingly, dividing firms into markup quartiles shows that average markups for firms in 1st to 3rd quartile remain stable and do not experience any sizeable variation during the period in question. Also in Diéz et al. (2019) it was the firms with very high markups that experienced sizeable markup increases. In the Slovak data I find opposite developments. As Figure 4 shows, the decline in the aggregate markup was mainly driven by decreasing markups of relatively large and high-markup firms.

Figure 4: Evolution of markups by quartiles

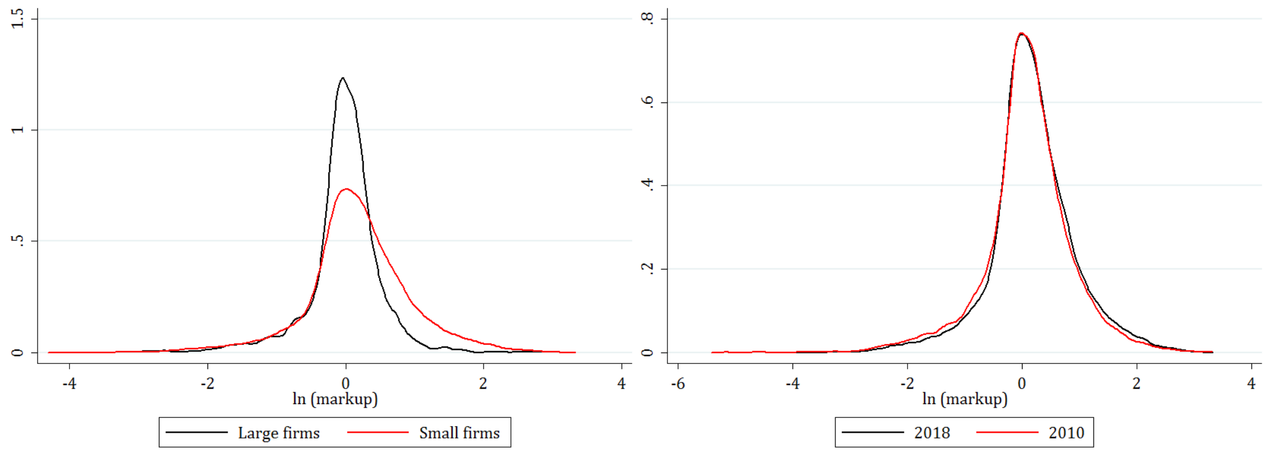


Note: Markups calculated as a weighted average of firm level markups in each quartile. Left panel (quartiles by value added), right panel (quartiles by markup).

Distribution of markups in Slovakia over time is relatively stable and does not change very much. In the right panel of Figure 5 there is a slight rightward movement of the markup distribution and the right tail is slightly longer and thicker. These movements indicate the increase of number of firms with very high markups. Left panel shows the comparison of markup distributions for small (less than 50 employees) and large (more than 50 employees) firms in 2018. Larger firms have markups oscillating around the value of 1 and are less dispersed. For smaller firms the right tail is thicker and markups experience greater variation. These results are partly in line with Diéz et al. (2019) and De Loecker et al. (2020) who show that markups are negatively correlated with firm size. But as is the case in this paper, size must be measured in number of employees and not as relative output size in order to reach such conclusion.

[13] Firm size in their study is defined as sales share within the economy or respective sector.

Figure 5: Kernel density distribution of firm markups



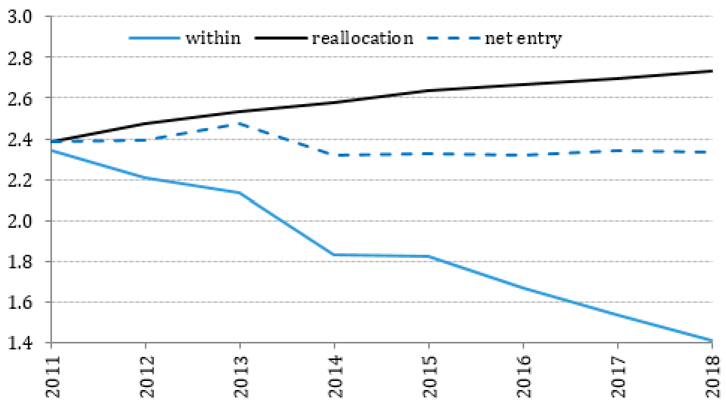
Quartile decomposition shown in the Figure 4 indicates that there are some relatively large firms (in terms of value added) that act as key drivers in the aggregate markup evolution. Density distributions from the Figure 5 show that there was a rightward, although very small, movement of the markup distribution. To investigate whether the decrease in the aggregate markup is driven by a few firms in the top/bottom of the distribution, as it is for example in De Loecker et al. (2020), I further decompose the decrease in the aggregate weighted markup into the component that is due to the change in the markup itself, and the component that is due to the reallocation of economic activity towards high/low markup firms. I again follow De Loecker et al. (2020) and decompose the change ($\triangle\mu_t$) as follows:

$$\triangle\mu_t = \sum_i s_{i,t-1}\triangle\mu_{it} + \sum_i \triangle s_{it}\widetilde{\mu_{i,t-1}} + \sum_i \triangle s_{it}\triangle\mu_{it} + \sum_{i\in Entry} s_{it}\widetilde{\mu_{it}} - \sum_{i\in Exit} s_{i,t-1}\widetilde{\mu_{i,t-1}}, \quad (10)$$

where $\widetilde{\mu_{it}} = \mu_{i,t-1} - \mu_t$ and $\widetilde{\mu_{i,t-1}} = \mu_{i,t-1} - \mu_{t-1}$. The first term measures the average change that is merely due to a change in the markup, while keeping the market shares unchanged from last period (the within effect). The second and third term jointly measure the effect of reallocation. The second term represents the change that is due to an increase in market share while keeping the markup fixed. If this term is increasing, it captures the fact that firms with higher markups now have a higher market share and hence there is an increase in the weight of the high markup firms. The third term (the cross term effect) measures the joint change in markups and market share. The last two terms measure the effect of entry and exit on markups. This captures the change in the composition of firms in the market meaning that if entering firms have on average higher markups than this term will be positive. However, it must be noted that entry and exit of firms in the data include both real market entry and exit and the fact that some firms enter and exit the database.

The results from the decomposition (10) are presented in the Figure 6. The three lines each represent a hypothetical exercise where each component from (10) is separately added to the level of the initial aggregate markup in 2010. The firm-level decomposition shows that the decrease in the aggregate markup is driven for the most part by the within effect. This suggests that markups declined across the board for most firms. Net entry virtually does not contribute to the change in the weighted markup although the reallocation effect is positive, the within effect always dominates. These results show that the decline in markups in Slovakia is widespread and stems from change in markups at the firm level.

Figure 6: Change in aggregate markup - firm-level decomposition

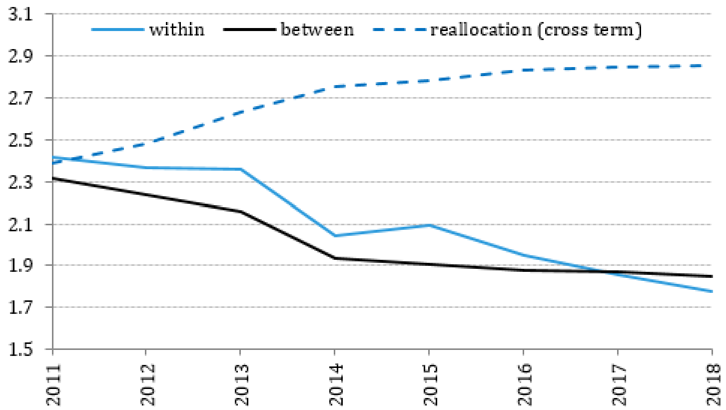


Lastly, in contrast with the firm level decomposition, I can also decompose the change in he aggregate markup at the sectoral level. This decompositon is very similar to the one in equation (10) but since the the number of sectors is fixed it only has three terms - the within effect, the between effect and the cross term effect (reallocation). The decompositon can be written as follows:

$$\triangle\mu_t = \sum_s s_{s,t-1}\triangle\mu_{st} + \sum_s \triangle s_{st}\mu_{s,t-1} + \sum_s \triangle s_{st}\triangle\mu_{st}. \tag{11}$$

Figure 7 shows the results of the sectoral decomposition from the equation (11). The three lines each again represent a hypothetical exercise where each component from (11) is separately added to the level of the initial aggregate markup in 2010. The sectoral decomposition shows, that for the most part, it is the within and between effect that drive the evolution of the aggregate markup. From the Figure 2 it is clear to see that the decline is present mainly in the service and utility sector. The within effect development is in line with the firm-level evidence from (10) but it is also the declining share of large sectors in the economy that compliments the decrease in the markup. The results from the sectoral decomposition are similar to the ones found in De Loecker et al. (2020) where the within effect also dominates but in Slovak firm level data I did not find convincing evidence to support the reallocation thesis of superstar firms.

Figure 7: Change in aggregate markup - sectoral decomposition



In sum, I showed that the aggregate value added markup decreased over the past years and the decrease came mainly from the utility and service sector. Markups tended to be higher for relatively value-added-weighted larger firms and they are also higher in larger sectors. Smaller firms (size indicated by number of employees) tend to have higher markups, but there are some large firms with higher markups that drive the evolution of aggregate markup. Markup decomposition shows that at the firm level the within effect is the main driver of aggregate markup movements and the change in markups occurs within and between sectors at the same time.

5.2 Markups and firm size

Equation (6) shows that under cost minimization, markups are negatively related to the amount and costs of variable inputs. If the wedge between price and marginal costs is large and positive, firms do not need to increase the amount of labor and intermediate inputs to scale up production and increase profits. Under monopolistic competition with heterogeneous markups, two identical firms in terms of profit margin (profits divided by sales) may have different sizes depending on market power. Under monopolistic competition with homogeneous markups and with standard Dixit-Stiglitz CES demand, firms differ in size through differences in their productivity. One such case is undistorted economy as in Hsieh & Klenow (2009). Allowing for heterogeneous markups introduces a new type of *wedge* that affects firm size as well. A firm with larger markup will employ fewer workers and use less intermediate inputs but it can have the same profit margin as a larger firm with smaller markup. Higher markups permit firms to maximize profits using smaller amount of inputs through charging higher prices. Market power thus creates substantial welfare loses.

In order to empirically investigate the relationship between markups and firm characteristics such as firm size and labor share I run rich set of fixed effects regressions. In the baseline regressions I am agnostic about the exogeneity of markups. One may argue that market structure, other competing firms and internal firm decisions (other than the choice of optimal amount of variable inputs) determine markups. Marketing strategy, quality improvements or change in consumer preferences are also more likely to influence price policy rather than the amount of labor and intermediate inputs. Also bundle pricing, taxes and consumer income influence demand therefore affect output prices. Given the large number of other potential factors influencing the price of goods and services sold, thus markup as well, some may find the exogeneity assumption amply convincing. Also it is worth mentioning that neither De Loecker et al. (2020) nor Diéz et al. (2019) discuss the exogeneity of markups with respect to firm size and profits. Diéz et al. (2019) treat the firm size (both in number of employees or market share) as an explanatory variable whereas in De Loecker et al. (2020) the markup is treated as the explanatory variable in the labor share and market power regressions. Diéz et al. (2018) discuss the endogeneity of markups with respect to firm investment rate and instrument the markup of the *i-th* firm with the median markup of the other firms in the same subsector (excluding the *i-th* firm). In Atkin et al. (2015) authors also regress markups on employment finding positive relationship between the firm size and markups. However, this positive correlation, as argued by the authors, correlates with the fact that larger firms produce higher quality products which is thus reflected in higher prices. Therefore it might not be the firm size but rather than the product quality improvements that drive the size of markups. For now I follow De Loecker et al. (2020), Diéz et al. (2019) and Atkin et al. (2015) and treat the RHS and LHS variables in regressions as they do. Treating the firm size as the explanatory variable also stems from the first order conditions.

Markup decompositions and density distributions suggest that there is a negative correlation between firm size (mainly in terms of employment) and markups. To empirically confirm this suggestive evidence I run firm size regressions similar to Diéz et al. (2019) and Atkin et al. (2015). Slovak firm level data shows that, on average, lower markups are indeed associated with larger firms. Table 2 presents the results. In all specifications the coefficients on the elasticity of firm employment w.r.t markups is negative and statistically significant. It indicates that 1 % increase in the firm employment leads to 0.26% to 0.5% decline in the markup and the relation is not linear which is indicated by the statistically significant quadratic term. What is interesting is that both labor productivity and TFP are positively related to markups, more productive firms have higher markups. For example, under monopolistic competition models with heterogeneous firms, an increase in TFP would decrease marginal costs which in turn would permit firms increase markups without increasing prices. Unfortunately, the data does not contain information on firm specific prices for goods and services sold or marginal costs. Therefore, I cannot plausibly verify whether more productive firms have lower markups as a result of decreasing marginal costs or pass their productivity premia directly to production or quality improvements with little or no change for demand for variable inputs.

Table 2: Value added markups and firm size

VARIABLES	(1) Markup	(2) Markup	(3) Markup
Employment	-0.524***	-0.512***	-0.264***
	(0.0269)	(0.0298)	(0.0227)
Employment sq.	0.0596***	0.0450***	0.0312***
	(0.00455)	(0.00439)	(0.00355)
Capital intensity		0.00184*	-0.00907***
		(0.00103)	(0.00124)
TFP		0.729***	
		(0.0127)	
Labor productivity			0.725***
			(0.0104)
Constant	0.923***	-6.021***	-6.121***
	(0.0336)	(0.158)	(0.145)
Observations	241,835	188,845	241,827
R-squared	0.734	0.908	0.891
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Adj. R-sq. within	0.0208	0.617	0.599
Adj. R-sq.	0.641	0.876	0.853
Legal form		YES	YES

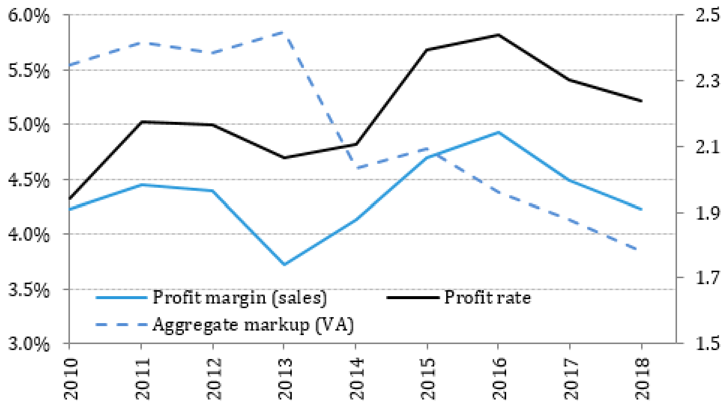
Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Note: Capital intensity measured as a ratio of capital stock to employment. TFP estimated from the corresponding production function. Labor productivity measured as a ratio of valued added to employment. All variables in logs. Standard errors clustered by NACE 3-digit sector.

5.3 Markups, profitability and market power

As rightfully mentioned in De Loecker et al. (2020) the documented rise in markups in the U.S. does not necessarily imply that firms have more market power, and therefore higher economic profits. According to the authors, increasing markups can come from a variety of reasons that are not associated with a decline in aggregate welfare. For example, a decrease in marginal costs, an increase in fixed costs or innovation, an increase in demand or in its elasticity, a change in the market structure, new product varieties, all lead to increasing markups without necessarily implying higher prices or profits. But with the absence of detailed price-level data I, similarly to the other studies, must resort to the alternative indicators of market power. Following Cooper & Ejarque (2003) who argue that in their model profitability is associated with market power, I use profit margins and profit rates as proxy measures for such developments. I also investigate whether sectoral firm sales shares are correlated with markups to provide a clearer picture on the association of markups and market power.

Figure 8: Profitability and the aggregate markup



Note: The aggregate profit margin calculated as a sales weighted average of individual firm profit margins. The aggregate profit rate uses net total assets as weights. Gross profits before taxes. The profit rate and the profit margin on the left axis. The aggregate value added markup on the right axis.

Figure 8 presents the evolution of the aggregate profitability and the aggregate markup. Both the profit margin (profits divided by sales) and the profit rate (profits divided by total net assets) roughly copy movements in the aggregate markup (mainly from 2014 onward when the data starts to cover all firms). The unweighted average (not reported) is strongly negative implying that both profit rates and margins are positive mainly for relatively large firms. Therefore as stated in the Section 5.1, small firms do have higher markups but the evolution of the aggregate markup and, in this case, (positive) profitability is in the most part driven by large firms (large both in terms of sales and assets).

I also find positive relationship between markups and profitability at the firm level. No matter whether I choose profit margin, profit rate or EBITDA margin (EBITDA divided by sales) the positive correlation of markups with different measures of profitability indicates that higher markups do imply higher market power. The elasticity of markup w.r.t. the profit margin oscillates around 0.15, i.e. 10% increase in the markup leads, on average, to 1.5% increase in the profit margin. Inclusion of the quadratic term shows that relationship is not monotonic and an increase in profit margins is slower for firms with very high markups. Control variables have signs as expected where larger and more productive firms have also higher profitability.[14]

To provide a more detailed picture on the correlation between markups and profitability I also regress markups on various cost items to find out whether movements in markups react to changes in firm costs. If this is the case, and markups rise to compensate the increase in firm costs, then implied increase in markups and profitability does not necessarily mean that firms exert market power. The results of these regressions are presented in Table 4. By construction, the relation between the personnel costs in equation (6) and markups should be negative. This is exactly what can be seen in the Column 1. The negative elasticity of labor input reaches -0.29 and -0.38, respectively, indicating that 10% increase in the personnel costs implies 2.9% to 3.8% decrease in the firm markup. In terms of intermediate consumption the coefficient is positive and significant reaching 0.07 (column 2) and 0.17 in the specification with all cost items included (column 7). But this magnitude is small and rise in costs of goods sold (excluding wages) affect markups only marginally. Other costs items such as miscellaneous costs and depreciation are positively related to markups but the coefficients are again very small and economically do not contribute much to movements in markups. In this case, 10% increase in miscellaneous costs and depreciation leads to 0.1% and 0.2% increase in the markup, respectively. This is a negligible contribution. I also regress firm markups on a change in firm net capital to investigate whether firms compensate the change in net investments by increasing their markups. I find positive relation but the coefficient is again very small (columns 6 and 7) thus ruling out the notion that markups rise in reaction to rising costs. De Loecker et al. (2020) arrive to very similar conclusion. Although in their case, the elasticity of SG&A costs w.r.t. markups is higher (0.56), nevertheless, it is still lower then unity. Other cost times such

[14]Results for the profit rate and the EBITDA margin are reported in the Appendix. The elasticity w.r.t the profit rate oscillates around 0.2 and 0.14 w.r.t. the EBITDA margin.

as advertising or R&D expenditure have elasticities very close to zero. These findings strengthen the fact that the interplay between markups and profitability signals that firms exercise market power. Markups in Slovakia evolve in excess of marginal costs as well.

Table 3: Value added markups and profit margin

VARIABLES	(1) Profit margin	(2) Profit margin	(3) Profit margin
Markup	0.164***	0.137***	0.139***
	(0.00805)	(0.00785)	(0.00705)
Markup sq.	-0.0142***	-0.00975**	-0.0125***
	(0.00415)	(0.00443)	(0.00381)
Capital intensity		-0.00361***	-0.00468***
		(0.000401)	(0.000358)
TFP		0.0435***	
		(0.00358)	
Employment		0.0350***	0.0434***
		(0.00878)	(0.00751)
Employment sq.		-0.00313**	-0.00358***
		(0.00149)	(0.00121)
Labor productivity			0.0339***
			(0.00357)
Observations	361,128	187,967	240,313
R-squared	0.552	0.643	0.626
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Adj. R-sq. within	0.189	0.210	0.209
Adj. R-sq.	0.442	0.517	0.496
Legal form		YES	YES

Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: Capital intensity measured as a ratio of capital stock to employment. TFP estimated from the corresponding production function. Labor productivity measured as a ratio of valued added to employment. All variables in logs. Standard errors clustered by NACE 3-digit sector.

Table 4: Value added markups and costs development

VARIABLES	(1) Markup	(2) Markup	(3) Markup	(4) Markup	(5) Markup	(6) Markup	(7) Markup
Personnel costs	-0.290***						-0.385***
	(0.00908)						(0.00916)
Inter. consumption		0.0732***					0.174***
		(0.00933)					(0.0137)
Variable costs			0.0541***				
			(0.0122)				
Depreciation				0.024***			0.025***
				(0.00130)			(0.00158)
Miscellaneous					0.0073***		0.0073***
					(0.000817)		(0.00104)
Net investment						0.003***	0.0031***
						(0.000517)	(0.000684)
Constant	3.261***	-0.734***	-0.521***	-0.0269**	0.147***	0.170***	1.815***
	(0.0968)	(0.116)	(0.154)	(0.0115)	(0.0111)	(0.00891)	(0.235)
Observations	241,835	241,835	363,782	363,465	330,706	258,328	187,302
R-squared	0.749	0.731	0.680	0.683	0.690	0.721	0.789
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Adj. R-sq. within	0.0767	0.0104	0.00622	0.0142	0.00442	0.00385	0.116
Adj. R-sq.	0.662	0.638	0.602	0.605	0.609	0.648	0.715

Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: All variables in logs. Net investment calculated as log difference in net capital stock. Standard errors clustered by NACE 3-digit sector.

To complete this section, I investigate whether a firm's share of value added in its respective sector correlates with its markup. Under standard oligopoly models a firm's output share (in this case value added share) is a sufficient statistic to calculate its markup. In these models higher output shares not only indicate higher markups but also stronger market power. I follow Diéz et al. (2019) and regress firm markups on their sectoral value added shares. Results are reported in Table 5. I do this separately for 3-digit and 4-digit sectors, respectively. Using only market shares and not controlling for additional regressors I find a positive non-linear relationship meaning that firms with higher market shares also have higher markups (Column 1). This result is an exact opposite compared to Diéz et al. (2019). Adding more control variables drastically lowers the coefficient on market share but the relationship still holds (Column 2). The same pattern holds when regressing markups on market shares at 4-digit industry level.[15] Only when taking logs of the market share the relationship between markups and relative firm output size becomes insignificant but after the inclusion of control variables the relationship recuperates its significance. The slight inconsistency of statistical significance of market shares at more granular level is somehow unexpected. All in all, there is some empirical positive relation between market power and markups but this relation depends very much on model specification. Thus I conclude that other firm characteristics such as firm size (in terms of employment) are statistically better determinants of firm markups.

[15] Reported in the Appendix.

Table 5: Value added sectoral shares and markups - NACE 3-digit level

VARIABLES	(1) NACE 3-digit	(2) NACE 3-digit	(3) NACE 3-digit	(4) NACE 3-digit
Market share	11.81***	2.973***		
	(1.333)	(0.715)		
Market share sq.	-14.62***	-3.853***		
	(3.159)	(1.136)		
Employment		-0.495***		-0.687***
		(0.0299)		(0.0304)
Employment sq.		0.0402***		0.0487***
		(0.00467)		(0.00450)
Capital intensity		0.00184*		0.000435
		(0.00103)		(0.00101)
TFP		0.726***		0.542***
		(0.0128)		(0.0184)
log(Market share)			0.0520	0.158***
			(0.0409)	(0.0307)
log(Market share) sq.			-0.0247***	-0.00271
			(0.00240)	(0.00221)
Observations	241,835	188,845	241,835	188,845
R-squared	0.732	0.908	0.826	0.912
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Adj. R-sq. within	0.0114	0.618	0.358	0.633
Adj. R-sq.	0.638	0.876	0.765	0.881
Legal form		YES		YES

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Note: Standard errors clustered by NACE 3-digit sector.

6 Robustness checks

So far in the paper I have used value added and two-factor production function specification to calculate markups and investigate the relation between markups, firm size and profitability. In this section I turn to alternative calculation and use firm gross output (sales) and add intermediate consumption (material, energy and services) to variable inputs to re-estimate the FOCs, markups and their relation to various firm characteristics. In addition, I also turn my attention to the relation between labor share and markups.

6.1 Production function approach - gross output

One can plausibly argue that using value added to calculate markups does not measure firm's market power at the product market but rather constitutes a measure of monopsonistic power at the input (labor) market. Since the only variable input in two-factor production function specification is labor, calculated markups measure only a wedge between a firm's price and marginal product of labor. Firm price setting policy may depend also on the amount and price of purchased intermediate inputs and therefore it should be incorporated into the cost minimization problem. Using the same optimization problem as in (3), but introducing a bundle of variable inputs V_{it}, the problem can be analogically written as:

$$\Lambda(K_{it}, V_{it}, \lambda_{it}) = q_{it}V_{it} + r_{it}K_{i,t-1} - \lambda_{it}(F(\cdot) - \overline{Y_{it}}), \tag{12}$$

where q_{it} and r_{it} denote input factor prices, V_{it} is the bundle of variable inputs (sum of personnel costs and intermediate consumption). Then the minimization problem w.r.t. the variable input yields the markup such that:

$$\mu_{it}^V = \theta_{it}^V \frac{P_{it}Y_{it}}{q_{it}V_{it}}, \tag{13}$$

where θ_{it}^V stands for the output elasticity of the bundle of variable inputs. Another way of properly exploiting the nature of three-factor production function is to include labor and materials separately. Using the number of employees and intermediate consumption as inputs and sales as output, the problem can be written as:

$$Y_{it} = F_{it}(A_{it}, K_{i,t-1}, L_{it}, M_{it}), \tag{14}$$

where K_{it}, L_{it}, M_{it} denote capital stock, labor and intermediate inputs, respectively. Variable inputs L_{it}, M_{it} adjust perfectly while capital stock K_{it} faces adjustment frictions. In terms of cost minimization I consider the Lagrangian objective function:

$$\Lambda(K_{it}, L_{it}, M_{it}, \lambda_{it}) = w_{it}L_{it} + r_{it}K_{i,t-1} + m_{it}M_{it} - \lambda_{it}(F(\cdot) - \overline{Y_{it}}), \tag{15}$$

where w_{it}, r_{it}, m_{it} denote input factor prices. I assume that firms are price takers on input factor market. The first order conditions with respect to the two variable inputs are:

$$FOC_{L_{it}} := w_{it} - \lambda_{it}\frac{\partial(F(\cdot))}{\partial L_{it}} = 0, \tag{16}$$

$$FOC_{M_{it}} := m_{it} - \lambda_{it}\frac{\partial(F(\cdot))}{\partial M_{it}} = 0. \tag{17}$$

Multiplying all terms in equation (16) by $\frac{L_{it}}{Y_{it}}$ and all terms in equation (17) by $\frac{M_{it}}{Y_{it}}$ and rearranging terms yields an expression for the output elasticity of variable inputs:

$$\theta_{it}^L \equiv \frac{\partial(F(\cdot))}{\partial L_{it}}\frac{L_{it}}{Y_{it}} = \frac{1}{\lambda_{it}}\frac{w_{it}L_{it}}{Y_{it}}, \tag{18}$$

$$\theta_{it}^M \equiv \frac{\partial(F(\cdot))}{\partial M_{it}}\frac{M_{it}}{Y_{it}} = \frac{1}{\lambda_{it}}\frac{m_{it}M_{it}}{Y_{it}}. \tag{19}$$

Substituting marginal cost for the markup to price ratio, I again obtain a simple expression for the firm markup:

$$\mu_{it}^L = \theta_{it}^L \frac{P_{it}Y_{it}}{w_{it}L_{it}}, \tag{20}$$

$$\mu_{it}^M = \theta_{it}^M \frac{P_{it}Y_{it}}{m_{it}M_{it}}. \tag{21}$$

Since under this specification I have two markups, one for each variable input, I sum the output elasticities and expenditures on variable inputs such that it is possible to derive one markup encompassing both L_{it} and M_{it}:

$$\mu_{it} = (\theta_{it}^M + \theta_{it}^L)\frac{P_{it}Y_{it}}{m_{it}M_{it} + w_{it}L_{it}}. \tag{22}$$

In order to empirically derive firm markups, similarly as in the Subsection 3.2, one would need to estimate the corresponding output elasticities. Contrary to the value added specification and Levinsohn-Petrin (2003) approach used earlier in the paper, I now use the Olley & Pakes (1996) method to estimate the production function using sales instead of value added. Since LP approach uses intermediate inputs as the proxy variable which under the gross output specification constitute frictionless variable input, the OP method uses investment as proxy instead and thus is more suitable for this type of estimation. Therefore the production function can be written as:

$$(P_{sit}Y_{sit}) = \theta_3 Capital_{si,t-1} + \theta_4 Inputs_{sit} + \tau_{st} + \omega_{sit} + \epsilon_{sit} \tag{23}$$

or by replacing the input bundle V_{it} with number of employees and intermediate consumption, the production function can be written as:

$$(P_{sit}Y_{sit}) = \theta_5 Capital_{si,t-1} + \theta_6 Labor_{sit} + \theta_7 InterCons_{sit} + \tau_{st} + \omega_{sit} + \epsilon_{sit} \tag{24}$$

where $P_{sit}Y_{sit}$ represents log of firm sales, $Capital_{si,t-1}$ stands for log of sum of net fixed and intangible assets from the previous year and $Inputs_{sit}$ stands for log of variable inputs (sum of personnel costs and intermediate consumption). In the equation (24) $Labor_{sit}$ stands for log of number of employees and $InterCons_{sit}$ for log of intermediate consumption. Time dummies, productivity and the error term have the same representation as in the equation (7). Subscripts s, i, t stand for sector, firm and year, respectively. Firm investment, the proxy variable used in the OP estimation method is calculated as follows:

$$I_{it} = K_{it} - K_{i,t-1} + \delta K_{it}, \tag{25}$$

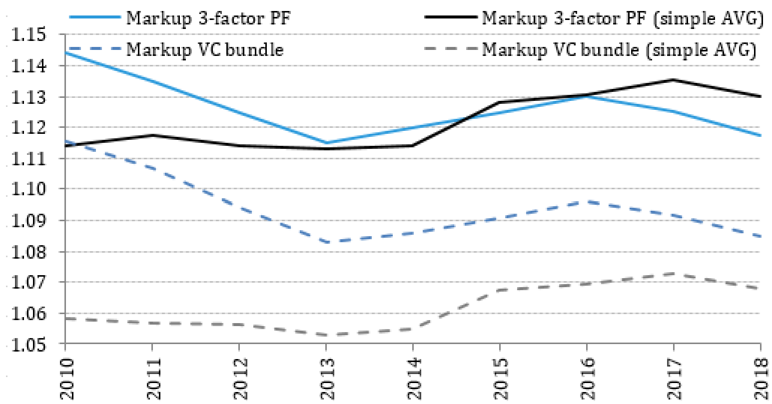
where I_{it} represents investment of firm i in year t and δK_{it} is capital depreciation. Capital stock and its depreciation come directly from the data.

6.2 Evolution of the aggregate markup - gross output

This section reports on the evolution and distribution of markups estimated from the standard approach using sales as a measure of firm output. I will always report and compare markups from both specifications, that is from (13) and (22). Compared to Figure 1 there is a clear level shift in the size of the aggregate markup. Markups estimated this way are on average 50 percent smaller and range from 1.08 to 1.15, depending on the specification. Although they also experience declining tendency over the period in question, they are largely stable and their decline is marginal. Both sales markups declined by less than 1 percent between 2012 to 2018 (Figure 9, blue lines). For comparison, the aggregate value added markup declined by 25% over the same period.

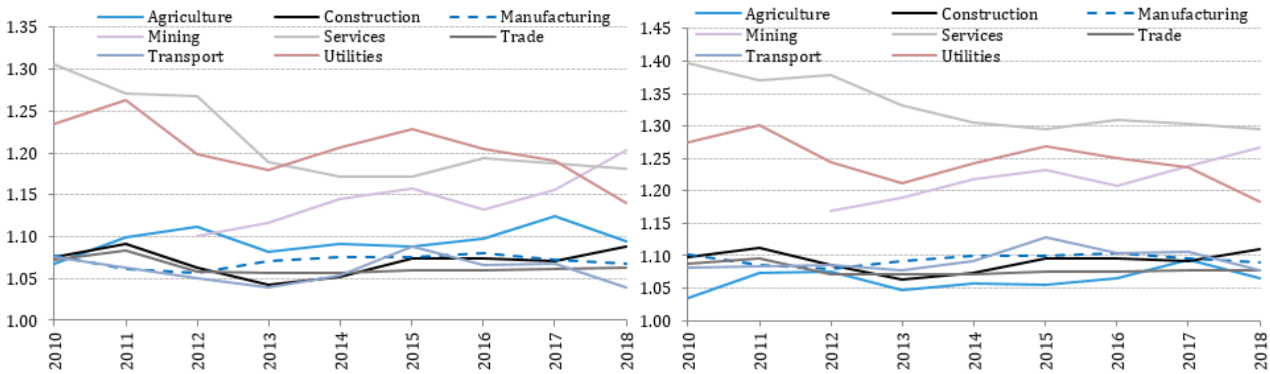
Looking at the covariance between relative firm output size and markups, one can see that the results differ depending on the markup specification. In Figure 9, similarly as in the baseline value added case, the markup calculated using the bundle of variable inputs from (13) displays the same properties. The aggregate weighted markup (blue dashed line) is always above the average markup (grey dashed line) showing that relatively larger firms (in terms of sales) have higher markups. The story changes when using the second specification in (22) where markups are calculated from the 3-factor production function. Here, starting from 2015, the covariance between markups and firm sales share becomes negative implying that on average firms with smaller sales have higher markups (black solid line is above the blue solid line).

Figure 9: Aggregate markup - sales



Note: The weighted average markups equal the sales-share-weighted average of firm level markups for each PF specification. Simple average is calculated as an arithmetic mean of individual firm markups. Solid lines represent markups calculated according to equation (22). Dashed lines use markups from equation (13).

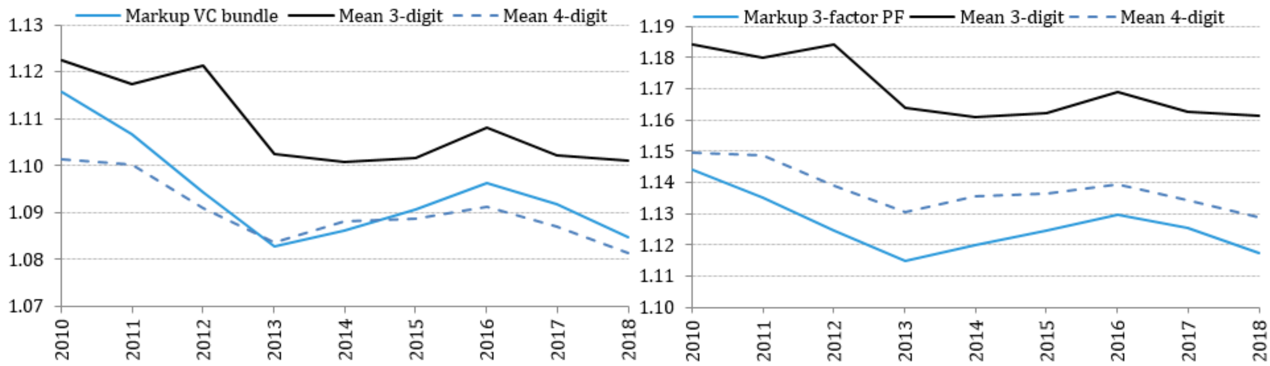
Figure 10: Sectoral markups - sales



Note: Sectoral markup equals the sales-share-weighted average of firm level markups. Weights are calculated as a ratio of firm sales in total sector sales. Markups according to equation (13) - left panel. Markups from equation (22) - right panel.

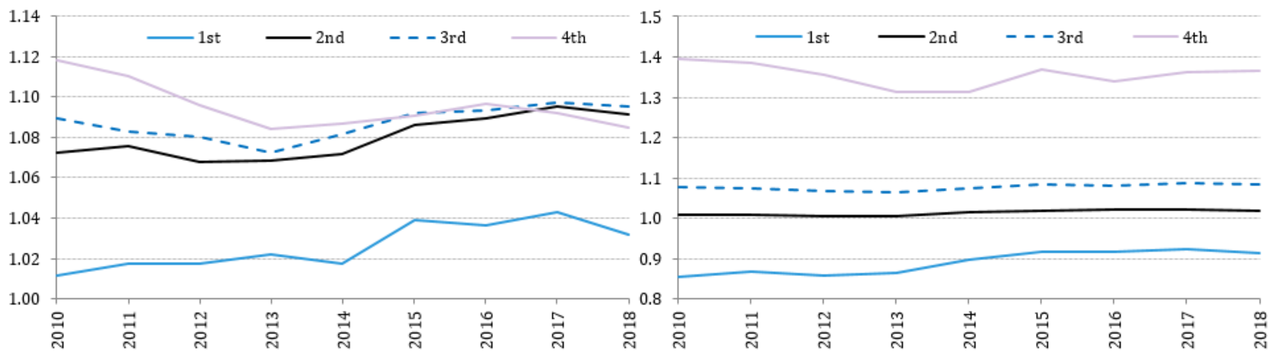
From the sectoral perspective the evolution of markups largely stays the same, where again, highest markups can be found in services and utilities (Figure 10). The only exception is mining sector, which under the two alternative PF specifications experiences high and increasing industry markup. It is no surprise that mining, utilities and services have relatively high markups. In case of the mining sector, mining probably owes its high markups mainly to concentration, geographic factors and regulation. Coal reserves are concentrated in specific areas thus limiting competition and domestic mining industry is heavily subsidized through price regulation. For utilities, although the gas and electricity market is fully liberalized, the sector as a whole experiences relatively high level of markups as well, partly thanks to the network nature of the industry. The story for services may not be so straight, but again, high markup firms in ICT, casinos, telecommunication sectors and spatial non-tradability of services together with the prevalence of smaller of firms (in terms of number of employees) might contribute to relatively high markups in this sector.

Figure 11: Aggregate weighted vs. mean sectoral markups - sales



Note: Mean sectoral markups calculated as a simple unweighted average of sectoral markups. Markups according to equation (13) - left panel. Markups from equation (22) - right panel.

Figure 12: Evolution of markups by quartiles - equation (13)

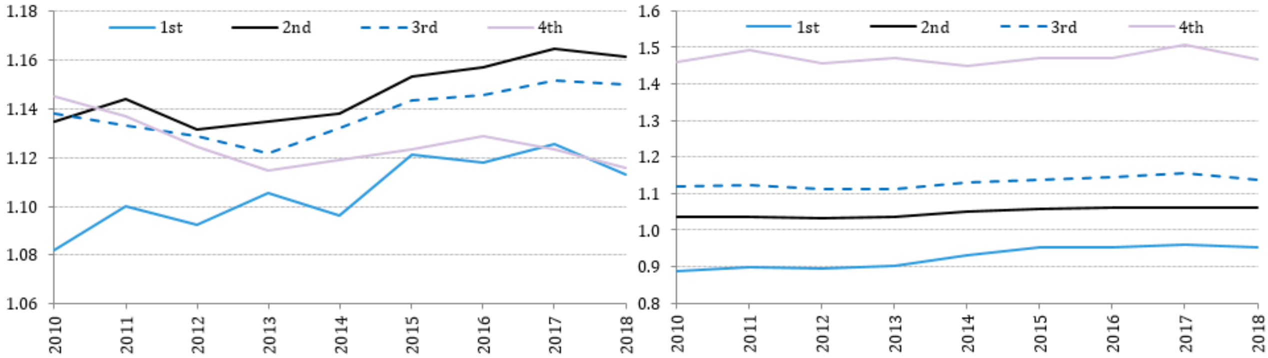


Note: Markups calculated as a weighted average of firm level markups in each quartile. Left panel (quartiles by sales), right panel (quartiles by markup). Markups according to equation (13).

Using the decomposition from (9) and seeing the evolution of markups in Figures 11, 12 and 13 show how more detailed analysis of markups may change the results depending on the production function specification. In the baseline value added case, the weighted aggregate markup was always larger than mean markups (firm as well as sectoral) implying that firms with greater value added have also higher markups. Sales markups calculated from (13) and (22) do not display such properties (Figure 11). Looking at the arithmetic mean of markups at NACE 3-digit level, it is clear to see that in both alternative specifications smaller sectors have higher markups (black line is above the blue line) which is contrary to the baseline results presented in Figure 3 from the previous section. That is, both Diéz et al. (2019) and De Loecker et al. (2020) are *correct* in a sense that their claims about the relation between markups and relative output sizes seem to depend on the choice of variables and production function specification.

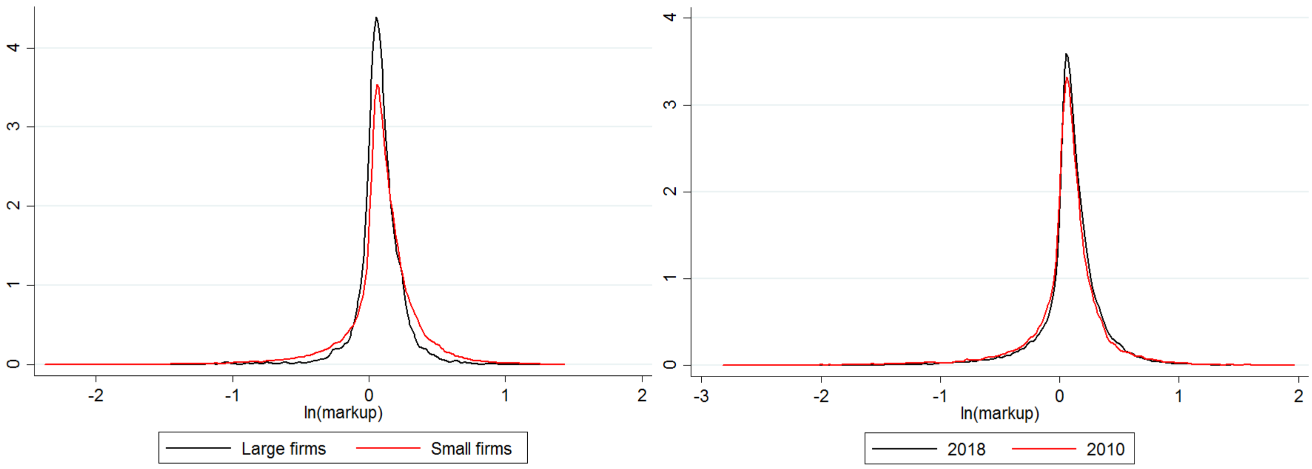
The sales quartile distribution also displays differing properties. While in the baseline case the relatively largest firms (in terms of value added) experienced significant decline in markups starting from 2014, sales markups are on average stable over this period (left panels, Figures 12 and 13). Also it is not the firms from the 4th quartile that have the highest markups but the firms around the median sales from 2nd and 3rd sales quartile see relatively higher and increasing markups.

Figure 13: Evolution of markups by quartiles - equation (22)



Note: Markups calculated as a weighted average of firm level markups in each quartile. Left panel (quartiles by sales), right panel (quartiles by markup). Markups according to equation (22).

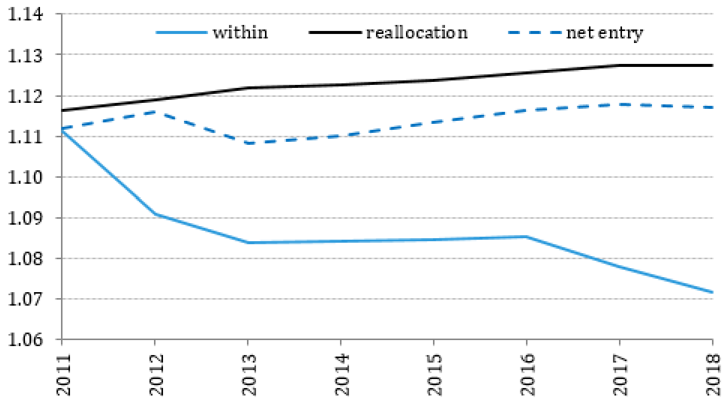
Figure 14: Kernel density distribution of firm markups - equation (22)



Note: Density distribution looks very similar for both alternative markup specifications, thus for the sake of simplicity I report only one. Left panel = year 2018.

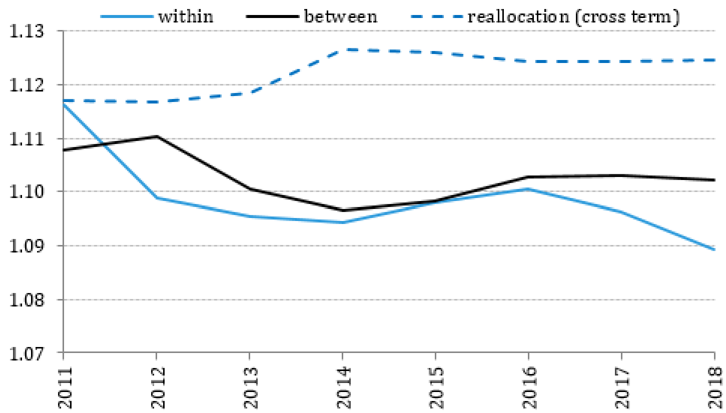
Density distributions and markup change decompositions are in line with the value added baseline case. Smaller firms (less than 50 employees) have markups more dispersed and outliers present on both sides of the distribution meanwhile the overall distribution changes very slightly between 2010 and 2018. Identically as in the baseline value added case, the change in the aggregate markup is driven mainly by the within sector component (Figures 15 and 16).

Figure 15: Change in aggregate markup, firm-level decomposition - equation (13)



Note: Change decomposition is very similar for both alternative markup specifications, thus for the sake of simplicity I report only one.

Figure 16: Change in aggregate markup, sectoral decomposition - equation (13)



Note: Change decomposition is very similar for both alternative markup specifications, thus for the sake of simplicity I report only one.

In sum, robustness checks in most cases verify the results from the value added specification. Aggregate markup declined, markups are high in utilities and services and their distribution does not change very much over time. It seems again that smaller firms (in terms of number of employees) have higher markups and the decline in the aggregate markup is indeed driven by the within firm and sectoral component. On the other hand, some more detailed features of the markup distribution differ and it seems like the choice of inputs and production function specification may affect the additional results to some extent.

6.3 Markups, firm size and labor share - gross output

As for further robustness checks I will re-estimate the regressions from Section 5 using sales markups from definitions (13) and (22). I will also investigate whether markups are negatively related to labor shares as in De Loecker et al. (2020). Table 6 provides results on the relation between firm size and markups. I again find inverse relationship but the magnitude of the effect is significantly lower compared to the value added case. In the baseline results I have found that 1% increase in the firm employment leads to 0.26% to 0.5% decline in the markup whereas in the case with sales markups the elasticity oscillates around 0 with statistically significant negative elasticity around -0.03. Quantitatively this suggests that 1% increase in firm employment leads to only 0.03% decline in the firm markup which is an economically negligible effect. Signs of the coefficients on control variables are in line with the baseline results where again, given all other variables constant, more productive firms have on average higher markups.

Table 6: Sales markups and firm size

VARIABLES	(1) VC bundle	(2) VC bundle	(3) VC bundle	(4) 3-factor	(5) 3-factor	(6) 3-factor
Employment	-0.0274**	-0.00115	-0.0253***	-0.0282**	-0.00879	-0.0257***
	(0.0108)	(0.00523)	(0.00614)	(0.0110)	(0.00835)	(0.00625)
Employment sq.	0.00660***	-0.000810	0.00378***	0.00705***	0.00402**	0.00417***
	(0.00171)	(0.00107)	(0.000931)	(0.00177)	(0.00163)	(0.000967)
Capital intensity		0.00103***	-0.000779*		0.00273***	-0.000786*
		(0.000236)	(0.000405)		(0.000394)	(0.000407)
TFP		0.792***			0.251***	
		(0.0412)			(0.0201)	
Labor productivity			0.121***			0.121***
			(0.00628)			(0.00628)
Constant	0.0567***	-0.0555***	-0.961***	0.107***	-0.637***	-0.908***
	(0.0139)	(0.00718)	(0.0674)	(0.0140)	(0.0653)	(0.0688)
Observations	268,249	214,962	244,780	268,249	214,960	244,780
R-squared	0.688	0.936	0.780	0.721	0.809	0.815
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Adj. R-sq. within	0.0005	0.774	0.302	0.0006	0.236	0.301
Adj. R-sq.	0.581	0.914	0.703	0.626	0.743	0.751
Legal form			YES		YES	YES

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Note: Capital intensity measured as a ratio of capital stock to employment. TFP estimated from the corresponding production function. Labor productivity measured as a ratio of valued added to employment. All variables in logs. Standard errors clustered by NACE 3-digit sector.

In their paper, De Loecker et al. (2020) discus some macroeconomic implications of rising markups including the evolution of labor shares (aggregate labor compensations as a share of GDP). It is now a well known fact that in the last three decades we have seen a steady decline in labor shares across the developed world.[16] Economic researchers are therefore trying to provide an explanation for this phenomenon. There are many candidates but not one of them provide a single comprehensive answer. For example Karabarbounis & Neiman (2013) state that the decrease in relative price of investment leads to the substitution of capital for labor thus decreasing labor's share in output. This proposition relies on the fact that the elasticity of substitution between capital and labor must be higher than 1. Karabarbounis & Neiman (2013) do find that the elasticity is higher than 1 but many other studies find opposite results.[17]

Some other studies such as Koh et al. (2014) stress the fact that growing importance of intangible capital pushed firms to invest more thus spending less on labor. De Loecker et al. (2020) dismiss this explanation since under perfect competition rise in intangible investment should not lead to rise in market power (profit rate). From the institutional point view the usual suspect in the literature for the decline of labor share is declining union membership. For example Fichtenbaum (2011) finds that the decline in unionization in the U.S. from 1997 to 2006 explains about 29 percent of the decline in labor's share of income. But on the other hand, Elsby et al. (2013) find little support for capital-labor substitution, nor for the role of a decline in unionization. They, however, do find some support for offshoring labor-intensive work as a potential explanation [18]

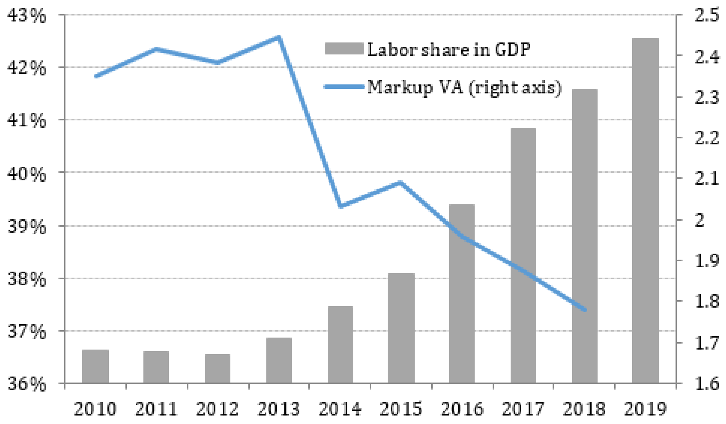
De Loecker et al. (2020) build on first order conditions from the cost minimization problem estimation

[16] See for example Autor et al. (2020).
[17] See De Loecker et al. (2020).
[18] See De Loecker et al. (2020).

and try to explain the decrease in the labor share by the rise in markups and market power. They relate their firm level estimates with macro developments and show that due to reallocation of economic activity toward high-markup firms, the negative effect of markups on the labor share in aggregate is predominantly driven by few large firms with high markups and low firm labor shares.

As for Slovakia, recent years have seen a strong labor market dynamism with wages and employment rising steadily since 2014. Between 2014 and 2019 GDP grew around 3% on average, employment around 2% and nominal wages by 5% with cumulative growth of 32%. There were no talks or any major developments regarding declining union membership. Intangible investment (proxy for R&D investment) is low for international standards and is not crowding-out resources for labor compensation. Through the lens of international trade literature, Slovakia is more likely to be a destination country for off-shoring rather than being a country that off-shores. These developments together with decreasing markups and strong labor market in the recent years should indicate an increase in the labor share, and in fact, macroeconomic data supports these developments. Aggregate labor share rose from 37% in 2013 to almost 43% in 2019 meanwhile the aggregate markup declined (Figure 17).[19]

Figure 17: Aggregate labor share and markup



Note: Source Eurostat.

Figure 17 reports only a suggestive evidence of the negative relation between markups and labor share. Therefore I turn to firm level analysis and empirically estimate regressions with labor share as the dependent variable to verify the conclusions of De Loecker et al. (2020). I use the share of personnel costs in sales as well as in value added. Results are presented in Tables 7 and 8. The results indeed document the inverse relationship between firm markups and labor's share of income. When looking at the share of personnel costs in sales (Table 7), the estimated elasticity of labor share w.r.t. the firm markup moves around 1, that is, 1% increase in the firm markup leads to 1% decrease in the firm labor share on average. The elasticity of labor's share in value added w.r.t. the firm markup is also statistically significant and ranges from -1.2 to -2.8, depending on the specification. It is interesting that TFP and labor productivity are negatively related to the labor share (Table 8). This additional result is consistent with past research which points to the fact that more productive firms in Slovakia have lower labor shares.[20] It is also consistent with the *superstar* hypothesis of Autor et al. (2020). Combining these results with the change decompositions from earlier sections it is clear to see that the rise in the aggregate labor share must be a within firm/sectoral phenomenon since the decrease in the aggregate markup was widespread and happened across the entire economy.

[19]It is more suitable to report the markup estimated from the value added specification since GDP is a sum value added.
[20]Vyskrabka (2018)

Table 7: Sales markups and labor share

VARIABLES	(1) VC bundle	(2) VC bundle	(3) VC bundle	(4) 3-factor	(5) 3-factor	(6) 3-factor
Markup	-1.071***	-0.876***	-1.123***	-1.084***	-1.058***	-1.175***
	(0.0186)	(0.0522)	(0.0498)	(0.0174)	(0.0251)	(0.0566)
Markup sq.	0.147***	0.206***	0.523***	0.148***	0.201***	0.477***
	(0.0267)	(0.0348)	(0.0640)	(0.0279)	(0.0363)	(0.0643)
Capital intensity		-0.0112***	-0.0116***		-0.0114***	-0.0117***
		(0.00136)	(0.00132)		(0.00133)	(0.00131)
TFP		-0.132***			0.0356**	
		(0.0463)			(0.0154)	
Employment		0.714***	0.793***		0.718***	0.793***
		(0.0279)	(0.0280)		(0.0279)	(0.0280)
Employment sq.		-0.0619***	-0.0731***		-0.0622***	-0.0729***
		(0.00472)	(0.00477)		(0.00473)	(0.00477)
Labor productivity			-0.00875			-0.00911
			(0.0152)			(0.0153)
Constant	-1.901***	-2.961***	-2.966***	-1.848***	-3.025***	-2.901***
	(0.00867)	(0.125)	(0.175)	(0.00893)	(0.131)	(0.172)
Observations	404,121	214,423	244,016	404,121	214,423	244,016
R-squared	0.856	0.915	0.901	0.855	0.915	0.901
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Adj. R-sq. within	0.180	0.239	0.209	0.179	0.238	0.208
Adj. R-sq.	0.821	0.886	0.866	0.820	0.885	0.866
Legal form		YES	YES		YES	YES

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Note: Capital intensity measured as a ratio of capital stock to employment. TFP estimated from the corresponding production function. Labor productivity measured as a ratio of valued added to employment. All variables in logs. Standard errors clustered by NACE 3-digit sector.

Table 8: Sales markups and labor share in value added

VARIABLES	(1) VC bundle	(2) VC bundle	(3) VC bundle	(4) 3-factor	(5) 3-factor	(6) 3-factor
Markup	-2.775***	-2.616***	-1.193***	-2.796***	-2.811***	-1.192***
	(0.117)	(0.137)	(0.0669)	(0.114)	(0.144)	(0.0717)
Markup sq.	0.178*	0.324**	0.0147	0.240**	0.399***	0.0457
	(0.0952)	(0.140)	(0.0512)	(0.0991)	(0.147)	(0.0553)
Capital intensity		-0.00831***	0.0103***		-0.00827***	0.0103***
		(0.00137)	(0.000987)		(0.00133)	(0.000995)
TFP		-0.205***			-0.0565***	
		(0.0199)			(0.0115)	
Employment		0.324***	0.252***		0.326***	0.253***
		(0.0228)	(0.0268)		(0.0228)	(0.0268)
Employment sq.		-0.0352***	-0.0296***		-0.0355***	-0.0292***
		(0.00363)	(0.00403)		(0.00362)	(0.00406)
Labor productivity			-0.644***			-0.645***
			(0.0161)			(0.0164)
Constant	-0.220***	-0.460*	5.209***	-0.0810***	-0.179	5.277***
	(0.0107)	(0.249)	(0.213)	(0.0143)	(0.259)	(0.215)
Observations	367,537	198,899	243,956	367,537	198,899	243,956
R-squared	0.777	0.831	0.909	0.776	0.830	0.909
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Adj. R-sq. within	0.415	0.436	0.718	0.413	0.435	0.717
Adj. R-sq.	0.722	0.771	0.877	0.721	0.771	0.877
Legal form		YES	YES		YES	YES

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Note: Capital intensity measured as a ratio of capital stock to employment. TFP estimated from the corresponding production function. Labor productivity measured as a ratio of valued added to employment. All variables in logs. Standard errors clustered by NACE 3-digit sector.

6.4 Markups, profitability and market power - gross output

In this brief section I verify whether the alternative markup specifications also support the conclusion regarding the positive relation between markups and profitability. As usual, I will re-estimate the regressions from Section 5.3 using sales markups from definitions (13) and (22). I start with profitability with the results reported in Table 9. Following results largely support the previous findings. Sales markups are strongly related to all measures of profitability but their effect on profit margin is five times stronger compared to the value added specification. The elasticity of profit margin w.r.t. sales markups reaches 0.8 whereas in the value added case the elasticity is around 0.15.[21] In addition, control variables behave as expected.

[21]The results from profit rate as well as for EBITDA margin are reported in the Appendix.

Table 9: Sales markups and profit margin

VARIABLES	(1) VC bundle	(2) VC bundle	(3) VC bundle	(4) 3-factor	(5) 3-factor	(6) 3-factor
Markup	0.779***	0.757***	0.761***	0.780***	0.819***	0.789***
	(0.0484)	(0.0462)	(0.0439)	(0.0512)	(0.0594)	(0.0524)
Markup sq.	-0.0413	-0.0798	-0.371***	-0.0409	-0.0728	-0.320***
	(0.0321)	(0.113)	(0.0576)	(0.0334)	(0.111)	(0.0583)
Capital intensity		-0.00427***	-0.00507***		-0.00426***	-0.00503***
		(0.000664)	(0.000439)		(0.000658)	(0.000428)
TFP		0.0661***			0.00730**	
		(0.00756)			(0.00352)	
Employment		0.0248**	0.0259***		0.0243**	0.0258***
		(0.00953)	(0.00632)		(0.00959)	(0.00625)
Employment sq.		-0.00234	-0.00227**		-0.00224	-0.00240**
		(0.00160)	(0.00110)		(0.00161)	(0.00110)
Labor productivity			0.0341***			0.0345***
			(0.00384)			(0.00400)
Constant	-0.0608***	-0.0987**	-0.366***	-0.0996***	-0.155***	-0.412***
	(0.00399)	(0.0447)	(0.0494)	(0.00577)	(0.0479)	(0.0504)
Observations	401,974	211,483	243,201	401,974	211,483	243,201
R-squared	0.569	0.653	0.667	0.568	0.652	0.665
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Adj. R-sq. within	0.210	0.230	0.309	0.209	0.229	0.305
Adj. R-sq.	0.463	0.532	0.551	0.463	0.531	0.548
Legal form		YES	YES		YES	YES

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

Note: Capital intensity measured as a ratio of capital stock to employment. TFP estimated from the corresponding production function. Labor productivity measured as a ratio of valued added to employment. All variables in logs. Standard errors clustered by NACE 3-digit sector.

Another interesting finding is that sales markups react to changes in costs only very weakly. The results are presented in Table 10.[22] The elasticity of various cost times is indeed positive and statistically significant but the magnitude of the effect is virtually zero. High markups do not compensate for the rise in costs. Compared to the value added specification, on one hand, sales markup are strongly related to profitability, but on the other, they do not reflect movements in costs. For the most part, markups evolve in excess of marginal costs and are strongly correlated with profitability. These findings suggest that movements in markups indeed imply changes in market power. In the Appendix I report regressions of sales markups on firm sales shares in their respective NACE 3-digit and 4-digit sectors. I again find inconsistent results and statistically unconvincing findings. In specifications with control variables market share loses significance and in logarithmic specifications the market share variable changes sign.

[22]Regression results using markup from definition (22) reported in the Appendix. The results remain robust and strengthen the fact that sales markups do not react to changes in costs.

Table 10: Sales markups and costs developments

VARIABLES	(1) VC bundle	(2) VC bundle	(3) VC bundle	(4) VC bundle	(5) VC bundle	(6) VC bundle	(7) VC bundle
Personnel costs	-0.00633***						-0.0129***
	(0.00133)						(0.00158)
Inter. consumption		0.00876***					0.00254
		(0.00306)					(0.00384)
Variable costs			0.00533				
			(0.00397)				
Depreciation				0.00744***			0.00732***
				(0.000415)			(0.000547)
Miscellaneous					0.00219***		0.00110***
					(0.000229)		(0.000337)
Net investment						0.00147***	0.00124***
						(0.000167)	(0.000215)
Constant	0.108***	-0.0674*	-0.0268	-0.0188***	0.0361***	0.0426***	0.0964*
	(0.0137)	(0.0377)	(0.0500)	(0.00398)	(0.00366)	(0.00241)	(0.0568)
Observations	412,658	412,658	412,658	412,270	372,226	298,832	213,248
R-squared	0.628	0.628	0.628	0.631	0.638	0.667	0.720
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Adj. R-sq. within	0.00261	0.00249	0.00185	0.00908	0.00222	0.00187	0.0107
Adj. R-sq.	0.537	0.537	0.537	0.540	0.544	0.580	0.623
Legal form							YES

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

Note: All variables in logs. Standard errors clustered by NACE 3-digit sector.

7 Conclusion

In this paper I have empirically evaluated the evolution of markups in Slovakia using the production function approach recently popularized by De Loecker et al. (2020). I have found empirical regularities which are consistent with the contemporary markup literature. I showed that the aggregate markup in Slovakia decreased over the past years and the decrease came mainly from the utility and service sector. Markups tend to be higher for relatively larger firms and they are also higher in larger sectors (in terms of value added). Smaller firms (size indicated by number of employees) tend to have higher markups, but there are some large firms with higher markups that drive the evolution of aggregate markup. In Autor et al. (2020)) the authors find that larger and more productive firms have higher markups. In Slovak data it is smaller but more productive firms that display such property. Markup decompositions show that at the firm level the within effect is the main driver of aggregate markup movements and the change in markups occurs within and between sectors at the same time. The data further implies that markups are indeed a suitable measure for market power since the rise in markups is in excess of costs and markups are highly correlated with profitability. Robustness checks largely validate the baseline results but in some areas results might depend on the choice of inputs and production function specification.

There are many other areas that are especially interesting for the market power research but were beyond the scope of this study. For example, further research could analyse cross-country differences in aggregate markups and labor shares at the macro level and shed more on light on true macroeconomic impact of rising/decreasing market power. However, this approach requires rich and detailed firm level data which must be internationally comparable in order to calculate consistent markups across countries. Another fruitful area might be to evaluate the effect of international trade on firm markups and set up a model of a small open economy to carry out various counterfactual policy relevant analyses. Last but no least, the exogeneity of markups in relation to firm optimizing behaviour is not properly studied therefore rewards thorough attention.

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Appendices

Table 11: Value added markups and profit rate

VARIABLES	(1) Profit rate	(2) Profit rate	(3) Profit rate
Markup	0.222***	0.197***	0.196***
	(0.0105)	(0.0114)	(0.0121)
Markup sq.	-0.0166**	-0.0118	-0.0159**
	(0.00779)	(0.00796)	(0.00748)
Capital intensity		-0.00767***	-0.00891***
		(0.000622)	(0.000631)
TFP		0.0475***	
		(0.00477)	
Employment		0.0236**	0.0403***
		(0.0103)	(0.0114)
Employment sq.		-0.00124	-0.00275
		(0.00166)	(0.00172)
Labor productivity			0.0395***
			(0.00463)
Observations	353,760	186,204	237,661
R-squared	0.519	0.590	0.578
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Adj. R-sq. within	0.177	0.182	0.185
Adj. R-sq.	0.400	0.446	0.430
R-sq.	0.519		
Legal form		YES	YES

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

Note: Capital intensity measured as a ratio of capital stock to employment. TFP estimated from the corresponding production function. Labor productivity measured as a ratio of valued added to employment. All variables in logs. Standard errors clustered by NACE 3-digit sector.

Table 12: Value added markups and EBITDA margin

VARIABLES	(1) EBITDA margin	(2) EBITDA margin	(3) EBITDA margin
Markup	0.160***	0.146***	0.143***
	(0.00767)	(0.00771)	(0.00701)
Markup sq.	-0.0131***	-0.0105**	-0.0128***
	(0.00474)	(0.00467)	(0.00421)
Capital intensity		0.000440	3.99e-05
		(0.000282)	(0.000280)
TFP		0.0266***	
		(0.00280)	
Employment		0.0309***	0.0390***
		(0.00684)	(0.00632)
Employment sq.		-0.00256**	-0.00341***
		(0.00119)	(0.00106)
Labor productivity			0.0236***
			(0.00283)
Observations	325,454	188,097	240,567
R-squared	0.626	0.707	0.683
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Adj. R-sq. within	0.250	0.281	0.271
Adj. R-sq.	0.528	0.604	0.572
Legal form		YES	YES

Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Note: Capital intensity measured as a ratio of capital stock to employment. TFP estimated from the corresponding production function. Labor productivity measured as a ratio of valued added to employment. All variables in logs. Standard errors clustered by NACE 3-digit sector.

Table 13: Value added sectoral shares and markups - NACE 4-digit level

VARIABLES	(1) NACE 4-digit	(2) NACE 4-digit	(3) NACE 4-digit	(4) NACE 4-digit
Market share	5.868***	0.762***		
	(0.402)	(0.235)		
Market share sq.	-5.672***	-0.670***		
	(0.451)	(0.245)		
Employment		-0.506***		-0.619***
		(0.0297)		(0.0313)
Employment sq.		0.0429***		0.0490***
		(0.00437)		(0.00450)
Capital intensity		0.00184*		0.00108
		(0.000986)		(0.000972)
TFP		0.727***		0.620***
		(0.0118)		(0.0148)
log(Market share)			0.0473	0.0665***
			(0.0317)	(0.0213)
log(Market share) sq.			-0.0243***	-0.00335*
			(0.00265)	(0.00185)
Observations	241,835	188,845	241,835	188,845
R-squared	0.732	0.908	0.816	0.910
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Adj. R-sq. within	0.0129	0.617	0.323	0.625
Adj. R-sq.	0.639	0.876	0.752	0.879
Legal form		YES		YES

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Note: Standard errors clustered by NACE 4-digit sector.

Table 14: Sales markups and profit rate

VARIABLES	(1) VC bundle	(2) VC bundle	(3) VC bundle	(4) 3-factor	(5) 3-factor	(6) 3-factor
Markup	0.647***	0.700***	0.644***	0.640***	0.736***	0.653***
	(0.0424)	(0.0409)	(0.0445)	(0.0402)	(0.0448)	(0.0511)
Markup sq.	0.0335	0.163***	-0.127**	0.0318	0.148***	-0.115**
	(0.0538)	(0.0385)	(0.0507)	(0.0513)	(0.0420)	(0.0525)
Capital intensity		-0.00721***	-0.00957***		-0.00718***	-0.00956***
		(0.000824)	(0.000693)		(0.000825)	(0.000688)
TFP		0.0623***			-0.000150	
		(0.00909)			(0.00334)	
Employment		-0.0200	0.000892		-0.0208*	0.000900
		(0.0124)	(0.0108)		(0.0125)	(0.0107)
Employment sq.		0.00325	0.00113		0.00332*	0.000959
		(0.00202)	(0.00168)		(0.00201)	(0.00166)
Labor productivity			0.0786***			0.0790***
			(0.00413)			(0.00415)
Constant	-0.0387***	0.00844	-0.691***	-0.0711***	-0.0217	-0.729***
	(0.00618)	(0.0490)	(0.0572)	(0.00780)	(0.0519)	(0.0582)
Observations	391,640	207,801	240,005	391,640	207,801	240,005
R-squared	0.499	0.576	0.577	0.499	0.575	0.576
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Adj. R-sq. within	0.131	0.141	0.187	0.130	0.140	0.186
Adj. R-sq.	0.376	0.428	0.428	0.376	0.428	0.428
Legal form		YES	YES		YES	YES

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Note: Capital intensity measured as a ratio of capital stock to employment. TFP estimated from the corresponding production function. Labor productivity measured as a ratio of valued added to employment. All variables in logs. Standard errors clustered by NACE 3-digit sector.

Table 15: Sales markups and EBITDA margin

VARIABLES	(1) VC bundle	(2) VC bundle	(3) VC bundle	(4) 3-factor	(5) 3-factor	(6) 3-factor
Markup	0.856***	0.817***	0.779***	0.860***	0.883***	0.805***
	(0.0609)	(0.0555)	(0.0499)	(0.0655)	(0.0737)	(0.0608)
Markup sq.	-0.0707*	-0.126	-0.373***	-0.0666	-0.103	-0.314***
	(0.0403)	(0.170)	(0.0735)	(0.0425)	(0.160)	(0.0725)
Capital intensity		0.000755	-0.000232		0.000764	-0.000200
		(0.000480)	(0.000216)		(0.000470)	(0.000221)
TFP		0.0640***			0.00588*	
		(0.00633)			(0.00334)	
Employment		0.0335***	0.0220***		0.0332***	0.0219***
		(0.00944)	(0.00543)		(0.00943)	(0.00539)
Employment sq.		-0.00295**	-0.00197*		-0.00287**	-0.00209**
		(0.00129)	(0.00100)		(0.00131)	(0.00101)
Labor productivity			0.0260***			0.0266***
			(0.00435)			(0.00454)
Constant	0.00148	-0.138*	-0.321***	-0.0408***	-0.194**	-0.369***
	(0.00519)	(0.0764)	(0.0840)	(0.00771)	(0.0789)	(0.0853)
Observations	360,383	212,088	243,489	360,383	212,088	243,489
R-squared	0.649	0.713	0.744	0.649	0.712	0.741
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Adj. R-sq. within	0.302	0.324	0.428	0.300	0.321	0.421
Adj. R-sq.	0.557	0.614	0.655	0.557	0.612	0.651
Legal form		YES	YES		YES	YES

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

Note: Capital intensity measured as a ratio of capital stock to employment. TFP estimated from the corresponding production function. Labor productivity measured as a ratio of valued added to employment. All variables in logs. Standard errors clustered by NACE 3-digit sector.

Table 16: Sales markups and costs developments - markup definition (22)

VARIABLES	(1) 3-factor	(2) 3-factor	(3) 3-factor	(4) 3-factor	(5) 3-factor	(6) 3-factor	(7) 3-factor
Personnel costs	-0.00625***						-0.0127***
	(0.00132)						(0.00157)
Inter. consumption		0.00883***					0.00246
		(0.00306)					(0.00383)
Variable costs			0.00550				
			(0.00397)				
Depreciation				0.00748***			0.00732***
				(0.000413)			(0.000547)
Miscellaneous					0.00222***		0.00110***
					(0.000230)		(0.000338)
Net investment						0.00151***	0.00124***
						(0.000166)	(0.000215)
Constant	0.158***	-0.0176	0.0217	0.0315***	0.0861***	0.0914***	0.149**
	(0.0138)	(0.0380)	(0.0503)	(0.00391)	(0.00371)	(0.00235)	(0.0578)
Observations	412,658	412,658	412,658	412,270	372,226	298,832	213,248
R-squared	0.663	0.663	0.662	0.665	0.674	0.703	0.753
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Adj. R-sq. within	0.00258	0.00250	0.00186	0.00914	0.00224	0.00188	0.0106
Adj. R-sq.	0.580	0.580	0.580	0.584	0.589	0.625	0.668
Legal form							YES

Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: All variables in logs. Standard errors clustered by NACE 3-digit sector.

Table 17: Sales markups and market share - NACE 3-digit level

VARIABLES	(1) VC bundle	(2) VC bundle	(3) VC bundle	(4) VC bundle	(5) 3-factor	(6) 3-factor	(7) 3-factor	(8) 3-factor
Market share	1.889***	0.141			2.035***	0.212		
	(0.257)	(0.294)			(0.275)	(0.326)		
Market share sq.	-2.440***	-0.186			-2.611***	-0.354		
	(0.503)	(0.371)			(0.534)	(0.422)		
Employment		-0.000565		-0.0262***		-0.00804		-0.0981***
		(0.00545)		(0.00803)		(0.00855)		(0.00940)
Employment sq.		-0.000983		0.00172		0.00379**		0.0127***
		(0.00111)		(0.00144)		(0.00171)		(0.00185)
Capital intensity		0.00103***		0.000483**		0.00272***		0.000786*
		(0.000233)		(0.000194)		(0.000394)		(0.000443)
TFP		0.792***		0.772***		0.251***		0.213***
		(0.0413)		(0.0465)		(0.0202)		(0.0176)
log(Market share)			-0.0655***	-0.0292**			-0.0583***	-0.104***
			(0.0185)	(0.0138)			(0.0190)	(0.0207)
log(Market share) sq.			-0.00988***	-0.00299***			-0.00956***	-0.0106***
			(0.00133)	(0.000865)			(0.00135)	(0.00127)
Constant	0.0297***	-0.0561***	0.176**	-0.0466	0.0804***	-0.662***	0.263***	-0.507***
	(0.00149)	(0.00728)	(0.0723)	(0.0798)	(0.00152)	(0.0626)	(0.0746)	(0.119)
Observations	268,249	214,962	268,249	214,962	268,249	214,962	268,249	214,960
R-squared	0.688	0.936	0.723	0.937	0.722	0.809	0.753	0.820
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R-sq. within	0.00186	0.774	0.113	0.777	0.00212	0.236	0.115	0.281
Adj. R-sq.	0.582	0.914	0.628	0.915	0.626	0.743	0.669	0.758
Legal form								YES

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Note: Standard errors clustered by NACE 3-digit sector.

Table 18: Sales markups and market share - NACE 4-digit level

VARIABLES	(1) VC bundle	(2) VC bundle	(3) VC bundle	(4) VC bundle	(5) 3-factor	(6) 3-factor	(7) 3-factor	(8) 3-factor
Market share	0.993***	0.122			1.010***	0.0983		
	(0.103)	(0.121)			(0.106)	(0.123)		
Market share sq.	-0.981***	-0.143			-0.998***	-0.125		
	(0.111)	(0.123)			(0.113)	(0.125)		
Employment		-0.000457		-0.0237***		-0.00832		-0.0840***
		(0.00488)		(0.00704)		(0.00833)		(0.0103)
Employment sq.		-0.00104		0.000875		0.00385**		0.0106***
		(0.00102)		(0.00115)		(0.00162)		(0.00169)
Capital intensity		0.00102***		0.000467***		0.00272***		0.000977**
		(0.000212)		(0.000168)		(0.000380)		(0.000423)
TFP		0.791***		0.773***		0.251***		0.220***
		(0.0374)		(0.0411)		(0.0171)		(0.0149)
log(Market share)			-0.0430***	-0.00994			-0.0413**	-0.0658***
			(0.0159)	(0.00845)			(0.0162)	(0.0156)
log(Market share) sq.			-0.00862***	-0.00207***			-0.00854***	-0.00860***
			(0.00142)	(0.000587)			(0.00143)	(0.00132)
Constant	0.0285***	-0.0818***	0.210***	0.0295	0.0795***	-0.636***	0.269***	-0.441***
	(0.00135)	(0.0207)	(0.0462)	(0.0566)	(0.00137)	(0.0629)	(0.0475)	(0.0757)
Observations	268,249	214,960	268,249	214,962	268,249	214,960	268,249	214,962
R-squared	0.688	0.936	0.719	0.937	0.722	0.809	0.749	0.820
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R-sq. within	0.00222	0.774	0.101	0.778	0.00229	0.236	0.101	0.278
Adj. R-sq.	0.582	0.914	0.623	0.915	0.626	0.743	0.663	0.757
Legal form		YES				YES		

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

Note: Standard errors clustered by NACE 4-digit sector.

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