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Unravelling the Markups Changes: The Role of Demand Elasticity and Concentration *

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Abstract

We propose a framework allowing to identify sources changes in aggregate markups. Our approach derives from the conjectural variation theory and allows to evaluate the role of price elasticity of demand as well as concentration in shaping the markups. In the empirical part, we show that a decline in the aggregate markups in Poland, showed by Gradzewicz and Mućk (2019), can be explained to a large extent by rising demand elasticity, while rising concentration has mitigated this effect. We also document that at the industry level the globalization trends, e.g. international fragmentation, increasing standardization and tighter integration with global economy, affect both demand elasticity and markups but in a theory-consistent, inverse way. Besides, we identify factors which are specific to demand elasticity (product varieties and a home bias) and the markups (import content of exports).

Keywords: markups, price elasticity of demand, globalization
JEL Classification Numbers: C23, D22, D4, F61, L11

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Introduction

In the recent years there is a growing interest in the evolution of markups in the macroeconomic literature. It started in the US economy with the works of Barkai (2020) and De Loecker et al. (2020), both indicating a significant rise of markups of price over marginal costs (see also Caballero et al., 2017; Hall, 2018). Simultaneously, there is an evidence that in the US the rise of markups is accompanied by rising concentration — see e.g. Autor et al. (2020), Gutiérrez and Phillippon (2017) or Bajgar et al. (2019). In the European counties the evidence on markups is more scarce – Calligaris et al. (2018) or De Loecker and Eeckhout (2018) find rather heterogeneous but generally upward trends. Bajgar et al. (2019) show that in many European countries concentration also rises, although to a lesser extent than in the US.

As discussed by Syverson (2019), concentration is sometimes used as a proxy measure for markups, as a standard Cournot oligopoly model implies a positive relationship between the market concentration and the average market power. With fewer firms, each firm has less competition to take into account and more ability to raise price above marginal cost. But concentration is informative on relative revenue and includes no information on costs or profits. In many contexts concentration proves to be a bad proxy for market power as they may diverge as e.g. in the case of the monopolistic competition. A negative correlation between concentration and markups is also implied by a substitution effect in a class of models with heterogeneous firms selling differentiated goods (see e.g. Foster et al., 2008; Melitz, 2003). In these models a higher degree of substitutability implies on the one hand that a firm's residual demand becomes more elastic which lowers the price-cost margins. On the other hand, a rise in substitutability make it harder for higher-cost firms to operate and forces them to exit, leading to higher concentration. Thus, these models predict a negative correlation between market power and concentration, conditional on changes in substitution between products. Syverson (2004), among others, show that the negative correlation can be observed empirically.

Another strand of the literature trying to link concentration to markups builds on the conjectural variations models, first introduced by Bowley (1924), and is known as the Structure-Conduct-Performance (SCP) approach. It was popular till the 1970s and is extensively surveyed by Bresnahan (1989). It concentrates on estimating a conduct parameter, purported to measure the competitiveness of a market. But since the 1980s the industrial organization literature, given rising concerns on the relation between concentration and market power, forgo the approach. The example of the criticism is Corts (1999) who showed that the estimated conduct parameter need not even be positively correlated with the true measure of the elasticity-adjusted price-cost margin.

Our paper tries to re-examine the concentration-markup relationship. Our starting point is the conjectural variation theory but our contribution is to use it in a different way compered to the criticized SCP literature, in particular we do not use it to identify markups. Instead, we first use the markup identification method proposed by De Loecker and Warzynski (2012) and then we utilize the relations predicted by the conjectural variation theory to decompose the changes in markups into two components: (1) the change in the number of symmetric firms in the given industry, (2) the change in the price elasticity of demand. The former measures the change in the structure of the supply and the underlying market concentration, whereas the latter measures the change in the demand for products of the industry. Changes in the demand component are also indirectly related to changes in substitutability, as we are identifying the demand elasticity as perceived by the firm. Thus, our approach allows to empirically (and approximately) assess the role of substitution in the models in the spirit of Melitz (2003). To our knowledge this is the first attempt to identify the sources of markup changes.

On empirical grounds, we show the importance of changes in the demand elasticity to the development of markups in Poland. We focus on Poland because it offers an interesting and non-trivial example. Despite the rising concentration on the aggregate level, the aggregate markups are falling (Gradzewicz and Muck, 2019). Based on our approach we find that the decline in markups in Poland can be explained by the rising demand elasticity.

In addition, we document extensively that a bunch of measures of industry structure affect both the demand elasticity and markups, but in an inverse way, as predicted by the theory. In particular, we document that changes in the price elasticity of demand and its effect on markups can to large extent be explained by the globalization trends. These include: the international fragmentation of production with an accompanying vertical specialization, increasing standardization and overall tighter integration of Poland with the global economy. However, we also identify factors that are related solely to the demand elasticity or to the markups. In particular, the price elasticity of demand is affected by two opposite effects, i.e., home bias and rising variety, both not influencing markups directly. Furthermore, our empirical analysis shows that the foreign value added at exports (an import content of exports), as a measure that affects primary firms' costs, affects markups directly and not via the elasticity of demand.

The rest of the paper is organized as follows. The next section presents the theoretical background, i.e., the conjectural variation theory and the resulting concentration-markup relation. Then, we discuss data sources and issues related to the identification of markups and the measurement of concentration. The next section presents the results of empirical application for Poland. It is followed by the more detailed empirical analysis indicating how the measures of industry structure affect both demand elasticity and markups. The final section offers some concluding remarks and comments.

1 Theoretical background

Our starting point is the conjectural variation theory.[1] Consider a homogeneous product Q with an inverse demand function $P(Q)$ (with $P'(Q) < 0$). There are N firms in an industry, each producing q_i (so $Q = \sum_{i=1}^{N} q_i$) with a cost function $C(q_i)$. The profits of the jth firm are:

$$\Pi_j(q_j) = P\left(q_j + \sum_{i\neq j} q_i\right) \cdot q_j - C(q_j). \tag{1}$$

A firm j chooses q_j to maximize profits $\Pi_j(q_j)$. We assume that the firm formulates a conjecture about the combined output response of the other firms to a unit change in its

[1] The conjectural variation theory was first introduced by Bowley (1924) and is surveyed extensively by Bresnahan (1989).The derivation here follows Perry (1982) and Corts (1999).

own output level

$$\frac{d(\sum_{i\neq j} q_i)}{dq_j} = r_j, \tag{2}$$

where $-1 < r_j < N-1$. This condition nests a wide range of possible market equilibria.[2] It explicitly incorporates the special cases of:

(i) the competitive equilibrium, with $r_j = -1$, so the firm expects the rest of the industry to absorb exactly its output expansion by a corresponding output reduction; as a result each firm is a price-taker;

(ii) the Cournot equilibrium (the Nash equilibrium in quantities), with $r_j = 0$, so the rival's quantities are taken as given and unchanging with the firm's decision;

(iii) collusive equilibrium, where firm j's output changes are matched by all other $N-1$ firms, so $r_j = N-1$; in this case the industry behaves like a single monopolist splitting total production symmetrically among all firms in the industry, so as to maximize joint profits.

The first order condition of the firm j with respect to its output is:

$$\frac{d\Pi_j(q_j)}{dq_j} = P\left(q_j + \sum_{i\neq j} q_i\right) + P'\left(q_j + \sum_{i\neq j} q_i\right)(1+r_j)q_j - C'(q_j) = 0, \tag{3}$$

so that in equilibrium, each firm perceives no incentive to change its output level. When we assume that all firms are identical (let N^* be a number of symmetric firms in the industry) and they share the same conjecture about their rivals' reactions, $r_j = r$ then we can consider a symmetric equilibrium with $Q = N^* \cdot q$. Equation (3) simplifies to:

$$P(Q) + (1+r)P'(Q) \cdot \frac{Q}{N^*} - C'\left(\frac{Q}{N^*}\right) = 0. \tag{4}$$

and can be expressed as:

$$P(Q) = C'\left(\frac{Q}{N^*}\right) - \frac{1+r}{N^*}\frac{dP(Q)}{dQ} \cdot \frac{Q}{P(Q)} \cdot P(Q). \tag{5}$$

When we define the price elasticity of the demand as: $\theta \equiv -\frac{dQ(P)}{dP}\frac{P}{Q} = -\left(\frac{dP(Q)}{dQ}\right)^{-1} \cdot \frac{P}{Q}$ (note that $\theta > 0$) and assume the invertibility of demand function then $-\frac{dP(q)}{dQ} \cdot \frac{Q}{P} = \frac{1}{\theta}$. The price equation (4) becomes:

$$P(Q) = C'\left(\frac{Q}{N^*}\right) + \frac{1+r}{N^*}\frac{1}{\theta} \cdot P(Q). \tag{6}$$

Defining the markup μ as a price over the marginal cost (so $\mu \equiv \frac{P(Q)}{C'(\frac{Q}{N^*})}$) and divide (6) by $C'\left(\frac{Q}{N^*}\right)$ we get the following relation:

$$\mu = 1 + \frac{1+r}{N^*}\frac{\mu}{\theta}. \tag{7}$$

[2] The parameter $\Theta = 1 + r_j$ is called a conduct parameter.

Assuming the Cournot equilibrium ($r = 0$), this relation further simplifies to:

$$\mu = 1 + \frac{\mu}{N^* \theta}. \tag{8}$$

Given N^* – the number of symmetric firms in the industry and μ – the average markup in the industry we may recover the elasticity of demand for the product of the industry as:

$$\theta = \frac{\mu}{N^*(\mu - 1)} = \frac{1}{N^*} \frac{\mu}{\mu - 1}. \tag{9}$$

Relation (8) is static, but if we allow N^* and θ to vary in time, then we can treat equation (8) as a relation $\mu_t = \mu(N_t^*, \theta_t)$ of the form:

$$\mu_t = \frac{1}{1 - \frac{1}{N_t^* \theta_t}} = \frac{N_t^* \theta_t}{N_t^* \theta_t - 1}. \tag{10}$$

It follows that the change of markup $\Delta\mu_t$ may be expressed as:

$$\Delta\mu_t = -\frac{\theta_t N_t^*}{(N_t^* \theta_t - 1)^2} \frac{\Delta N_t^*}{N_t^*} - \frac{N_t^*}{(N_t^* \theta_t - 1)^2} \Delta\theta_t. \tag{11}$$

The equation (11) decomposes the change in markups into two sources of variation[3]: (i) due to the change of the demand elasticity and (ii) due to the change in the structure of the industry, proxied by the number of symmetrical firms in the Cournot equilibrium. An increase of the number of symmetrical firms in the equilibrium by 1% drives the markup down by $\frac{\theta_t N_t^*}{(N_t^* \theta_t - 1)^2}$. If the demand for products of the industry gets more elastic and θ_t rises by 1, the markups fall by $\frac{N_t^*}{(N_t^* \theta_t - 1)^2}$.

The previous literature (see e.g. Bresnahan, 1989) used the above theory and the relation given by (7) to estimate the conduct parameter using the information on Lerner index as a proxy for markups, the number of firms in the industry and the estimates of the demand elasticity. However, Corts (1999) criticizes this approach and shows it is unable to estimate the conduct parameter accurately. He stressed that "the CPM estimates of market power can be seriously misleading. In fact, the conduct parameter need not even be positively correlated with the true measure of the elasticity-adjusted price-cost margin, so that some markets are deemed more competitive than a Cournot equilibrium even though the price-cost margin approximates the fully collusive joint-profit maximizing price-cost margin".

We take into account the critique of Corts (1999) and assume that in the relatively short time span we analyze the nature of competition, measured by the conduct parameter is constant and close to the Cournot equilibrium.[4] As we are interested in changes, so it allow us to use relation (9) to determine the demand elasticity and equations (11) and (10) to perform markup decomposition and counterfactual analysis, respectively. The approach presented here relies on the external derivation of markups and concentration, discussed in the next section.

[3] See Appendix A for the decomposition in case of non-Cournout equilibria.

[4] Different assumption on he conduct parameter Θ are irrelevant for the decomposition, provided it is a constant.

2 Data sources and measurement

Our data cover the 15-years period (2002-2016) and come from annual financial reports and balance sheets of all Polish enterprises (excluding firms from agriculture, financial sector and some specific non-market services) employing at least 10 employees in full time equivalent. The data are collected by the Central Statistical Office (CSO). The full data is an unbalanced panel of almost 770 thousand observations—about 120 thousand firms observed for on average 6.4 years. In the last year of the analysis data cover 90% of employment and 85% of value added of the enterprise sector, as reported by CSO. This full data is used to calculate concentration measures. However, the measurement of markups (described below) is more data-demanding and we apply carefully chosen data cleaning procedures, described in detail in Gradzewicz and Mućk (2019). The trimmed sample with which it is possible to calculate markups contains 576.4 thousand observations on 82.1 thousand firms observed for 7.02 years on average. It covers ca. 75% of both employment and value added in the enterprise sector in the last year of the analysis. The subsequent analysis is performed at the industry level and the whole economy levels and we treat sectoral means of markups as proper measures of sectoral and economy-wide averages.

2.1 Measurement of markups

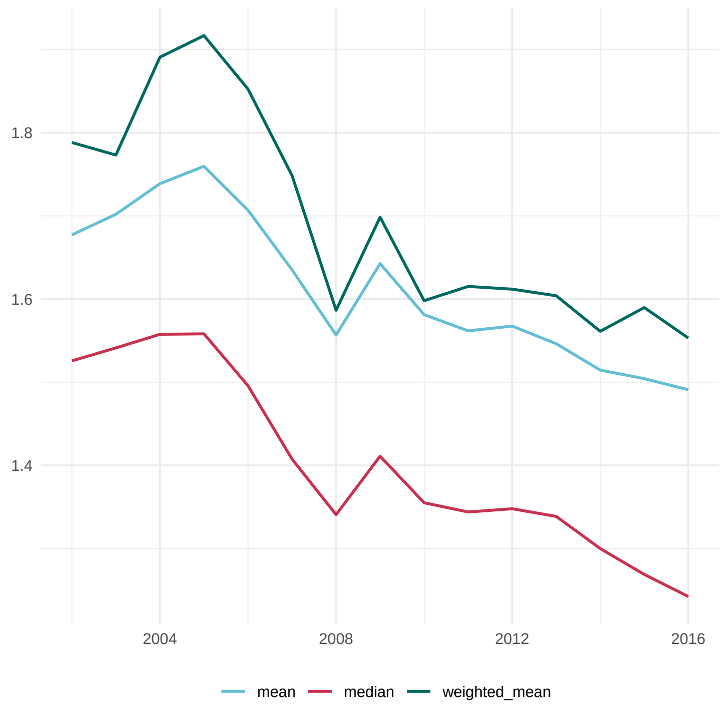
Monopolistic markups are measured on a firm-year level (indexed by i and t) using the methodology developed by De Loecker and Warzynski (2012). We use the estimates of markups from the baseline calculations presented in Gradzewicz and Mućk (2019) and discuss here only the the most important issues (please, refer to the above reference for an in depth description). The identification of markups starts from the assumption of static cost minimization which gives, for any free to adjust production factor, the following relation:

$$\mu_{it} = \beta_{it}^{V} \left(\frac{P_{it}^{V} V_{it}}{P_{it} Q_{it}} \right)^{-1}. \tag{12}$$

In (12) β_{it}^{V} stands for the production function elasticity to the variable factor V, $P_{it}^{V} V_{it}$ is the nominal cost associated with this production factor and the term in bracket is the share of nominal factor cost in total revenues.

There is a set of additional assumptions imposed to identify markups and they relate mostly to individual firm's behavior (in contrast to assumptions described in section 1, which concern the industry). The first is cost minimization, which is consistent with pricing scheme in (3). One also needs to impose a specific production function to measure β_{it}^{V} and we use a translog form which is flexible enough to make the production elasticity firm- and period-specific. We assume the production function is defined for value added and we use capital and labor as production factors, using the latter factor as V in (12). Thus, we assume that labor is a variable input with no adjustment costs and no price distortions in the input market. Furthermore, we use the production function identification scheme proposed by Ackerberg et al. (2015), which builds on Levinsohn and Petrin (2003) and controls for both the bias due to simultaneity in productivity and factor demand and for the selection bias due to firms exiting the sample. There is also an additional caveat that we inherit from Gradzewicz and Mućk (2019) — we do not observe directly firm level prices and instead we use sectoral deflators in the production function estimation. It may

Figure 1: Median, unweighted and weighted mean markups in Poland



Source: Gradzewicz and Mućk (2019)

bias the estimates of production function elasticities, which could translate into biased average markups. As the bias concerns production elasticities, it should not distort the time path of markups so we try to minimize its negative effect on our results and focus here on the changes in variables under consideration, rather than on levels.

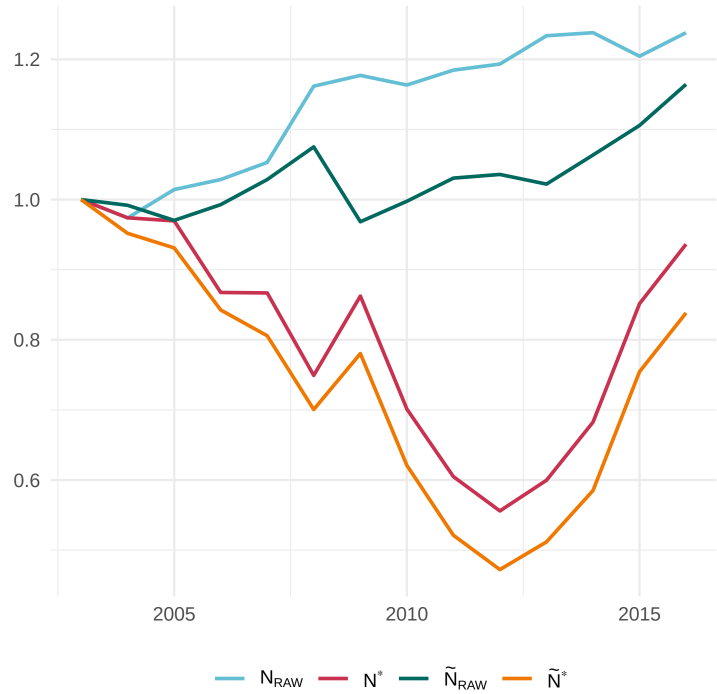
Figure 1, taken from Gradzewicz and Mućk (2019), shows the evolution of average markups in the polish economy since 2002. It is clearly visible that the markups are on average declining. Gradzewicz and Mućk (2019) also shows that the decline is robust to various adjustments in the identification scheme. Moreover, they show that the decline is also prevalent on a firm level – around 70% of enterprises experienced a fall of markup.

2.2 Measurement of concentration

The decomposition of markups described in section 1 requires N^* – a number of symmetric firms in the industry. A natural estimator, a number of firms, is unbiased unless there are no changes in the industry concentration. A commonly used measure that accounts for the concentration is an inverse of the Herfindahl-Hirshman Index (denoted as HHI). It can be easily shown that $HHI_t = \sum_i \left(\frac{P_{it}Q_{it}}{\sum_j p_{jt}Q_{jt}}\right)^2$ can be expressed as $HHI = N\sigma^2 + 1/N$, where σ^2 is the variance of firm market share. When firms are symmetric then each firm has the same market share, $\sigma^2 = 0$ and $N^* = HHI^{-1}$.

We measure N^* using our full dataset (before the cleaning procedures) as there are no missing values on nominal sales, which is only needed to determine HHI. Still, the measurement of HHI in our data is biased, as the data do not include small firms, employing less than 10 persons. In order to check the severity of this source of bias we use the aggregate information provided by the Polish Central Statistical Office and correct our

Figure 2: Changes in raw and symmetric firm number for the total enterprise sector and firms 10+ (2002=100)



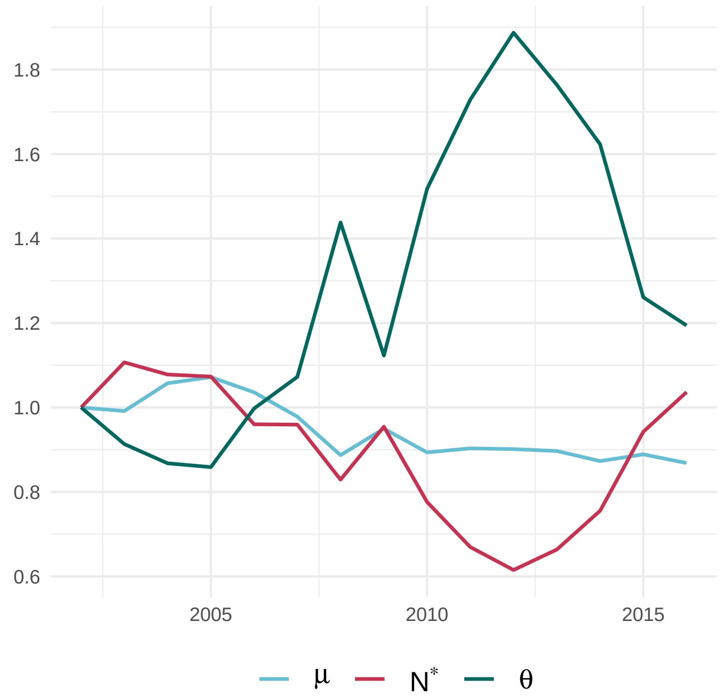
Note: N_{RAW} is the number of firms in our dataset, $\tilde{N}_{RAW}$ denotes the number of firms corrected by small enterprises, N is the number of symmetric firms and $\tilde{N}$ denotes the number of symmetric firms adjusted by small firms.

calculations with the number of small firms. When correcting the HHI index we assumed that the total sales generated by small firms (which we observe only in the aggregate of small firms) are equally spread among them.

Figure 2 shows the evolution of a raw number of firms, both in our dataset (N_{RAW}) and with small firms included ($\tilde{N}_{RAW}$) together with the number of symmetric firms, both in our dataset (N) and corrected for small firms ($\tilde{N}$). As we focus on changes, we normalize the series with the levels in 2003. The number of firms in the Polish economy has been rising at least since 2003. The rise is more pronounced for relatively larger firms.[5] In smaller firms the crisis year of 2009 was particularly responsible for a slower cumulative growth. Figure 2 also shows that a growing firm number was accompanied by rising concentration, as the number of symmetric firms was on a declining tendency till 2012. Only after 2012 there was a relatively sharp rise of N^*, but still the cumulative change since 2002 is negative. Moreover, figure 2 shows that the extent of firm concentration is underestimated in our dataset but the bias is time-invariant. In the subsequent analysis we will use a symmetric firm number from our full dataset as the aggregate data form the CSO do not allow for the sectoral split.

[5]The growth of the number of firms employing 10+ is comparable to official figures.

Figure 3: Markups, a number of symmetric firms and the demand price elasticity (2002=100)



3 Empirical application

In this section we will try to assess what is the role of concentration (measured as a number of symmetrical firms, discussed in section 2.2) in shaping monopolistic markups in Poland. First, we show the evolution of the derived the demand elasticity and then we use counterfactual analysis to assess the importance of both demand elasticity and concentration in shaping markups.

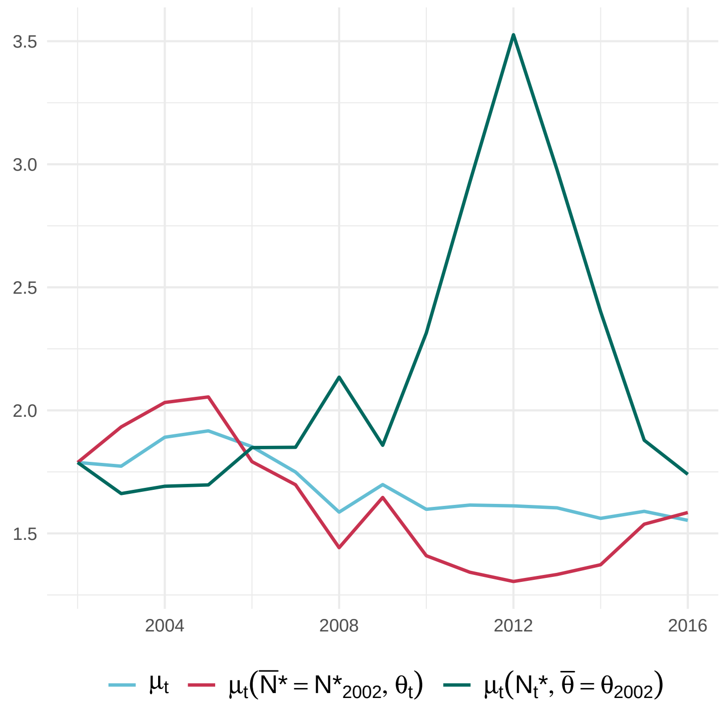
Given calculations of markups μ and a number of symmetric firms N^* we apply equation (9) to measure demand elasticity θ. Figure 3 shows the results. In the initial period there was a small increase of markups, but monopoly power exhibited a longer declining tendency. The decline of markups, by almost 10% till 2008, was accompanied by a decline of a number of symmetric firms by ca. 18% and a huge increase of demand elasticity, which rose by over 40% during this period. After 2008 the decline of markups slowed down substantially, but the underlying changes in θ and N^* continued. A number of symmetric firm continued to decline even further till 2012, but then concentration decreased substantially (reflected in an increase of N^*) and in 2016 stayed on a level similar to the one observed at the beginning of the sample. Demand elasticity mirrored the development of N^* — it continued to increase till 2012 reaching a level almost 90% higher than in 2002 and then fall sharply to a level only 20% higher than in 2002.

As we want to assess the relative importance of demand elasticity and concentration in shaping markups so we use equation (10) and simulate the hypothetical paths of markups μ holding either θ or N^* fixed.[6] Figure 4 shows the results. If we do not allow for changes

[6] It is also possible to use equation (11) for the purpose of our assessment, see Figure A.1 in the Appendix. However it generate relatively high variation in the results, so we decided to use counterfactual

in concentration then the resulting path of markups is very similar to the one observed in reality. Even more, absent changes in concentration the markups for most of the time would decline more than in reality.[7] In turn, if there were no changes in demand elasticity, then the markups would actually rise substantially (especially at the beginning of 2000's) for most of the time, due to rising concentration.

Figure 4: Counterfactual path of the markups with fixed demand elasticity and concentration



Note: the series denoted by $\mu_t\left(\bar{N}^* = N^*_{2002}, \theta_t\right)$ is the counterfactual path of the markups with the number of symmetric firms that is fixed at the initial value, i.e., value in 2002. It measures the effect of changes in demand elasticity. The term $\mu_t\left(\bar{N}^*_t, \bar{\theta} = \theta_t\right)$ quantifies the effect of changes in concentration since the demand elasticity is fixed.

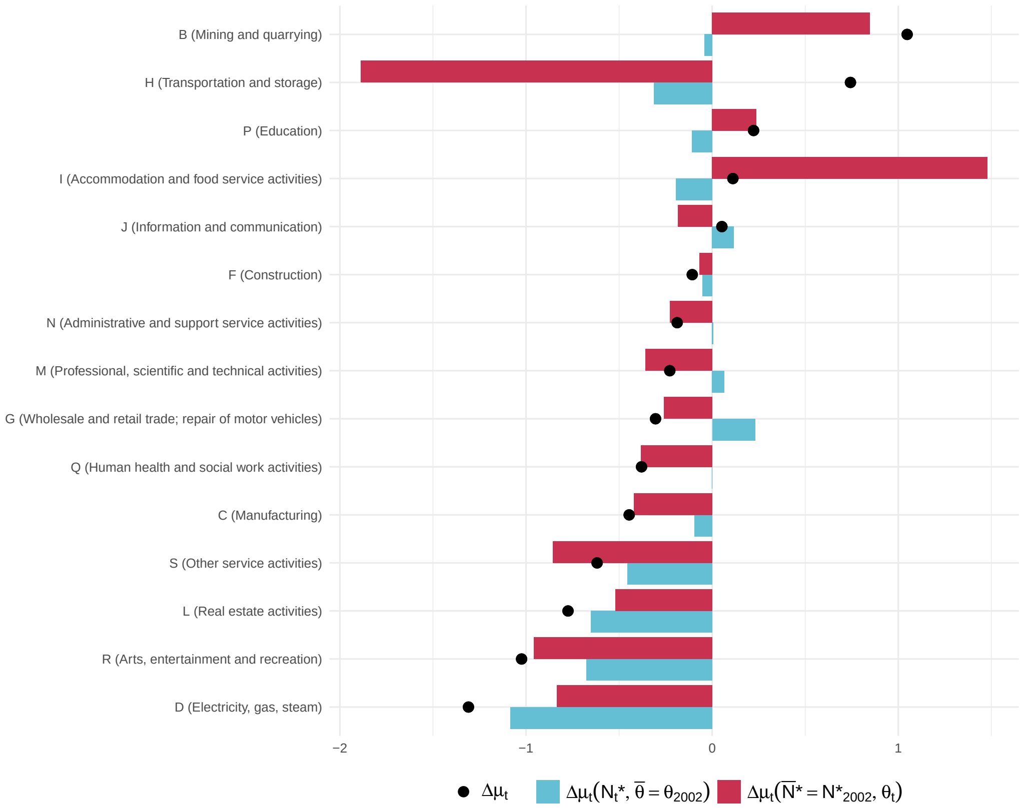
The aggregation in the results for the whole economy could hide divergent underlying sectoral tendencies. Figure 5 shows it is not the case. It illustrates actual (cumulated over the period 2002-2016) changes in markups for 1-digit NACE industries[8], together with hypothetical cumulated changes, with either concentration or demand elasticity fixed. Few observations emerge. First, declines of markups prevail on industry level, rising only in specific sectors, like mining or transportation. Second, in most industries the direction of changes in markups is associated with changing demand elasticity. In industries with falling markups, the fall is always (at least partially) due to changing θ. The same is true for most cases with rising markups. Third, changes in concentration are less correlated with markups, but in industries with the greatest markup declines, it is due to both rising θ and rising concentration.

paths. The main conclusions from the both approaches are similar.

[7] Although in the whole analyzed period both time series converge to a similar level.

[8] The results are roughly the same with less aggregated industries, we do not present them to save place.

Figure 5: Counterfactual changes in the markups with fixed demand elasticity and fixed concentration at the industry level (2002-2016)



Note: the series denoted by $\mu_t\left(\bar{N}^* = N^*_{2002}, \theta_t\right)$ is the counterfactual change of the markups with the number of symmetric firms that is fixed at the initial value, i.e., value in 2002. It measures the effect of changes in demand elasticity. The term $\mu_t\left(\bar{N}^*_t, \bar{\theta} = \theta_t\right)$ quantifies the effect of changes in concentration since the demand elasticity is fixed.

Summing up, our analysis showed that the fall of markups observed in Poland originated in the rise of the demand elasticity. Rising concentration was actually a counteracting factor. Moreover, the pattern observed for the whole economy is also dominant on a sectoral level and is not driven by aggregation. Our theoretical model does not allow to investigate the reasons for the increase in elasticity, so in the next section we will use econometric techniques to gauge what structural factors affected demand elasticity and markups.

4 Econometric analysis

In this section we analyze the empirical link between demand elasticity and its potential drivers. We also perform the analysis for markup changes since the demand elasticity drivers could affect to some extents markups directly. It also allow us to indicate factors that affect solely markups or demand elasticities.

Our empirical analysis is performed on a 2-digit NACE industrial aggregation. This choice is related to the definition of homogeneous product and is mainly data-driven. Most of the potential determinants of demand elasticity and markups are measured using the World Input-Output database (WIOD, Timmer et al., 2015, explained below) and its resolution limits our analysis.

We consider here the following regression:

$$\theta_{jt} = \mathbf{x}'_{jt}\beta + \varepsilon_{jt}, \tag{13}$$

where θ_{jt} is the demand elasticity, $\mathbf{x}_{jt}$ is a set of explanatory variables and ε_{jt} denotes the error term which is assumed to be idiosyncratic. We also consider an analogous regression explaining the variation in markups:

$$\mu_{jt} = \mathbf{z}'_{jt}\gamma + \omega_{jt}, \tag{14}$$

where μ_{it} is the markup in the j-th industry, $\mathbf{z}_{jt}$ is a set of explanatory variables and ω_{jt} is the error term. To control for systematic differences between industries we included the industry fixed effects in all regressions. Furthermore, we also tried to account for common unobservable factors by introducing time effects in (13) and (14).

For the sake of brevity, we consider regressions explaining variation in θ as well as μ. As it has been explained in theoretical section, the changes in demand elasticity could be transmitted in changes in markups. If some factors affect both markups and demand elasticity then the signs of β and γ should be opposite.

A key empirical problem in estimating underlying parameters of especially (13) is an enormous variation in calculated θ_{jt}. Recalling the derivation of the demand elasticity (9) it is straightforward to observe that the effect of small changes in markups on θ can be extreme in industries with almost perfect competition, i.e., when markups are very close to zero. This implies that the variation in some industries could be immense due to the appearance of outliers. We address this issue by applying a robust regression technique. [9]

As explanatory variables, i.e. $\mathbf{x}_{jt}$ and $\mathbf{z}_{jt}$, we use a set of industry characteristics that are calculated based on the WIOD database Timmer et al. (2015). Our set of regressors includes: the share of directly imported final goods in the final demand of a given industry (denoted as $\mathcal{IMP}^{\mathcal{FD}}_{jt}$), the share of intermediates in the gross output ($\mathcal{INT}_{jt}$), the share of exports in the gross output ($\mathcal{EXP}_{jt}$), the foreign value added at export (measuring the share of imported intermediates in exports, $\mathcal{FVAX}_{jt}$) and the upstreamness index, which measures the distance to the final demand ($\mathcal{UPS}_{ij}$). All variables with the corresponding descriptive statistics are described in table B.1 in the Appendix B.

4.1 Baseline regressions

We start our analysis with the linear model. Table 1 presents baseline estimation results for such models. In each two-column block we present the estimates from regression for the demand elasticities and markups, respectively. The third and fourth block includes both industry and time fixed effects, whereas the first two blocks only the industry effects. The second and fourth block distinguishes additionally export intensity in final and intermediate goods.

[9]The concept of a robust regression is to limit the importance of outlying observations. The detailed procedure is as follows. First, observations with above unitary Cook's distance, which measures the effect of omitting observation on estimation results, are excluded. Second, the weighted least squares estimator is iteratively applied with weights calculated using on the previous step residuals.

In most cases the estimates in the markup equations have an opposite sign than in the demand elasticity equations. This suggests that a given factor drives demand elasticity and its effect is consistently transmitted into markups. For instance, the estimates on intermediates share in output ($\mathcal{INT}_{jt}$) are negative in the demand elasticity regression while they are significantly positive for the markups. A possible explanation of this effect refers to the product standardization. If the industry delivers more intermediates then its products become more standardized because they are sharing similar technologies to the other supplying firms. Thus, the higher degree of standardization translates into lower variety and pushes down demand elasticity which rises markups.

Table 1: The regression results for the price elasticity of demand and markups

	θ	μ	θ	μ	θ	μ	θ	μ
$\mathcal{IMP}_{jt}^{\mathcal{FD}}$	-0.061***	0.330*	-0.075***	0.635***	-0.052*	0.399*	-0.066**	0.827***
	(0.027)	(0.200)	(0.028)	(0.212)	(0.030)	(0.205)	(0.031)	(0.217)
$\mathcal{INT}_{jt}$	-0.200***	2.600***	-0.204***	2.792***	-0.203***	2.293***	-0.206***	2.519***
	(0.042)	(0.314)	(0.042)	(0.323)	(0.050)	(0.339)	(0.050)	(0.354)
$\mathcal{EXP}_{jt}$	0.088***	0.374**			0.090***	0.345**		
	(0.022)	(0.161)			(0.025)	(0.169)		
$\mathcal{EXP}_{jt}^{\mathcal{FIN}}$			0.134***	0.009			0.126***	-0.142
			(0.032)	(0.242)			(0.034)	(0.242)
$\mathcal{EXP}_{jt}^{\mathcal{INT}}$			0.032	0.888***			0.048	1.012***
			(0.028)	(0.215)			(0.032)	(0.229)
$\mathcal{FVAX}_{jt}$	0.268***	-5.343***	0.281***	-5.589***	0.243***	-5.350***	0.249***	-5.914***
	(0.049)	(0.368)	(0.050)	(0.378)	(0.077)	(0.520)	(0.077)	(0.546)
$\mathcal{UPS}_{jt}$	0.004	-0.135**	0.011	-0.187***	0.004	-0.130**	0.009	-0.207***
	(0.008)	(0.060)	(0.009)	(0.068)	(0.009)	(0.062)	(0.010)	(0.069)
Constant	-0.309***	1.063***	-0.311***	1.078***	-0.342***	1.485***	-0.346***	1.581***
	(0.030)	(0.222)	(0.031)	(0.236)	(0.035)	(0.241)	(0.036)	(0.253)
Observations	582	582	582	582	582	582	582	582
Industry effects	✓	✓	✓	✓	✓	✓	✓	✓
Time effects					✓	✓	✓	✓

Note: the superscripts ***, ** and * denote the rejection of null about parameters' insignificance at 1%, 5% and 10% significance level, respectively. The expressions in round brackets stand for standard errors. The detailed description of explanatory variables is delegated to table B.1.

The demand elasticity (markups) is negatively (positively) related to the share of directly imported goods in final demand ($\mathcal{IMP}_{jt}^{\mathcal{FD}}$). This relationship seems to be counterintuitive. From the perspective of an importing country a rising share of imported final goods in total supply of goods on the market might be perceived as an increase in variety of available goods. As a result it should move up the demand elasticity. However, our estimation results are inconsistent with the above intuition. A potential explanation for the negative relationship between demand elasticity and import content of final demand might be a home bias. If domestic consumers prefer purchasing domestic rather than imported goods the rising share of foreign products drives the price elasticity of demand down and domestic firms yield higher markups.

The estimation results also imply that the international fragmentation of production shapes both demand elasticity and markups. This is captured by the estimates on the foreign value added at exports ($\mathcal{FVAX}_{jt}$), which isa a typical proxy of backward participation in Global Value Chains and it measures the import content of gross exports. In general, imported intermediates usually embed specific technologies that are probably not available for domestic suppliers. As the industry imports more such intermediates to sell abroad then its products probably become more standardized which pushes down the demand elasticity. The effect of higher degree of standardization is transmitted in the markups.

So far we explained cases with the opposite signs of the underlying estimates for demand elasticity and markups but it is not always the case. For instance, the distance from final demand $\mathcal{UPS}_{jt}$ affects markups negatively, whereas the estimation results suggest it has no effect on the demand elasticity. The more distant is an industry from the final demand, the lower the markup it may charge. The literature (see e.g. Gradzewicz and Mućk, 2019) usually finds a non-linear relation in case of upstreamness and we return to this issue in the next section.

More strikingly, the estimated effect of the export intensity is incoherent, i.e., it is positive for both markup and demand elasticity. Despite this inconsistency it can be explained as follows. On the one hand, in case of the demand elasticity, the positive relationship can be related to a larger variety of goods that is faced by domestic firms in foreign markets. Foreign consumers have probably a better access to a global market with more varieties. However, this effect is not transmitted into lower markups of domestic firms. On the other hand, export intensity seems to directly push the markups up. This, in turn, may be related to the export premium (see e.g. De Loecker and Warzynski, 2012). To better understand the above ambiguity we consider additional regressions, in which export intensity is divided into: (i) exports of final goods and (ii) exports of intermediates. The estimation results suggest that the export premium is important mostly for producers of intermediates while for them the variety effect for demand elasticity is insignificant. Exporters of final goods are in turn affected only by the positive effect of varieties on demand elasticity for their products.

4.2 Non-linear regressions

In the next step, we consider a non-linear relationships between demand elasticity and the variables of interest. The previous estimation results occurs to be inconsistent because, contrary to the theoretical background discussed in the section 1, the signs are not always opposite. Therefore, we introduce a more flexible functional form and extend our regression by introducing quadratic terms. It allows to control for a complex nature of structural factors affecting industries.

Table 2 summarizes the extended set of the estimation results while the implied extrema of estimated relationships are presented in table B.2 in the Appendix B. It turns out that the relationship between the share of imported final goods and demand elasticity is U-shaped. In industries offering mostly domestic final goods the home bias plays a crucial role. When the share of imported final goods is raising the home bias effect is offset by an effect of increasing varieties. For final goods, which are mostly imported, the positive role of the variety effect is predominant in shaping demand elasticity. However, this effect is not transmitted into markups.

Table 2: The regression results for the price elasticity of demand and markups (quadratic relationship)

	θ	μ	θ	μ	θ	μ	θ	μ
$\mathcal{IMP}_{jt}^{\mathcal{FD}}$	-0.249***	-0.061	-0.201***	-0.074	-0.249***	0.036	-0.199***	-0.286
	(0.058)	(0.434)	(0.058)	(0.418)	(0.063)	(0.441)	(0.064)	(0.434)
$\mathcal{IMP}_{jt}^{\mathcal{FD}^2}$	0.299***	-0.228	0.185***	-0.362	0.317***	-0.565	0.193***	-0.221
	(0.058)	(0.435)	(0.056)	(0.402)	(0.062)	(0.435)	(0.060)	(0.405)
$\mathcal{INT}_{jt}$	-0.634***	-0.407	-0.652***	0.000	-0.526***	-1.040	-0.542***	-0.249
	(0.157)	(1.176)	(0.162)	(1.162)	(0.183)	(1.284)	(0.185)	(1.258)
$\mathcal{INT}_{jt}^2$	0.457***	2.483**	0.453***	2.067**	0.391***	2.058*	0.383**	1.536
	(0.136)	(1.022)	(0.141)	(1.009)	(0.150)	(1.056)	(0.153)	(1.042)
$\mathcal{EXP}_{jt}$	0.215***	-0.536*			0.211***	-0.513*		
	(0.039)	(0.292)			(0.043)	(0.300)		
$\mathcal{EXP}_{jt}^2$	-0.241***	1.867***			-0.254***	2.192***		
	(0.049)	(0.365)			(0.053)	(0.373)		
$\mathcal{EXP}_{jt}^{\mathcal{INT}}$			0.011	-2.615***			-0.048	-1.900***
			(0.077)	(0.555)			(0.082)	(0.557)
$\mathcal{EXP}_{jt}^{\mathcal{INT}^2}$			-0.112	7.077***			-0.038	6.143***
			(0.118)	(0.849)			(0.126)	(0.856)
$\mathcal{EXP}_{jt}^{\mathcal{FIN}}$			0.327***	1.460**			0.354***	1.347**
			(0.088)	(0.628)			(0.095)	(0.644)
$\mathcal{EXP}_{jt}^{\mathcal{FIN}^2}$			-0.337***	-0.111			-0.377***	0.006
			(0.097)	(0.698)			(0.105)	(0.716)
$\mathcal{FVAX}_{jt}$	0.273*	0.961	0.311*	-0.986	0.078	3.367**	0.117	1.162
	(0.160)	(1.201)	(0.165)	(1.186)	(0.242)	(1.698)	(0.240)	(1.631)
$\mathcal{FVAX}_{jt}^2$	-0.028	-10.564***	-0.062	-6.451***	0.169	-12.383***	0.125	-8.148***
	(0.213)	(1.601)	(0.220)	(1.580)	(0.278)	(1.953)	(0.277)	(1.880)
$\mathcal{UPS}_{jt}$	0.205***	-1.440***	0.189***	-1.680***	0.204***	-1.611***	0.192***	-1.713***
	(0.041)	(0.309)	(0.044)	(0.318)	(0.045)	(0.314)	(0.048)	(0.329)
$\mathcal{UPS}_{jt}^2$	-0.049***	0.364***	-0.042***	0.434***	-0.049***	0.421***	-0.043***	0.448***
	(0.010)	(0.073)	(0.011)	(0.075)	(0.011)	(0.075)	(0.012)	(0.079)
Constant	-0.365***	1.689***	-0.333***	1.979***	-0.406***	1.526***	-0.370***	1.660***
	(0.050)	(0.373)	(0.051)	(0.367)	(0.054)	(0.381)	(0.055)	(0.377)
Observations	582	582	582	582	582	582	582	582
Industry effects	✓	✓	✓	✓	✓	✓	✓	✓
Time effects					✓	✓	✓	✓

Note: the superscripts ***, ** and * denote the rejection of null about parameters' insignificance at 1%, 5% and 10% significance level, respectively. The expressions in round brackets stand for standard errors. The detailed description of explanatory variables is delegated to table B.1.

A non-linear relationship explains well some previous ambiguity in the results. Namely, the link between export intensity and demand elasticity (markup) is hump-shaped (U-shaped). On the one hand, for sectors with less internationally traded goods the export expansion translates into higher demand elasticity since consumers at foreign markets have an access to a higher variety of available goods. As a results, a shift toward foreign sales moves up demand elasticity in such industries and triggers the fall of markups. On the other hand, as firms become more focused on foreign sales this effect is weakened. It can be related to a larger dependence of foreign consumers on these products, driving the demand elasticity down and markups up. Although the signs between regression explaining θ_{jt} and μ_{jt} are consistent these effects operate through different channels (see the 3rd and 4th columns of table 2). The price elasticity of demand is mainly linked to the exports of final goods while exports of intermediates shapes predominantly the markups.

The implied relationship between the distance from the final demand and the demand elasticity is hump-shaped. This suggest that firms operating in the middle stages of the production chain face higher demand elasticity. The above link is unambiguously transmitted into markups which leads to the so-called smile curve, which describes a U-shaped relationship between the position in the production chains and markups (a similar effect was also described in Gradzewicz and Mućk, 2019). In addition, this empirical pattern is consistent with the smile curve hypothesis, which predicts that the gains are evenly distributed across the vertically specialized production chain. In this vein, Timmer et al. (2014) or Meng et al. (2020) show that the gains from the GVC participation are the highest for firms that are either at the beginning of the production process (e.g. R&D, design) or very close to the final use (e.g. marketing, advertising, post-sale services).

Importantly, the effect of production fragmentation is amplified by international integration. This is captured by the negative estimates on the squared foreign value added at exports, as well as previously discussed relationship with the export intensity. Intuitively, as production becomes more vertically specialized and firms use more imported intermediates their products become more standardized which limits their market power.

Summing up, the above estimates illustrate that the impact of structural changes is quite heterogenous among industries. Nevertheless, it is straightforward that the international fragmentation of production (international vertical specialization) has driven price elasticity of demand and this effect has been consistently transmitted into the markups changes. Concurrently, there have been other factors, like the interplay between home bias and the variety of goods, that have shaped demand elasticity but their impact has not be passed on the markups.

Conclusions

The aim of the article is to investigate the theoretical link and assess the empirical role that changes in concentration and demand have on the evolution of markups. We use a dataset for Poland as it offers an interesting and non-trivial example — despite the rising concentration on the aggregate level, the aggregate markups are falling, as documented by Gradzewicz and Mućk (2019).

We utilize the conjectural variation theory (see Bresnahan, 1989) to show the relation between markups and concentration and to separate the changes in markups into two components, one related to the supply (number of symmetric firms) and one related to the demand (its price elasticity). It is consistent with the excellent discussion in Syverson (2019). To the best of our knowledge it is the first attempt to show the sources of markup changes. Using a dataset for Poland we empirically show the importance of changes in the demand elasticity for the development of markups, both at the aggregate level and in most industries. We showed that the observed decline of markups can, to a large extent, be attributed to rising perceived demand elasticity.

We refrain from building any demand system on top of the enterprise sector to understand the movements of demand elasticity. Instead we use the econometric techniques to check the significance of possible factors affecting demand elasticity on a sectoral level. We do not observe any direct empirical counterpart to product substitutability, but instead we use measures of changes in the structure of demand faced by production sectors. The underlying logic is as follows: if various sources of demand have different price elasticities then changes in the structure of demand should change the perceived effective demand elasticity. We use measures related to globalization as during the period of the analysis the enterprise sector of Poland was significantly shaped by the globalization forces.

We empirically show that measures of industry structure affect both the demand elasticity and markups, but in an inverse way (as it actually should be). Moreover, our analysis suggest that most relations are non-linear. Our econometric results indicate that the share of intermediates in gross output exhibits an U-shaped relationship with demand elasticity (and is predominantly negative). The share of exports in gross output exhibits mostly positive, but generally a hump-shaped relationship with the demand elasticity, reflecting the interplay of the effects of the variety and the export premium. The share of imported intermediates in exports (foreign value added at exports) exhibits a humped-shaped relationship, but only with markups. This is expected, because it is a factor affecting firms' costs and not the demand and it is consistent with Gradzewicz and Mućk (2019). Moreover, the demand elasticity seems to be a humped-shaped function of the distance to the final demand and a U-shaped function of the share of directly imported final goods in the final demand.

Our results indicate that the globalization has non-trivial and highly non-linear effects on the production sectors of the economy.

References

Ackerberg, D., K. Caves, and G. Frazer (2015). Identification Properties of Recent Production Function Estimators. *Econometrica 83*(6), 2411–2451.

Antras, P., D. Chor, T. Fally, and R. Hillberry (2012, May). Measuring the upstreamness of production and trade flows. *American Economic Review 102*(3), 412–416.

Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. Van Reenen (2020, May). The Fall of the Labor Share and the Rise of Superstar Firms. *The Quarterly Journal of Economics 135*(2), 645–709.

Bajgar, M., G. Berlingieri, S. Calligaris, C. Criscuolo, and J. Timmis (2019, January). Industry Concentration in Europe and North America. Technical Report 18, OECD Publishing.

Barkai, S. (2020). Declining Labor and Capital Shares. *The Journal of Finance 75*(5), 2421–2463.

Bowley, A. (1924). *The Mathematical Groundwork of Economics: An Introductory Treatise.* Reprints of Economic Classics. Clarendon Press.

Bresnahan, T. F. (1989, January). Chapter 17 Empirical studies of industries with market power. In *Handbook of Industrial Organization*, Volume 2, pp. 1011–1057. Elsevier.

Caballero, R. J., E. Farhi, and P.-O. Gourinchas (2017, May). Rents, Technical Change, and

Risk Premia Accounting for Secular Trends in Interest Rates, Returns on Capital, Earning Yields, and Factor Shares. *American Economic Review 107*(5), 614–620.

Calligaris, S., C. Criscuolo, and L. Marcolin (2018, April). Mark-ups in the digital era. OECD Science, Technology and Industry Working Paper 2018/10, OECD Publishing.

Corts, K. S. (1999, February). Conduct parameters and the measurement of market power. *Journal of Econometrics 88*(2), 227–250.

De Loecker, J. and J. Eeckhout (2018, June). Global Market Power. Working Paper 24768, National Bureau of Economic Research.

De Loecker, J., J. Eeckhout, and G. Unger (2020, May). The Rise of Market Power and the Macroeconomic Implications. *The Quarterly Journal of Economics 135*(2), 561–644.

De Loecker, J. and F. Warzynski (2012, May). Markups and Firm-Level Export Status. *American Economic Review 102*(6), 2437–2471.

Foster, L., J. Haltiwanger, and C. Syverson (2008, March). Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability? *American Economic Review 98*(1), 394–425.

Gradzewicz, M. and J. Mućk (2019). Globalization and the fall of markups. Technical Report 304, Narodowy Bank Polski, Economic Research Department.

Gutiérrez, G. and T. Phillippon (2017). Investmentless Growth: An Empirical Investigation. *Brookings Papers on Economic Activity*, 89–169.

Hall, R. E. (2018, November). Using Empirical Marginal Cost to Measure Market Power in the US Economy. Working Paper 25251, National Bureau of Economic Research.

Levinsohn, J. and A. Petrin (2003). Estimating Production Functions Using Inputs to Control for Unobservables. *Review of Economic Studies 70*(2), 317–341.

Melitz, M. J. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica 71*(6), 1695–1725.

Meng, B., M. Ye, and S.-J. Wei (2020). Measuring smile curves in global value chains*. *Oxford Bulletin of Economics and Statistics*.

Perry, M. K. (1982). Oligopoly and Consistent Conjectural Variations. *The Bell Journal of Economics 13*(1), 197–205.

Syverson, C. (2004, May). Product Substitutability and Productivity Dispersion. *The Review of Economics and Statistics 86*(2), 534–550.

Syverson, C. (2019, August). Macroeconomics and Market Power: Context, Implications, and Open Questions. *Journal of Economic Perspectives 33*(3), 23–43.

Timmer, M., E. Dietzenbacher, B. Los, R. Stehrer, and G. de Vries (2015). An illustrated user guide to the world input-output database: The case of global automotive production. *Review of International Economics 23*(3), 575–605.

Timmer, M. P., A. A. Erumban, B. Los, R. Stehrer, and G. J. de Vries (2014, May). Slicing up global value chains. *Journal of Economic Perspectives 28*(2), 99–118.

Wang, Z., S.-J. Wei, and K. Zhu (2013, November). Quantifying international production sharing at the bilateral and sector levels. NBER Working Papers 19677, National Bureau of Economic Research, Inc.

A Markup decomposition for an unrestricted conduct parameter

Similar relations to the one described in section 1 can be derived without imposing the restriction of Cournot equilibrium, so for $r \in (-1, N-1)$. Then θ under symmetry becomes:

$$\theta = \frac{1+r}{N^*}\frac{\mu}{\mu-1}. \tag{A.1}$$

In this case μ can be derived as:

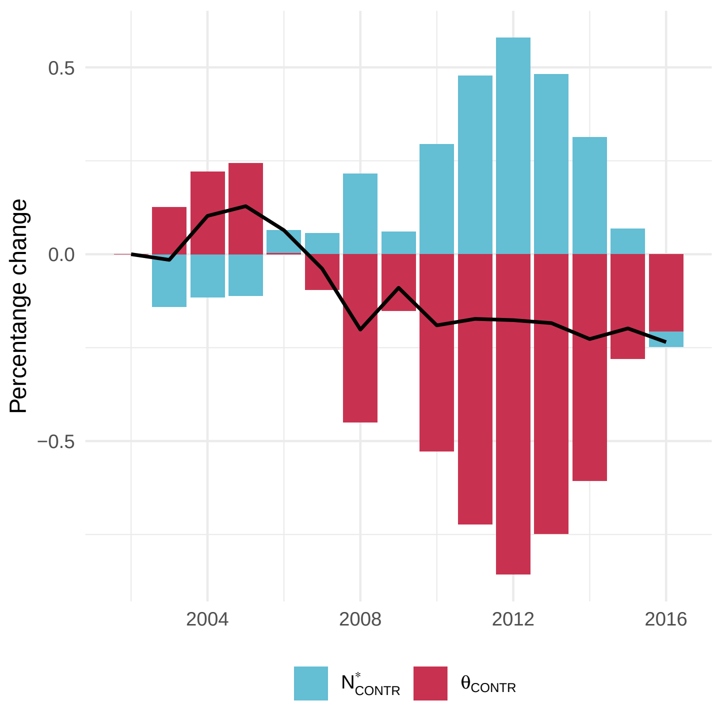
$$\mu_t = \frac{1}{1-\frac{1+r}{N_t^*\theta_t}} = \frac{N_t^*\theta_t}{N_t^*\theta_t-(1+r)}. \tag{A.2}$$

When we assume that the type of equilibrium (r) is time-invariant then μ is still given by $\mu(N_t^*, \theta_t)$ and it can be decomposed in the similar way using a slightly modified version of equation (11):

$$\frac{d\mu_t}{dt} = -\frac{(1+r)\theta_t}{(N_t^*\theta_t-(1+r))^2}\frac{dN_t^*}{dt} - \frac{(1+r)N_t^*}{(N_t^*\theta_t-(1+r))^2}\frac{d\theta_t}{dt}. \tag{A.3}$$

It follows that allowing for non-Cournout equilibrium, when the type of equilibrium is time-invariant, changes the level of θ and adjusts the weights in (A.3). It can be shown that with constant r the decomposition in (A.3) gives the same result as in (11).

Figure A.1: Decomposition of cumulated markup changes



Note: Results of the decomposition of cumulated change (since 2002) in markups (solid line) using Equation (11): blue bars (N^*_{CONTR}) represent a contribution of cumulated change of the number of symmetric firms to cumulated change of markups and red bars (θ_{CONTR}) represent the corresponding contribution of the demand elasticity θ.

B Additional tables

Table B.1: Description and descriptive statistics of the explanatory variables

Description of explanatory variables	
$\mathcal{IMP}^{\mathcal{FD}}_{jt}$	the share of directly imported final goods in final demand of a given industry
$\mathcal{INT}_{jt}$	the share of intermediates in gross output
$\mathcal{EXP}_{jt}$	the share of exports in gross output
$\mathcal{EXP}^{\mathcal{FIN}}_{jt}$	the share of exports of final goods in gross output
$\mathcal{EXP}^{\mathcal{INT}}_{jt}$	the share of exports of intermediates in gross output
$\mathcal{FVAX}_{jt}$	the foreign value added at export calculated with using the method proposed by Wang et al. (2013)
$\mathcal{UPS}_{it}$	the upstreamness index which measures the distance of a given industry from final demand calculated using the method proposed by (Antras et al., 2012)

Descriptive statistics							
	mean	max	min	p25	p5	p75	p95
$\mathcal{IMP}^{\mathcal{FD}}_{jt}$	0.238	0.978	0.002	0.022	0.004	0.408	0.850
$\mathcal{INT}_{jt}$	0.540	0.847	0.193	0.431	0.298	0.655	0.773
$\mathcal{EXP}_{jt}$	0.266	0.940	0.003	0.066	0.006	0.417	0.782
$\mathcal{EXP}^{\mathcal{FIN}}_{jt}$	0.106	0.766	0.000	0.010	0.002	0.113	0.473
$\mathcal{EXP}^{\mathcal{INT}}_{jt}$	0.160	0.594	0.001	0.040	0.003	0.279	0.441
$\mathcal{FVAX}_{jt}$	0.204	0.565	0.048	0.123	0.083	0.273	0.401
$\mathcal{UPS}_{jt}$	2.324	3.523	1.111	1.841	1.250	2.706	3.321

Table B.2: The implied extrema

	θ	μ	θ	μ	θ	μ	θ	μ
$\mathcal{IMP}^{\mathcal{FD}}_{jt}$	0.418***	-0.134	0.546***	-0.102	0.392***	0.032	0.514***	-0.648
	(0.051)	(1.179)	(0.090)	(0.676)	(0.055)	(0.370)	(0.093)	(2.085)
	0.318 - 0.517	-2.444 - 2.177	0.370 - 0.721	-1.428 - 1.224	0.284 - 0.500	-0.693 - 0.757	0.333 - 0.696	-4.735 - 3.439
$\mathcal{INT}_{jt}$	0.694***	0.082	0.720***	-0.000	0.672***	0.253	0.707***	0.081
	(0.069)	(0.205)	(0.075)	(0.281)	(0.087)	(0.195)	(0.097)	(0.358)
	0.560 - 0.829	-0.320 - 0.484	0.572 - 0.868	-0.551 - 0.551	0.500 - 0.843	-0.129 - 0.634	0.517 - 0.896	-0.621 - 0.783
$\mathcal{EXP}_{jt}$	0.446***	0.144**			0.414***	0.117**		
	(0.052)	(0.058)			(0.053)	(0.054)		
	0.345 - 0.548	0.031 - 0.256			0.310 - 0.519	0.012 - 0.222		
$\mathcal{EXP}^{\mathcal{INT}}_{jt}$			0.049	0.185***			-0.639	0.155***
			(0.301)	(0.022)			(3.133)	(0.028)
			-0.542 - 0.639	0.142 - 0.227			-6.781 - 5.502	0.099 - 0.210
$\mathcal{EXP}^{\mathcal{FIN}}_{jt}$			0.486***	6.569			0.469***	-108.146
			(0.067)	(38.816)			(0.062)	(12,483.011)
			0.355 - 0.617	-69.509 - 82.647			0.348 - 0.591	-24,574.398 - 24,358.105
$\mathcal{FVAX}_{jt}$	4.805	0.046	2.505	-0.076	-0.231	0.136***	-0.467	0.071
	(33.482)	(0.050)	(7.667)	(0.110)	(1.086)	(0.049)	(1.963)	(0.085)
	-60.818 - 70.428	-0.053 - 0.144	-12.522 - 17.532	-0.291 - 0.139	-2.360 - 1.897	0.041 - 0.231	-4.315 - 3.380	-0.095 - 0.237
$\mathcal{UPS}_{jt}$	2.089***	1.979***	2.242***	1.934***	2.062***	1.913***	2.228***	1.911***
	(0.088)	(0.090)	(0.122)	(0.082)	(0.099)	(0.084)	(0.134)	(0.083)
	1.917 - 2.262	1.802 - 2.155	2.003 - 2.481	1.773 - 2.095	1.868 - 2.255	1.749 - 2.077	1.965 - 2.490	1.748 - 2.073
Observations	582	582	582	582	582	582	582	582
Industry effects	✓	✓	✓	✓	✓	✓	✓	✓
Time effects					✓	✓	✓	✓

Note: The implied extrema base on estimation results that are reported in table 2. The superscripts ***, ** and * denote the rejection of null about parameters' insignificance at 1%, 5% and 10% significance level, respectively. The expressions in round brackets stand for standard errors which are calculated using delta method. The detailed description of explanatory variables is delegated to table B.1.