The Dynamics of Product and Labor Market Power: Evidence from Lithuania*

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December 21, 2023

Abstract

This paper characterizes the power dynamics of firms in both product and labor markets in Lithuania between 2004 and 2018. We first show that both markets are not perfectly competitive, as both price markups and wage markdowns are far from unitary and homogeneous. Interestingly, we unveil that the dynamics of these margins followed different patterns. On the one hand, both the dispersion and the economy-wide markup have increased, indicative of an increase in product market power. On the other hand, we document a decline in monopsony power, as both the heterogeneity and the aggregate level of markdowns have declined. Altogether, our results underline the importance of jointly analyzing product and labor markets when assessing firms' market power.

Keywords: Firm heterogeneity, Monopoly, Markups, Monopsony, Markdowns

JEL Codes: D4, E2, J3, L1

*We would like to thank seminar participants at the CEFER/KTU/VU workshop, 12th Annual Lithuanian Conference on Economic Research, and Bank of Lithuania seminar participants. The paper uses confidential data provided exclusively by Statistics Lithuania and accessed in a secure environment at the Bank of Lithuania. The views expressed in this paper are those of the authors and do not necessarily reflect the position of the Bank of Lithuania or the Eurosystem. All errors are ours.

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1 Introduction

The rise of firm's product market power is pervasive around the globe (De Loecker et al., 2020; Díez et al., 2021). However, firms can exert market power in both product and labor markets. This is key because the two markets are deeply connected (Dobbelaere and Mairesse, 2013; Yeh et al., 2022), with important welfare implications (Deb et al., 2022, 2023). On the one hand, product market power implies that firms can set prices above marginal costs. Higher prices translate into lower labor demand with potential implications for wages. On the other hand, firms with monopsony power are able to hire workers at wages lower than their marginal revenue of product which has, ultimately, implications for their pricing behavior. Despite their obvious relationship, the joint characterization of firms' power in both the product and labor markets still lacks systematic research. In this paper, we add to this literature by documenting the dynamics of price markups and wage markdowns in Lithuania using detailed firm-level data spanning over 15 years.

The Lithuanian economy provides an interesting environment to jointly analyze the dynamics of both product and labor market power. First, between 2000 and 2020, Lithuanian GDP more than doubled (in real terms) and the number of firms increased dramatically over the same period. The large firm entry has likely increased competition among firms in the product market. Second, accession to the European Union (EU) introduced the free movement not only of goods but also capital and workers. While access to capital was critical to support economic growth, the right to live and work with other EU members led to a wave of mass emigration. This high emigration episode combined with the high firm entry rate, led to a rise in the number of firms per worker, with potential implications for labor market competition and labor costs.

To characterize markups and markdowns in the cross-section and over time for the Lithuanian economy, we rely on a detailed dataset that includes virtually all limited liability companies between 2004 and 2018 and proceed with our analysis as follows. First, we estimate theory-based firm-level markups and markdowns using the production function approach (e.g., de Loecker and Warzynski, 2012; Yeh et al., 2022).

Equipped with these estimates, we document that both markups and markdowns are low relative to available evidence for several developed and emerging economies. The degree of dispersion of markups is similar, if not higher, than existing estimates for certain economies such as the US or France. However, the dispersion of markdowns is lower than the limited evidence in the literature to date, including the US and selected European economies. We find that the cross-sectional dispersion is mainly driven by firm heterogeneity, followed by sectoral composition, while pure time effects play no role. Importantly, our exercise reveals that the dispersion has changed over time: while firm-level heterogeneity of markups has increased between 2004 and 2018, the distribution of markdowns has become less dispersed.

Given the importance of firm heterogeneity, in a second step, we use regression analysis to investigate which firm characteristics contribute to differences in markups and markdowns. For markups, we find that firms with higher market shares (measured by sales or employment) have higher markups. We also find higher markups for firms with some degree of foreign ownership or more labor-intensive ones. However, young producers (firms with less than 5 years of activity) exhibit lower markups. It is interesting to note that producers involved in international trade, i.e., exporters and importers, have lower markups, which are even lower if productivity differences are taken into account. With respect to markdowns, we also find that firms with higher market shares exhibit higher markdowns. As expected, labor-intensive companies have lower markdowns, but half of the differences are likely explained by rent-sharing, as these employers have also higher markups. The regression results also point to young producers having lower markdowns and companies with some level of foreign control having higher markdowns. As for international trade, we observe that both exporters and importers have higher markdowns, but these differences are explained by the input mix since once employment and capital use are taken into account, the difference in markdowns disappears.

Finally, we characterize the macroeconomic implications of firm-level markups and markdowns. We start with a model-based aggregation approach to document the dynamics of aggregate markups and markdowns. We found the aggregate markup in Lithuania increased by about 2% from 2004 to 2018 and, at the same time, the aggregate markdown in the economy declined by 5%. To better understand the markup and markdown at the macro level, we then perform two types of decomposition analyses: (i) between-industry decomposition, as in Olley and Pakes (1996) (hereafter, OP), which allows us to investigate the movements of markups and markdowns across industries, (ii) within-industry decomposition, as in Foster et al. (2001) (hereafter, FHK), which allows us to explore the contribution of firm dynamics to the aggregate evolution of markups and markdowns.

The OP decomposition reveals that average markups across industries have mildly decreased over the past 15 years, but industries with higher markups are gaining weight over time, and this latter force is picking up its momentum toward the end of our sample. For markdowns, the OP decomposition indicates these two forces are moving in the same direction: average markdowns are getting smaller across industries, and industries with lower markdowns are also expanding their share over time. This exercise shows that sectoral reallocation is an important driver of the observed dynamics in the aggregate markup and markdown. For the FHK decomposition, we find that the within component (shift in markup distribution) is driving down aggregate markup while the reallocation component (reallocation of market shares toward firms with higher markups) is pushing up the markup over time. The latter dominates the former toward the end of our sample, driving up the aggregate markup. As for markdowns, the within and the reallocation components impact the aggregate markdown in a similar way as compared to the aggregate markup, except for the fact that their magnitudes are switched. The within term mostly dominates the reallocation force, suppressing the aggregate markdown over time. The composition of firms (entry and exit) only minimally contributes to the evolution of aggregate markups and markdowns.

Our paper adds to several strands of the literature. A large body of research has relied on the production function approach proposed by de Loecker and Warzynski

(2012) to characterize the market power of firms. Most of this literature has focused on product market power by analyzing firm-level price markups or the aggregate counterpart in several developed and developing economies using either raw materials or labor costs indistinctly to identify price markups (e.g., De Loecker and Eeckhout, 2018; García-Perea et al., 2021; de Ridder et al., 2022; Díez et al., 2022; De Loecker et al., 2020; Raval, 2023). Recently, some studies have started to use the production function approach to analyze firm power in the labor market by estimating firm-level wage markdowns but leaving aside the dynamics of product market power (Yeh et al., 2022; Díez et al., 2022). Our paper connects with this literature by analyzing product and labor market power within a unified framework using different sets of inputs to identify price markups and wage markdowns separately.

Our study complements a growing literature that follows a similar approach to ours by jointly investigating markups and markdowns (Dobbelaere and Kiyota, 2018; Brooks et al., 2021; Mertens, 2020; Kirov and Traina, 2023; Aoki et al., 2023; Mertens and Mottironi, 2023). While these studies have mainly used raw materials and wages to recover markups and markdowns, our analysis exploits a composite variable input (materials, energy, electricity, and other goods and services used in production) together with labor costs to apply the production function approach. Thus, we can identify both margins in a similar way for firms operating in very heterogeneous industries. Importantly, our analysis provides both a microeconomic characterization and an aggregate perspective of the dynamics, something that is often absent in existing studies.

Our work is also related to the broader literature that investigates firms' market power based on the production function approach, as discussed above, or using measures of market concentration (e.g., Covarrubias et al., 2020; Azar et al., 2022; Bighelli et al., 2023). Our analysis complements this line of work by looking at a country that featured substantial economic growth following the EU enlargement but where the product and labor markets were differently affected due to the integration of the goods market and the free movement of labor after the accession. In this regard, our work is also related to studies that have used EU enlargement to study the economic implications of integration (Baldwin, 1995; Baldwin et al., 1997; Dustmann and Frattini, 2011; Kennan, 2017; Caliendo et al., 2021). These papers exploit the EU shock to quantify the aggregate and welfare impact of economic integration. In contrast, our study adds to this line of work by characterizing the dynamics of firms' product and labor market power from the EU accession onwards.

Finally, some recent studies have documented firms' market power in Central and Eastern European countries, such as Hungary (Hornok and Muraközy, 2019), Poland (Gradzewicz and Mućk, 2023), and Slovenia (de Loecker and Warzynski, 2012). Our paper adds Lithuania to this list of economies, a country that stands out among the countries analyzed for its unique product and labor market characteristics. On the one hand, the entry of many firms means that they need to compete and innovate to survive in the product market. On the other hand, the decline in the working-age population means that firms also have to compete fiercely for workers. This intensification of competition in both product and input markets makes investigating firm power in Lithuania a particularly interesting case. Noteworthy, we document for the first time the joint dynamics of product and labor market power in CEE economies.

The rest of the paper is organized as follows. Section 2 provides the theoretical background to characterize markups and markdowns. Section 3 introduces the data and the empirical approach to obtain firm-level markups and markdowns as well as their aggregate counterparts. Section 4 documents the cross-sectional distribution of firm-level markups and markdowns, while Section 5 documents the aggregate implications. Section 6 concludes.

2 Markups and markdowns theoretical derivations

Consider an economy with a set of i firms producing goods using $J > 1$ inputs, denoted by the vector $\boldsymbol{X}_{it} = (X^1_{it}, \ldots, X^j_{it})'$. In each year t, firms purchase inputs to produce an output $Q_{it} = F(.)$, provided that their productivity level is equal to Ω_{it}.

Firms may face constraints due to monopsonistic forces or adjustment costs in certain inputs. This leads to the following cost minimization problem

$$\min_{X_{it},\forall j \in J} = \sum_{j=1}^{J} p^{j}_{it}(X^{j}_{it})(X^{j}_{it}) + \Phi^{j}_{t}(X^{j}_{it}, X^{j}_{it-1}) \quad s.t. \quad F(\mathbf{X}_{it};\Omega_{it}) \geq Q_{it}$$

where the function $\Phi^{j}_{t}(.)$ represents adjustment costs, $p^{j}_{it}(.)$ denotes input prices, and Q_{it} is output. In our framework, we consider that the firm produces using only three types of physical inputs: a flexible variable input C_{it}, which does not face adjustment costs or any other imperfection in its market, labor L_{it}, which is subject to monopsonistic forces, and capital K_{it}, which is a fixed input subject to adjustment costs.

To ensure an optimal demand of the flexible input C_{it}, the following first-order condition must be satisfied

$$\frac{p^{c}_{it}C_{it}}{P_{it}Q_{it}} = \frac{\lambda_{it}}{P_{it}} \cdot \frac{\partial F(\mathbf{X}_{it};\Omega_{it})}{\partial C_{it}} \cdot \frac{C_{it}}{Q_{it}} \tag{1}$$

where P_{it} is the output price and λ_{it} is the Lagrange multiplier associated with the output constraint. Additionally, λ_{it} is the marginal cost at the firm level. Therefore, the markup, μ_{it}, can be described as the ratio of output price to marginal cost as follows

$$\mu_{it} \equiv \frac{P_{it}}{\lambda_{it}} = \frac{e^{c}_{it}}{\alpha^{c}_{it}} \tag{2}$$

where $e^{c}_{it} = \frac{\partial F(\mathbf{X}_{it};\Omega_{it})}{\partial C_{it}} \frac{C_{it}}{Q_{it}}$ is the output elasticity of the variable input and $\alpha^{c}_{it} = \frac{p^{c}_{it}C_{it}}{P_{it}Q_{it}}$ is the share of this cost in output. $\mu_{it} > 1$ implies that a firm is pricing above its marginal cost.

Under the assumption that either firms or workers wield some level of market power in the labor market, the resulting monopsony forces constrain labor choices.[1] Consequently, the first-order labor condition is

[1] Labor choices may resemble each other in both monopsony and bargaining models. However, the interpretation varies depending on the model applied (Dobbelaere and Mairesse, 2013; Mertens, 2020). In a monopsony model, the markdown reflects the degree to which firms can reduce wages below competitive levels through the elasticity of labor supply ($\nu_{it} > 1$). In contrast, the markdown in a bargaining model signifies the extent to which workers can increase wages above competitive levels by leveraging their bargaining power ($\nu_{it} < 1$).

$$\frac{p_{it}^{l'}(L_{it})L_{it}}{p_{it}^{l}(L_{it})} + 1 = \frac{\lambda_{it}}{P_{it}} \frac{\partial F(\mathbf{X}_{it};\Omega_{it})}{\partial L_{it}} \cdot \frac{L_{it}}{Q_{it}} \cdot \frac{P_{it}Q_{it}}{p_{it}^{c}(L_{it})L_{it}} \tag{3}$$

The markdowns, ν_{it}, can thus be defined as

$$\nu_{it} \equiv \left(\frac{1}{\mu_{it}}\right) \cdot \frac{e_{it}^{l}}{\alpha_{it}^{l}} \tag{4}$$

where $e_{it}^{l} = \frac{\partial F(\mathbf{X}_{it};\Omega_{it})}{\partial L_{it}} \cdot \frac{L_{it}}{Q_{it}}$ is output elasticity of labor input and $\alpha_{it}^{l} = \frac{p_{it}^{l}(L_{it})L_{it}}{P_{it}Q_{it}}$ is the labor share. $\nu_{it} > 1$ implies that a firm is paying its workers below their marginal revenue product of labor, hence the presence of monopsony power.

If labor and goods markets were perfectly competitive, markups and markdowns would be constant and uniform across firms.[2] To test this hypothesis, we follow de Loecker and Warzynski (2012) to estimate output elasticities in equations (2) and (4) based on firm balance sheet data.

3 Data and measurement

3.1 Firm-level data and sample constraints

Our main data source is an annual survey of enterprises conducted by the Statistical Office of Lithuania from 2004 to 2018.[3] The dataset includes all types of limited liability companies but excludes sole proprietorships or associations, public administration units, and firms involved in financial and insurance activities. As it is mandated by law, the response rate is high, thus the dataset comprises the vast majority of Lithua-

[2]Under perfect competition, the price is fixed at the marginal cost. In other words, the output elasticities will equal the expenditure shares, resulting in markups and markdowns of one.

[3]The full data set is available for the period 1995-2020. However, we concentrate on the time frame between 2004 and 2018 for specific reasons. Initially, after Lithuania's admission to the European Union in 2004, Lithuanian accounting regulations were aligned with European legislation, resulting in a lack of complete comparability between important balance sheet items before 2004 and those in more recent years. Secondly, a reform implemented in 2019 altered the structure of labor costs by shifting the responsibility of social security contributions from companies to employees, the effects of which are not represented in our data. Additionally, we have excluded the year 2020 to mitigate the influence of the Covid-19 pandemic on our estimations.

nia's limited liability companies.[4]

The dataset provides a comprehensive range of information extracted from both balance sheets and income statements such as employment, industry, establishment and liquidation dates, ownership, assets, liabilities, equity, turnover, wage bill, costs of variable inputs (e.g., purchases of services, materials and utilities used in production), profits, and trade data. Furthermore, we used two-digit industry deflators from EU-KLEMS to express our monetary variables in real terms. Specifically, the gross output deflator is used to deflate turnover and profits, while the intermediate inputs deflator is applied to express the cost of variable inputs in real terms. Deflating the capital stock and wage bill is done with the value-added deflator. To obtain the analysis sample, we apply the following restrictions to the dataset.

First, we exclude firms in the primary sector or in education and health because they are underrepresented as these activities are usually carried out by individual firms or public institutions. Similarly, we eliminated the transportation sector due to the numerous legislative changes that occurred during the period and the energy supply sector because it is a highly regulated sector. Second, to prevent the inclusion of companies with misreporting behavior, we eliminate firms that enter and exit the survey. Moreover, we remove firms that consist of only one employee and firms in which the cost share of inputs (variable inputs and labor costs) in total sales is either less than zero or greater than one. Third, we exclude firm-year observations that contain missing, zero, or negative values for sales, fixed assets, wage bill, and variable costs (i.e., all costs that vary directly with the level of output). Finally, we only consider sectors with a minimum of 10 firms per year from 2004 to 2018. To manage outliers in our sample, we use winsorization techniques to adjust the distribution of production function variables (i.e., sales, capital, wage bill, and variable costs) within two-digit industries at the 2nd and 98th percentiles. Our final sample comprises 24,961 firms enlisted in 163,687 firm-year observations between 2004 and 2018. The production

[4]Table A.1 in Appendix A presents an overview of our raw dataset's coverage in terms of the number of firms and employment across various populations.

function variable descriptive statistics are presented in Table 1.[5]

Table 1. Summary statistics

	Mean	Std. Dev.	P10	P50	P90
Sales	1,250,747.13	5,505,491.50	28,337.48	212,769.42	2,550,606.00
Wage bill	196,125.84	605,882.19	7,133.05	43,217.79	448,430.00
Cost of intermediate input	833,256.56	3,954,614.00	10,354.39	112,437.49	1,607,538.25
Capital	456,374.59	4,921,049.00	893.48	21,738.46	489,066.19

Note: Descriptive statistics are computed over the 163,687 firm-year observations corresponding to 24,961 firms observed between 2004 and 2018. All variables are deflated using EU-KLEMS two-digit industry deflators and expressed in logarithms. Revenue corresponds to total sales revenue. Variable input cost refers to the cost of any input that is directly affected by the level of output, e.g., purchase of materials, energy, electricity, and other goods or services used in production. Capital refers to the value of fixed tangible assets.

3.2 Production function estimation

Our goal is to estimate the markups and markdowns of individual firms, denoted μ_{it} and ν_{it} respectively, using the equations (2) and (4). The cost shares of output, α^c_{it} and α^l_{it}, can be calculated directly from the data by taking the ratio of the cost of intermediate inputs and the wage bill over sales, respectively. To estimate the output elasticities, we assume that the productivity component is Hicks neutral and consider a vector of technology parameters, $\boldsymbol{\theta}$, that are constant across time but vary across industries. Thus, we can write the production function as $Q_{it} = \Omega_{it}\tilde{F}(\boldsymbol{X}_{it}; \boldsymbol{\theta})$. In the data, we measure output Q_{it} using firms' total sales revenue, Y_{it}, deflated by their industry-specific gross output deflator.

Let y_{it} stand for the (log) real sales revenue and assume that the data contain potential measurement errors, ϵ_{it}; the model to estimate is as follows

$$y_{it} = \omega_{it} + \tilde{f}(\boldsymbol{x}_{it}; \boldsymbol{\theta}) + \epsilon_{it}$$

where $x_{it} = (c_{it}, l_{it}, k_{it})$ refers to the vector of the real value of each input, expressed in logs.[6] To estimate $\boldsymbol{\theta}$, a simple approach would be to regress the (log) of sales revenue on inputs. However, as productivity levels, ω_{it}, are unobserved this approach would

[5] In Appendix B we document the dynamics of input and profit shares in our dataset.

[6] In the data, the variables refer to the real value of the cost of intermediate inputs, c_{it}, wage bill, l_{it}, and the value of fixed tangible assets, k_{it}.

yield biased estimates (García-Perea et al., 2021; de Ridder et al., 2022). To tackle this issue, we follow the two-step method proposed by Olley and Pakes (1996), relying on the identification strategy outlined in Ackerberg et al. (2015).

In the first stage, we assume that the unobserved productivity is a third-order expansion of the inputs denoted by the function $h(.)$. We then run an OLS on the following specification

$$y_{it} = g_t(\boldsymbol{x}_{it}; \boldsymbol{\theta}) + \epsilon_{it} \tag{5}$$

where $g_t(\boldsymbol{x}_{it}; \boldsymbol{\theta}) = h_t(\boldsymbol{x}_{it}) + \tilde{f}(\boldsymbol{x}_{it}; \boldsymbol{\theta})$.[7] Productivity is then computed as $\omega_{it} = \hat{g}_t - \tilde{f}(\boldsymbol{x}_{it}; \boldsymbol{\theta})$. Note that we eliminate measurement error at this initial stage, but we cannot separate the production function component from productivity, since they both depend on inputs. Therefore, under the assumption that ω_{it} follows an AR(1) Markov process, we construct productivity innovations as $\xi_{it} = \omega_{it} - m(\omega_{it-1})$ and rely on moment conditions for identification.[8] Since productivity innovation should be unaffected by inputs selected before time t, the estimation of θ can be achieved using the following moment conditions

$$\mathbb{E}\left(\xi_{it}(\theta) \begin{bmatrix} \boldsymbol{z}_{it-1} \\ \boldsymbol{k}_{it} \end{bmatrix} \right) = \boldsymbol{0}$$

where z_{it-1} represents an instrument vector including all one-period lagged values of every polynomial term containing c_{it} and l_{it} in the production function $\tilde{f}(\boldsymbol{x}_{it}; \boldsymbol{\theta})$. The value of capital is fixed at its current value as it is assumed to be predetermined and, hence, should be orthogonal to the innovation $\xi_{it}(\theta)$.

[7] In order to adequately correct for the measurement error in the first stage, it is necessary to take into account marginal costs or, more generally, market power. Accordingly, we add the firm's market share as an extra control variable in our model (e.g., De Loecker et al., 2020; Foster et al., 2022; de Ridder et al., 2022).

[8] We assume that $m(.)$ is a third-order expansion of the productivity measure (de Loecker and Warzynski, 2012).

3.3 Empirical firm-level markups and markdowns

To obtain the empirical markups and markdowns, we assume the following translog functional form for the production function[9]

$$\tilde{f}(\boldsymbol{x}_{it};\boldsymbol{\theta}) = \theta_c c_{it} + \theta_l l_{it} + \theta_k k_{it} + \theta_{cc} c_{it}^2 + \theta_{ll} l_{it}^2 + \theta_{kk} k_{it}^2 + \theta_{cl} c_{it} l_{it} + \theta_{ck} c_{it} k_{it} + \theta_{lk} l_{it} k_{it} \quad (6)$$

Following the procedure described above, we estimate θ by GMM separately for each of the 2-digit industries in the data.[10] Using the GMM estimates of equation (6), the firm-level markups are

$$\hat{\mu}_{it} = (\hat{\theta}_c + 2\hat{\theta}_{cc} c_{it} + \hat{\theta}_{cl} l_{it} + \hat{\theta}_{ck} k_{it}) \cdot \frac{\tilde{Y}_{it}}{C_{it}} = \frac{\hat{e}_{it}^c}{\tilde{\alpha}_{it}^c} \quad (7)$$

where $\tilde{Y}_{it} = \exp(y_{it} - \hat{\epsilon}_{it})$ is the measurement-corrected sales and $\tilde{\alpha}_{it}^c = \frac{C_{it}}{\tilde{Y}_{it}}$ is the variable input costs over corrected sales revenue. The firm-level markdowns are

$$\hat{\nu}_{it} = \left(\frac{\hat{\theta}_l + 2\hat{\theta}_{ll} l_{it} + \hat{\theta}_{cl} c_{it} + \hat{\theta}_{lk} k_{it}}{\hat{\mu}_{it}} \right) \cdot \frac{\tilde{Y}_{it}}{L_{it}} = \left(\frac{1}{\hat{\mu}_{it}} \right) \cdot \frac{\hat{e}_{it}^l}{\tilde{\alpha}_{it}^l} \quad (8)$$

where $\tilde{\alpha}_{it}^l = \frac{L_{it}}{\tilde{Y}_{it}}$ is the share of labor costs on corrected sales.

4 Markups, markdowns, and heterogeneous firms

In this section, we investigate the heterogeneity of markups and markdowns. In subsection 4.1, our analysis begins by examining the distribution over time and in the

[9] Alternatively, we could adopt a Cobb-Douglas production function. However, output elasticities in the Cobb-Douglas case are constant for firms in the same industry. Therefore, time variation would occur exclusively through changes in input shares, omitting differences in input utilization in production between firms. Moreover, recent work on markup estimation with revenue data indicates that the biases that emerge when using a Cobb-Douglas specification are more salient compared to a translog production function (de Ridder et al., 2022).

[10] After implementing the estimation, some firms exhibit negative elasticities, we exclude firm-year observations when this is the case for output elasticity with respect to the variable input and labor. Moreover, we account for outliers in the distribution of markups and markdowns by winsorizing their components at the 2% of the tails of the industry-specific distributions. We follow this indirect approach because we are ultimately interested in understanding the contribution of each component to the dispersion. Thus, this approach allows us to maintain consistency when decomposing the variance of markups and markdowns into their components.

cross-section, while in subsection 4.2, we examine the correlation between firm-level markups and markdowns with firm-level characteristics.

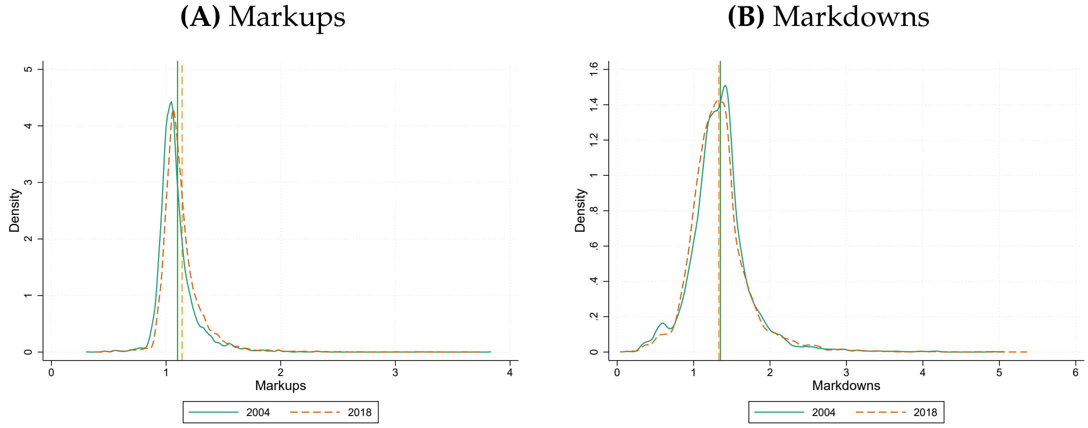
4.1 Distribution of markups and markdowns

Figure 1 plots the translog estimates of markups for the first and last year in the sample. Panel A shows that, in 2004, the average (median) markup was of 1.09 (1.05), implying that the average firm pays 92 cents on the marginal revenue earned. The numbers for 2018 point to an average (median) markup equal to 1.14 (1.09), implying that the average firm pays 88 cents on the marginal revenue earned. These figures indicate the existence of market power in the product market, as if all firms were in perfect competition, markups would be equal to unity for all. Importantly, the method to estimate markups via the production function approach that relies on revenues, rather than output, may result in biased estimates of the true level of markups (Bond et al., 2021), with the direction of the bias depending on the relationship between prices and inputs (de Ridder et al., 2022).[11] Bearing this in mind, our estimates are lower than those found in the existing literature. For instance, evidence on Slovenian manufacturing firms presented in de Loecker and Warzynski (2012) shows median firm-level markups ranging from 1.17 to 1.28. Garcia-Marin and Voigtländer (2019) report firm-level mean and median markups of 1.49 and 1.25 for Chilean manufacturing firms, while a median markup of 1.78 is estimated for the Colombian manufacturing sector in Tortarolo and Zarate (2018). de Ridder et al. (2022) find that the logarithm of firm-level markups for manufacturing firms in France was estimated to be 0.29 on average and 0.21 for the median. In our sample, these estimates correspond to 0.09 and 0.06, respectively.

Markdowns are computed using the ratio of output elasticities as denoted in equation (4), which eliminates the inherent bias when employing revenue data instead of quantity data (Yeh et al., 2022). Nonetheless, in cases where the number of non-

[11] For instance, in the absence of time effects, the correlation is negative, which would lead to an underestimation of the actual level.

Figure 1. Dispersion of markups and markdowns



Note: The vertical lines in the graph depict the average markup (markdowns) for selected years, i.e., 2004: 1.09 (1.05) and 2018: 1.14 (1.33).

production workers exceeds production workers, a distinct bias may arise. A potential consequence of this situation is that a substantial portion of the workforce may concentrate on driving demand rather than contributing to the final product (Bond et al., 2021). However, our findings in Figure 1 Panel B suggest that, despite this potential drawback, the average markdown in 2004 was 1.35 (1.32 for the median), while by 2018, the average (median) markdown decreased to 1.33 (1.30). These figures imply that Lithuanian workers earn about 75 cents on the marginal revenue product of labor. For comparison, data from Yeh et al. (2022) show that the US economy experienced an average markdown of 1.53 (1.36) from 1976 to 2014. Additionally, Díez et al. (2022) report an average markdown of 1.83 (1.58) for selected European economies including Austria, Belgium, Germany, Spain, Finland, France, Italy, Norway, Portugal, and Sweden from 2000 to 2017.

Although there might be bias in the level of markups and markdowns, the dispersion is consistently recovered, as the bias remains constant across firms (de Ridder et al., 2022). The densities in Figure 1 reveal a significant degree of dispersion in both markups and markdowns in the Lithuanian economy, again pointing to the existence of both product and labor market power. Moreover, the evidence also indicates that while the dispersion of markups has increased over time, the opposite is true in the case of markdowns, which suggests that different patterns took place. To better understand the observed dispersion, we pool the data and analyze the variance of (log) markups and markdowns by identifying differences among sectors, over time, and across firms between 2004 and 2018. To do this, we estimate a linear model in which we regress (log) markups or markdowns on sector and year-fixed effects and obtain the point estimates of these effects as well as the residuals. We then use these components to decompose the objects of interest as follows

$$var(y_{i(s,t)}) = var(\hat{\delta}_s) + var(\hat{\lambda}_t) + var(\hat{\epsilon}_{i(s,t)}) + 2 \times cov(\hat{\delta}_s, \hat{\lambda}_t) \tag{9}$$

where $y_{i(s,t)}$ represents the (log) markup or markdown of a firm i operating in sector s in year t, $\hat{\delta}_s$ corresponds to estimated sector fixed effects capturing permanent heterogeneity across sectors, and $\hat{\lambda}_t$ refers to year-fixed effects measuring *pure* time differences in markups or markdowns. $\hat{\epsilon}_{i(s,t)}$ represents firm-level markups or markdowns once sector and time components are accounted for.

Table 2 shows the total variance of markups and markdowns and the contribution of firms, sectors, and time to the dispersion.[12] The results suggest a relatively low dispersion of markups relative to markdowns. The apparently low level of markup dispersion in Lithuania is similar to the evidence for the US economy (Yeh et al., 2022) or Slovenian manufacturing firms (de Loecker and Warzynski, 2012), but higher compared to France (de Ridder et al., 2022). Conversely, we find that the dispersion of markdowns in Lithuania is about half of the existing evidence for the US (Yeh et al., 2022), and it is also lower than the dispersion reported by Díez et al. (2022) for a selected set of European economies.

Regarding the role of sectors, time, and firms in the dispersion of markups and markdowns, we document that most of the total observed dispersion is driven by firm heterogeneity. Specifically, we find that the dispersion in residualized markups and markdowns accounts for 68 and 76% of the observed dispersion, respectively, while the remainder is explained by differences across industries. Interestingly, the dispersion of the time effects, as well as the contribution of the covariance between sector

[12]We do not report the covariance term because its magnitude is minimal and it can be obtained as the difference between the total dispersion and the dispersion across sectors, time, and firms.

Table 2. Sectors, time, and firms in the variance of markups and markdowns

	Markups	Markdowns
Total dispersion	0.022	0.084
across sectors	0.006	0.021
across time	0.000	0.000
across firms	0.015	0.064

Note: Variance decomposition of (log) firm-level markups and markdowns based on the equation (9). The industry-specific distributions of markups and markdowns are winsorized at the 2% tails of their components. Sectors correspond to 53 two-digit NACE2 industries.

and time effects, is quantitatively zero, pointing to the importance of firm composition in driving both markups and markdowns. In Appendix C, we perform a variance decomposition for selected subperiods to quantify the contribution of the components to the overall dispersion of markups and markdowns. The results reveal that there is substantial heterogeneity in both input shares and output elasticities across firms, and that these components move in opposite directions, resulting in less dispersion of markups and markdowns than the one observed in their components. This result reinforces the importance of firm heterogeneity in the distribution of markups and markdowns in our context.

4.2 Firm-level heterogeneity

The findings discussed above suggest that firm heterogeneity plays a crucial role in the dispersion of both markups and markdowns. To better understand this heterogeneity, we correlate markups and markdowns with various sets of firm characteristics, as follows

$$y_{it} = \alpha + \beta D_{it} + \lambda_{st} + \epsilon_{it} \tag{10}$$

where y_{it} represents either the (log) markups, μ_{it}, or markdowns, ν_{it}, of firm i in year t. D_{it} is an indicator variable that identifies specific characteristics of firms under consideration, such as market power, labor share, age, international trade participation, or foreign ownership. Therefore, the coefficient β tells the difference in markups (or markdowns) between a given set of companies relative to the benchmark category that we define according to a specific firm-level characteristic.[13] However, it should be noted that these regressions do not allow for causal inference. The industry$\times$year fixed effects, denoted by λ_{st}, capture the unobserved shocks at a detailed industry level, such as demand shocks. ϵ_{it} is the error term.

The approach to estimating markups and markdowns also allows us to recover firm-level productivity, ω_{it}, from the estimation of the production function (see the discussion in section 3.2). We find a strong positive correlation between (log) firm-level markups and (log) firm-level TFP (see Figure A.1 in Appendix A.). In contrast, there is no clear correlation between firm-level markdowns and TFP, as shown in Figure A.2 in Appendix A. We therefore include these productivity estimates as an additional control in our regressions, considering that it is a possible driver of firm differences in markups and markdowns. Including productivity allows the coefficient β to reflect price (wage) differences across firms by accounting for differences in marginal cost or marginal productivity of labor (de Loecker and Warzynski, 2012).[14]

Moreover, as shown in equation (8), markdowns also embed differences in markups across firms. Therefore, when examining heterogeneous markdowns across firms, we also include estimated firm-level markups in our regressions to account for their relationship. For example, firms with high product market power may share rents with their workers to a greater extent (Mertens, 2022; Aoki et al., 2023), resulting in a negative relationship between markups and markdowns, which may bias the correlation between markdowns and other idiosyncratic factors of the firm. This negative correlation also holds in our context as well (see Figure A.3 in Appendix A) and, hence, we directly address this source of heterogeneity in our regressions.

We begin by discussing firm heterogeneity in markups along selected dimensions

[13]Note that for this regression to be informative about the relative difference in markups between two types of companies, the bias that arises due to the use of revenue data should be equal between the two groups.

[14]Since our TFP estimates are based on revenues, they do not map one-to-one with changes in marginal cost/productivity, but also represent the influence of demand conditions and market power (Foster et al., 2008).

in Table 3. The regression results show that firm-level markups increase with the firm's sales market share in the sector, a proxy for market power, consistent with oligopolistic competition models (e.g., Atkeson and Burstein, 2008).[15] Controlling for firm-level productivity, the uncovered correlation drops by 70%, suggesting that a substantial part of the markup differences among firms with higher market shares is due to higher productivity (potentially lower marginal costs). In other words, there is a positive bias in the simple correlation between market share and markups associated with efficiency differences among producers. We document a similar pattern when looking at the employment share of firms in a given sector, with markups decreasing by about 25% once firm-level productivity differences are taken into account. We also find a positive correlation between the share of labor in the firm (labor costs as a percentage of sales) and trade margins, which remains virtually unchanged when we control for productivity differences, suggesting that labor-intensive firms have higher markups.

Young firms, those less than 5 years in activity, have lower markups (regardless of productivity differences), consistent with models of firm dynamics and heterogeneous margins that suggest increasing markups over the life cycle of a producer (e.g., Peters, 2020). An alternative, albeit complementary, explanation for the lower markups for young firms could be that firm age picks up firm size (Haltiwanger et al., 2013). Thus, we also run the regression of markups on firm age controlling for size, and the negative relationship almost halves, suggesting that some of the effect is related to firm size.

Concerning international trade, we find lower markups for both exporters and importers. This contradicts, for example, findings in the literature pointing to higher markups for exporters (e.g., de Loecker and Warzynski, 2012; Tortarolo and Zarate,

[15] Mertens and Mottironi (2023) document a negative correlation between markups and sales for several European countries, including Lithuania. It is important to note that there are several differences between their study and our analysis. First, we use actual firm-level data and a translog production function, while their study is based on industry-level data and Cobb-Douglas estimates. Second, we use all firms in Lithuania between 2004 and 2018, while they focus on firms with at least 20 employees from 2000 to 2019. Third, we focus on firms with some market share, so we proxy for market power, and correlate it with (log) markups, while the other study correlates (log) median firm size in the sector, regardless of firms' market shares, with (log) median markups in that sector. In our sample, the correlation between (log) markups and (log) sales, conditional on year and industry fixed effects, is -0.005 (0.0006) and becomes 0.006 (0.0006) when markdowns are included as an additional control. Thus, the direction (and change) of the correlations is similar in both studies but weaker in our case.

Table 3. Firm-level markups and idiosyncratic factors

	Model 1		Model 2	
D_{it}	Coeff.	Std. Err.	Coeff.	Std. Err.
Sector's sales share $> 10\%$	0.069	0.018	0.018	0.014
Sector's employment share $> 10\%$	0.046	0.025	0.034	0.018
Firm's labor share $> 50\%$	0.085	0.004	0.080	0.004
Firm's age < 5years	-0.009	0.001	-0.008	0.001
Exports share of sales $> 10\%$	-0.009	0.002	-0.016	0.002
Imports share of sales $> 10\%$	-0.004	0.002	-0.014	0.002
Foreign ownership	0.013	0.002	0.010	0.002

Note: Each row corresponds to a separate regression of firm-level (log) markups, μ_{it}, on the selected variable of interest, D_{it}, as specified in equation (10). Model 2 extends Model 1 to include firm-level productivity, ω_{it}, as additional control. The distributions of markups is winsorized through their components at the 2% of the tails of the industry-specific distributions. All models control for industry$\times$year fixed effects. Standard errors are clustered at the firm level. In Model 2, the standard errors are computed using wild cluster bootstrap with 80 repetitions Cameron et al. (2008).

2018), but is consistent with evidence for Hungary pointing to no markup premium for exporters (Hornok and Muraközy, 2019). However, it is important to note that differences in markup levels are sensitive to the inputs used to calculate markups, and as shown by Doraszelski and Jaumandreu (2019), markups are lower for exporters when materials are used. These differences can be explained by the potential negative correlation between labor and material markups reported in Raval (2023) for several firm-level datasets (Chile, Colombia, India, Indonesia, Southern Europe, and a major US retailer). Importantly, our results suggest that producers who participate in international trade are more productive than those who do not, as controlling for firm-level productivity results in these firms having even lower markups.

Interestingly, we find that firms with some degree of foreign ownership have slightly higher markups, and these differences do not seem to be driven by heterogeneous productivity levels. This finding is broadly consistent with existing evidence[16]. For example, Muraközy and Russ (2015) find that the markups of foreign-owned firms are generally higher than those of domestic firms, especially greenfield FDI firms. Keller and Yeaple (2020) also find that US multinational firms charge higher markups than domestic firms.

[16]Our results differ from those in Dobbelaere and Kiyota (2018), who find a negative correlation between firm-level markups and foreign ownership status. This is not surprising because the aggregate markup in Japan is declining (Aoki et al. (2023)) and the MNEs in Japan are also more engaged in services in their study.

Table 4 reports point estimates reflecting the correlation between firm-level markdowns and firm characteristics. Similar to the case of markups, we find that markdowns increase with a firm's market share in an industry, whether measured by sales or employment. This suggests a link between concentration and employers' labor market power, i.e. the ability of firms to set wages below the marginal revenue product of labor (Marinescu et al., 2021; Azar et al., 2022; Yeh et al., 2022). Unlike for markups, this correlation does not change significantly when we include our estimate of firm-level productivity. Interestingly, we find that the correlation between market shares increases when heterogeneous markups are included, with the increase being larger when market shares are based on employment rather than sales. These observed changes in correlations once we control for the level of markups are consistent with a rent-sharing story: firms with high markups share more of their profits with their employees (Dobbelaere and Mairesse, 2013; Mertens, 2022; Aoki et al., 2023). In other words, given that markups increase with market concentration, the markdown differential increases once we account for the fact that wages tend to be higher for workers in firms with high markups. A similar pattern emerges for firms with a high labor share: while they have significantly lower markdowns (-0.208), this difference is halved once markups are taken into account (-0.109).

Table 4. Firm-level markdowns and idiosyncratic factors

	Model 1		Model 2		Model 3	
D_{it}	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Sector's sales share $>$ 10%	0.155	0.035	0.167	0.035	0.177	0.034
Sector's employment share $>$ 10%	0.131	0.041	0.134	0.040	0.190	0.039
Firm's labor share $>$ 50%	-0.208	0.006	-0.207	0.006	-0.109	0.003
Firm's age $<$ 5years	-0.047	0.002	-0.047	0.002	-0.057	0.002
Exports share of sales $>$ 10%	0.072	0.006	0.074	0.006	0.054	0.006
Imports share of sales $>$ 10%	0.090	0.006	0.093	0.006	0.075	0.006
Foreign ownership	0.038	0.005	0.038	0.005	0.052	0.005

Note: Each row corresponds to a separate regression of firm-level (log) markdowns, ν_{it}, on the selected variable of interest, D_{it}, as specified in equation (10). Model 2 extends Model 1 to include firm-level productivity, ω_{it}, as additional control, while Model 3 further adds (log) firm-level markups, μ_{it}. The distributions of markups and markdowns are winsorized through their components at the 2% of the tails of the industry-specific distributions. All models control for industry$\times$year fixed effects. Standard errors are clustered at the firm level. In Model 2 and 3, the standard errors are computed using wild cluster bootstrap with 80 repetitions Cameron et al. (2008).

Regarding firm age, the regression analysis shows that younger firms have lower markdowns. As noted above, firm age may partly reflect differences in size (employment). Similar to the case of markups, the coefficient on age decreases when we control for employment at the firm level, but the decrease is much larger, i.e., the difference in markdowns between young and mature firms goes from -0.047 to -0.011. Yeh et al. (2022) for the US and Díez et al. (2022) for a selected set of European countries report estimates for differences in markdowns across firm age net of firm size that are consistent with our findings.

In contrast to the case of markups, our results show that both exporters and importers have higher markdowns, regardless of productivity differences. These differences in markdowns are reduced when we include markup heterogeneity in the regression, with markdowns 24 and 17% lower for exporters and importers, respectively.[17] Importantly, once we control for labor and capital use at the firm level, the differences in markdowns are reversed, leading to slightly lower markdowns in these firms. This can be explained, for example, by the fact that large firms have stronger bargaining power (e.g., Autor et al., 2020) or by a higher degree of automation in these firms, which affects the wage-setting process (e.g., Acemoglu et al., 2020) and can explain the lower labor share observed in these firms. Thus, the observed higher markdowns for exporters and importers seem related to the underlying differences between producers who engage in international trade and those who do not. Once this heterogeneity is accounted for, wage markdowns are lower, consistent with traders paying higher wages to their workers (e.g., Macis and Schivardi, 2016; Frías et al., 2022).

Looking at firms with some foreign ownership, we find that these firms have higher markdowns. In addition, firm-level productivity differences do not change the uncovered correlation. However, as expected given our results from the regression of markups, these correlations become stronger once we control for differences in markups across firms. This is not surprising given the wage premiums among foreign-owned firms (e.g., Egger et al., 2018; van der Straaten et al., 2020), suggesting a similar rent-sharing story as discussed in the case of exporters. In addition, the higher wage-setting

[17] The positive bias in the correlation between markdowns and international trade status is due to both the negative correlation between markups and markdowns and the negative correlation between markups and international trade status conditional on productivity levels documented in Table 3.

power of MNEs may also contribute to the higher markdowns observed for these firms (Dobbelaere and Kiyota, 2018).

5 Economy-wide markups and markdowns

So far, we have characterized markups and markdowns at the firm level, identifying their dispersion and the variables that affect it. In this section, we analyze the aggregate dynamics of both markups and markdowns.[18]

5.1 Aggregation approach

To compute aggregate measures of markups and markdowns, we follow Edmond et al. (2022) and Yeh et al. (2022). For each industry j, we apply the empirical counterpart of the first-order condition (2), which yields the following definitions for $\mathcal{M}_t$ and $\mathcal{V}_t$

$$\hat{\mu}_{it} \equiv \frac{\hat{e}^c_{it}}{\hat{e}^c_{jt}} \cdot \frac{\tilde{Y}_{it}}{\tilde{Y}_{jt}} \cdot \frac{C_{jt}}{C_{it}} \cdot \mathcal{M}_{jt}$$

Let us define that $C_{jt} = \sum_{i,j \in \mathcal{J}_t} C_{it}$, where $\mathcal{J}_t(j)$ is the set of i firms in the j-th industry. By summing over the i firms and rearranging, we can obtain the markups of the j industries as

$$\begin{aligned} \mathcal{M}_{jt} &= \left(\sum_{i,j \in \mathcal{J}_t} \frac{\hat{e}^c_{it}}{\hat{e}^c_{jt}} \cdot \frac{\tilde{s}_{it}}{\hat{\mu}_{it}} \right)^{-1} \\ &= \hat{e}^c_{jt} \cdot \frac{\tilde{Y}_{jt}}{C_{jt}} \end{aligned} \tag{11}$$

[18] Importantly, while estimates based on (deflated) sales data will not be indicative of the actual level of markup (or markdown), they are informative about their dynamics (see de Ridder et al., 2022, for a detailed discussion of these issues).

where $\tilde{s}_{it} = \frac{\tilde{Y}_{it}}{\tilde{Y}_{jt}}$ is a firm's total sales relative to its industry (corrected of the measurement errors).[19] For a year t, the aggregate markups are then computed as

$$\mathcal{M}_t = \sum_{j}^{J} w_{jt}\mathcal{M}_{jt} \tag{12}$$

where w_{jt} represents the industry weights that measure firm's market shares based on sales or input costs. To aggregate markdowns at the industry level, we follow this process

$$\begin{aligned}\mathcal{V}_{jt} &= \frac{\sum_{i,j\in\mathcal{J}_t} \frac{\hat{e}^c_{it}}{\hat{e}^c_{jt}} \cdot \frac{\tilde{s}_{it}}{\hat{\mu}_{it}}}{\sum_{i,j\in\mathcal{J}_t} \frac{\hat{e}^l_{it}}{\hat{e}^l_{jt}} \cdot \frac{\tilde{s}_{it}}{\hat{\nu}_{it}\hat{\mu}_{it}}} \\ &= \frac{\hat{e}^l_{jt}}{\hat{e}^c_{jt}} \cdot \frac{C_{jt}}{L_{jt}}\end{aligned} \tag{13}$$

where $L_{jt} = \sum_{i,j\in\mathcal{J}_t} L_{it}$ is the industry labor costs. The economy-wide markdown is then computed following the same logic as for the markup. Formally,

$$\mathcal{V}_t = \sum_{j}^{J} w_{jt}\mathcal{V}_{jt} \tag{14}$$

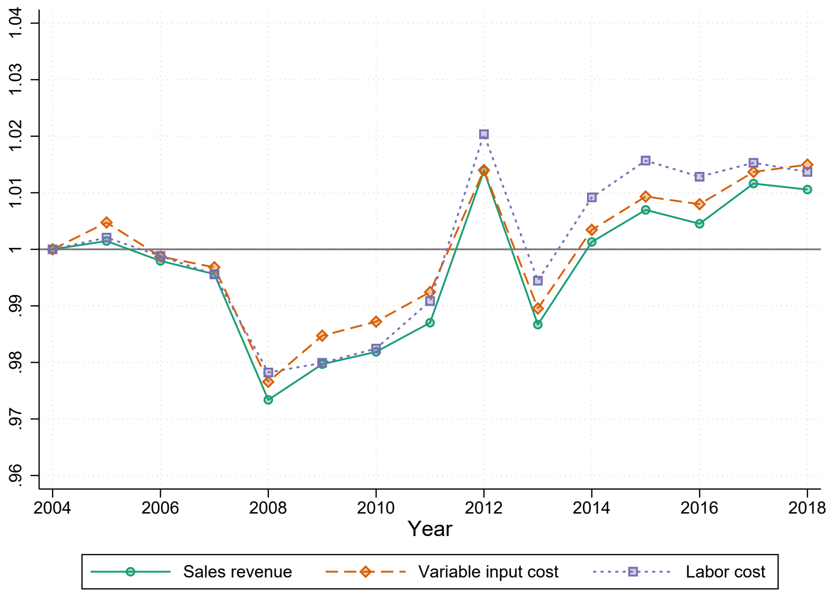
5.2 The dynamics of aggregate markups and markdowns

Figure 2 shows the evolution of the aggregate markup relative to its baseline in 2004. It decreased from 2004 to 2008, remained stable afterward, and then ultimately increased. Over the entire period, the aggregate markup increased by about 2%. In contrast, De Loecker et al. (2020) use balance sheet data and document a sales-weighted aggregate markup of 1.18 in 1980 and 1.67 in 2014 for the US. Using data from 134 countries, De Loecker and Eeckhout (2018) report a steady increase in the worldwide average markup from 1.17 in 1980 to 1.60 in 2016. The reported figures for Europe

[19]To simplify our analysis, we adopt the approach of using harmonic averages for markups and markdowns, as suggested by Yeh et al. (2022). This sales-weighted firm-level harmonic average of markups has the same theoretical basis as the cost-weighted arithmetic average of firm-level markups (see Edmond et al. (2022) for further details).

point to an increase of approximately 1.40 to 1.60 over a period comparable to ours (2004-2016). Similarly, based on data from 19 advanced economies, Díez et al. (2021) find that the sales-weighted aggregate markup increased from 1.22 to 1.29 between 2000 and 2015.[20] The specific numbers for Spain reported in García-Perea et al. (2021) indicate that markups increased by roughly 6% between 2004 and 2017, with a sharp increase during the GR driven by small firms. Finally, Aoki et al. (2023) report a slight decrease of 1% in the aggregate markup in Japan between 2005 and 2020.

Figure 2. Aggregate markup trends



Note: The aggregate markup is computed as specified in subsection 5.1. Each line corresponds to alternative NACE2-level weights used in the last step of the aggregation process described in equation (12). Each series is normalized to its 2004 (base) value.

Overall, the rise in the aggregate markup we documented for Lithuania was thus relatively small compared to other countries. Put differently, despite the strong input adjustments resulting from the GR, the overall product market power of Lithuanian firms remained relatively stable between 2004 and 2018. To better comprehend this trend, we decompose the aggregate markup into its two components, the variable input share and the output elasticity (see equation (11)). This is done by computing a

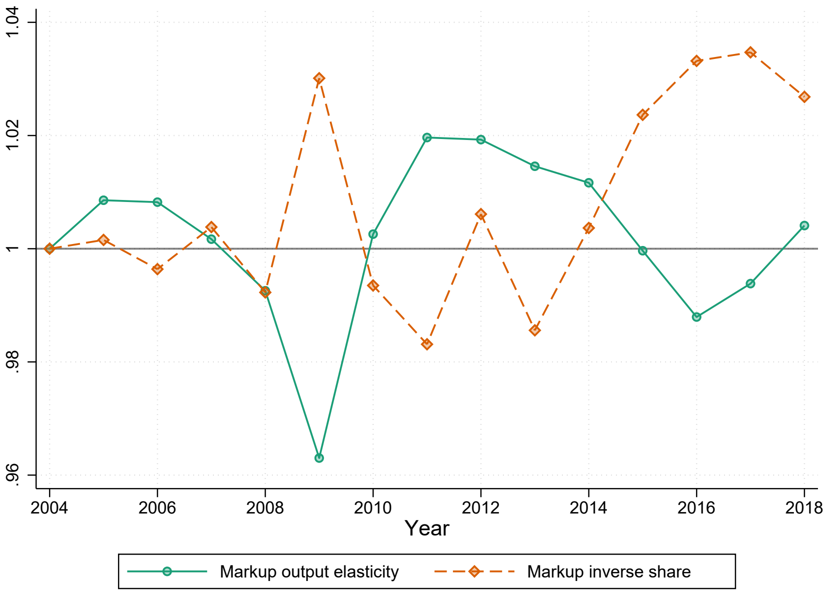
[20]The countries included in this set are Belgium, Bulgaria, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Great Britain, Greece, Italy, Japan, Korea, Latvia, Portugal, Romania, Russia, Spain, and the United States.

linear approximation around the industry average of the components, as follows

$$\begin{aligned} \mathcal{M}_{jt} &= \hat{e}^c_{jt} \cdot \varphi^c_{jt} \\ &\approx \underbrace{\hat{e}^c_{jt}\bar{\varphi}^c_{j.}}_{\mathcal{M}^{\hat{e}}_{jt}} + \underbrace{\bar{e}^c_{j.}\varphi^c_{jt}}_{\mathcal{M}^{\varphi^l}_{jt}} - \underbrace{\bar{e}^c_{j.}\bar{\varphi}^c_{j.}}_{\bar{\mathcal{M}}_{j.}} \end{aligned} \tag{15}$$

where $\varphi^l_{jt} = \frac{\tilde{Y}_{jt}}{C_{jt}}$ is the inverse of the share of variable inputs in sales. The first counterfactual markup, $\mathcal{M}^{\hat{e}}_{jt}$, captures changes in the markup due to variations in the output elasticity while holding the inverse share of variable inputs in sales at its period average. Similarly, the second counterfactual markup, $\mathcal{M}^{\varphi^c}_{jt}$, tracks changes in the markup due to variations in the inverse share of variable inputs in sales while holding the output elasticity fixed at its period average. Figure 3 displays the two counterfactual

Figure 3. Counterfactual markups



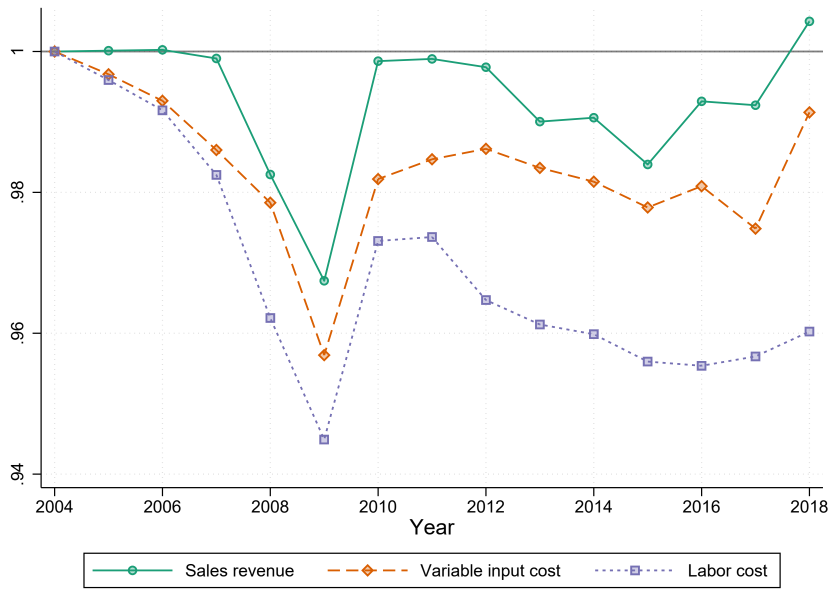
Note: The calculation of counterfactual aggregate markups, weighted by variable input shares, follows the procedure described in equation (15). "Markup output elasticity" refers to $\mathcal{M}^{\hat{e}}_{jt}$ and "Markup inverse share" to $\mathcal{M}^{\varphi^c}_{jt}$. Each series is normalized to its 2004 (base) value.

aggregate markups.[21] Amid the GR in 2009, these markups presented divergent dynamics. The counterfactual markup based on variations in the inverse input share,

[21]We weight the counterfactual markups and markdowns shown in Figures 3 and 5 by input costs rather than sales, as the theory advocates to account for distortions related to input choices (Edmond et al., 2022).

increased significantly as variable inputs declined more than sales (see Figure B.1 in Appendix B). In contrast, the counterfactual markup based on variations in output elasticity decreased significantly, indicating significant technological changes.[22] The difference between these two counterfactuals emphasizes the importance of applying the translog production function due to the pronounced shifts in output elasticity over the sample. Using a Cobb-Douglas function would have led to biased estimates of markup increases during the GR period and overestimated growth from 2014 to 2018 (see Figure A.4 in Appendix A).[23]

Figure 4. Aggregate markdown trends



Note: The aggregate markdown is computed as specified in subsection 5.1. Each line corresponds to alternative NACE2-level weights used in the last step of the aggregation process described in equation (12). Each series is normalized to its 2004 (base) value.

Figure 4 displays the evolution of the aggregate markdown compared to its level in 2004. The labor cost-weighted aggregate markdown declined gradually until the onset of the GR, followed by a sudden adjustment from 2009 to 2011. From 2012 to 2018, it continued to decrease steadily, reflecting the rise in the aggregate labor share (see Figure B.1 in Appendix B). The dynamics contrast with existing findings. For example, Yeh et al. (2022) examine the long-term dynamics of wage markdowns in

[22]Such procyclicality in aggregate markup contrasts with typical prediction in New Keynesian models (Nekarda and Ramey, 2020).

[23]For a Cobb-Douglas, the output elasticity with respect to the variable input is a constant (see equation (2)).

US manufacturing firms and document an increase of 10% (20%) between 1977 and 2012 (2002 and 2012). Following a comparable method, Díez et al. (2022) report that for a selected set of European countries, the aggregate labor cost-weighted markdown increased by 1.3% between 2000 and 2017, and by a similar amount when comparing 2008 and 2017.[24] Aoki et al. (2023) find that the aggregate markdown for Japanese firms increased by about 10% between 2005 and 2020, although the increase was larger for non-manufacturing firms than for manufacturing firms (15% vs. 7% increase).

The decrease in labor cost-weighted aggregate markdown in Lithuania signals a decline in monopsony power, likely due to intensified competition among firms seeking to attract workers amidst a shrinking labor pool. This is consistent with the higher labor market competition observed in Lithuania between 2000 and 2020, documented by Garcia-Louzao and Ruggieri (2023) through the analysis of firms' labor supply elasticities, and aligns with evidence pointing to *excess* wage growth associated to labor market tightness in Lithuania between 2008 and 2020, as reported in Garcia-Louzao and Jouvanceau (2023).

The trends in aggregate markdown in Lithuania can be better comprehended by decomposing it into two components, similar to the approach used for the aggregate markup. This is achieved by deriving a linear approximation around the industry averages as follows

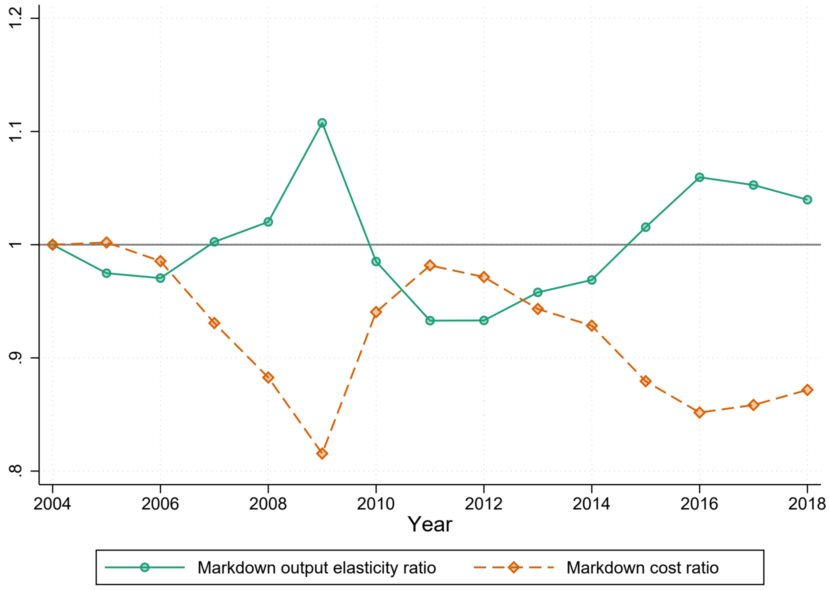
$$\begin{aligned}\mathcal{V}_{jt} &= \frac{\hat{e}^l_{jt}}{\hat{e}^c_{jt}} \cdot \frac{C_{jt}}{L_{jt}} \\ &\approx \underbrace{\varepsilon_{jt}\bar{\varphi}_{j.}}_{\mathcal{V}^{\varepsilon}_{jt}} + \underbrace{\bar{\varepsilon}_{j.}\varphi_{jt}}_{\mathcal{V}^{\varphi}_{jt}} - \underbrace{\bar{\varepsilon}_{j.}\bar{\varphi}_{j.}}_{\bar{\mathcal{V}}_{j.}} \end{aligned} \tag{16}$$

where $\varepsilon_{jt} = \frac{\hat{e}^l_{jt}}{\hat{e}^c_{jt}}$ is the ratio of output elasticities for variations in labor and variable input expenses, and $\varphi_{jt} = \frac{C_{jt}}{L_{jt}}$ is the cost ratio between variable input and labor expenses. The first counterfactual markdown, $\mathcal{V}^{\varepsilon}_{jt}$, reflects markdown changes due to variations in the elasticity ratio while holding the cost ratio at its period-average value. The sec-

[24] The countries are Austria, Belgium, Germany, Spain, Finland, France, Italy, Norway, Portugal, and Sweden.

ond counterfactual markup, $\mathcal{V}_{jt}^{\varphi}$, tracks markdown changes due to variations in the cost ratio while fixing the elasticity ratio at its period-average value.

Figure 5. Counterfactual markdowns



Note: The calculation of counterfactual aggregate markdowns, weighted by labor cost shares, follows the procedure described in equation (16). The term "Markdown output elasticity ratio" denotes $\mathcal{V}_{jt}^{\varepsilon}$ while the term "Markdown cost ratio" refers to $\mathcal{V}_{jt}^{\varphi}$. Each series is normalized to its 2004 (base) value.

Figure 5 shows the two counterfactual markdowns. The markdown based on the fluctuations of the cost ratio significantly decreased at the peak of the Great Recession in 2009 and continued to decline gradually from 2014 to 2018. In particular, the cost ratio dropped sharply in 2009 because variable input costs were reduced more than labor costs (see Figure B.1 in Appendix B). In contrast, between 2014 and 2018, the cost ratio increased because labor costs increased more rapidly than variable input costs. On the contrary, the counterfactual markdown based on the variations of the elasticity ratio had the opposite dynamics compared to the evolution of the cost ratio. It experienced a decline in 2009, as a result of an abrupt reduction in the elasticity of variable inputs. Following that, from 2014 to 2018, the elasticity ratio showed a gradual increase primarily attributed to the growing elasticity of labor. Thus, the fluctuations in the elasticity ratio highlight the importance of using translog production functions to estimate markdowns in Lithuania. In contrast, applying a Cobb-Douglas production function would result in a much larger declining dynamic in the aggregate markdown over the period, since the trends in the aggregate markdown would correspond solely to the fluctuations in the cost ratio (see Figure A.5 in Appendix A).

5.3 Decomposition of markups and markdowns

To further delve into the forces driving our aggregate markup and markdown dynamics, we perform various decomposition analyses in this section. We begin with the standard Olley and Pakes (1996) decomposition, which allows us to identify what is driving the change in aggregate markup and markdown at the industry level. Then, we follow Foster et al. (2001) decomposition to investigate reallocation effects across firms within a given industry.

Sectoral reallocation: OP decomposition

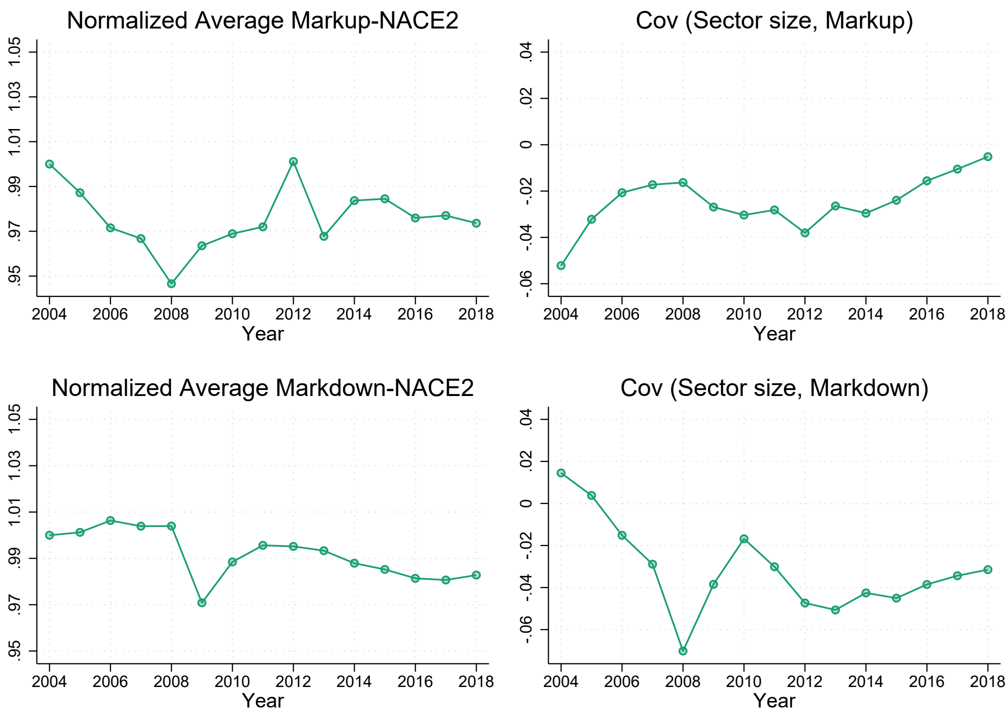
The Olley and Pakes (1996) method allows us to decompose the aggregate markup and markdown into the following two components

$$\breve{X}_t = \bar{\breve{X}}_t + \underbrace{\sum_j (\tilde{s}_{jt} - \bar{\tilde{s}}_t)(\breve{X}_{jt} - \bar{\breve{X}}_t)}_{\text{Cov(sector size, } \breve{X})}$$

where $\breve{X}_t \in \{\mathcal{V}_t, \mathcal{M}_t\}$. Here, $\breve{X}_t = \sum_j \tilde{s}_{jt} \breve{X}_{jt}$ in which $\tilde{s}_{jt}$ measures the size of sector j in the economy (either from variable input cost or labor cost perspective), and $\breve{X}_{jt}$ is the harmonic average of x_{it} of sector j. Thus, this method decomposes the weighted sector average into two parts: an unconditional average across sectors, and a covariance term between the sector size and the sector's markup/markdown.

Figure 6 displays the outcome of the OP decomposition when defining a sector j at the two-digit NACE2 level. For markups, we find the unconditional average markup declined by about 3% over the last 15 years. The covariance term between sector size and markup remains consistently below zero, indicating that throughout our sample, sectors with higher markups are smaller than those with lower markups. Interestingly, this covariance term is becoming less negative, suggesting that sectors with higher markups are expanding over time. This latter force dominates the cross-industry decline in markups, which eventually resulted in an increase of 2% of the aggregate markup, as documented in Section 5.2. The finding that the between-sector reallocation is dominating the within-sector trend is consistent with our within-industry decomposition (see the FHK decomposition below) but stands in contrast with the existing evidence. For the US, De Loecker et al. (2020) find that across sectors, the within component is the primary driver of the rise in aggregate markup, whereas the between-sector only contributes mildly. In the case of Spain, García-Perea et al. (2021) finds the between-sector reallocation only exhibits cyclical fluctuations without significant impacts on the trend of aggregate markup. The relevance of the sectoral reallocation we observe is consistent with the large economic transformation experienced by the Lithuanian economy in the last two decades (Garcia-Louzao and Tarasonis, 2023).

Figure 6. OP decomposition of markup and markdown



Note: OP (Olley and Pakes (1996)) decomposition for markup and markdown at the two-digit NACE2 level, with mean normalized to its 2004 (base) value.

For markdowns, we observe a 1.5% decline in the unconditional average markdown over the same period. The covariance term between sector size and markdown mostly remains below zero throughout our sample, except for the very initial couple of years. This indicates that sectors with lower markdowns are larger than those with higher markdowns. Importantly, this covariance term is becoming more negative over time, suggesting that sectors with lower markdowns are expanding. Both the unconditional average markdown and the covariance term are moving in the same direction, which makes both forces contribute to driving down the aggregate markdown by 5% in the past 15 years. To the best of our knowledge, we are the first to document the reallocation of markdown at the sectoral level. In our context, we document that both within-sector and between-sector components are pushing down the aggregate markdown, suggesting that the whole economy is experiencing a reduction in monopsony power. This finding is likely to be at odds with trends in several developed economies where increased monopsony power has been documented (e.g., Yeh et al., 2022; Díez et al., 2022; Aoki et al., 2023). However, it is consistent with recent evidence for Lithuania suggesting that competition in the labor market has increased between 2000 and 2020, resulting in less wage-setting power of firms (Garcia-Louzao and Ruggieri, 2023).

Firm dynamics: FHK decomposition

Despite its usefulness for understanding industry dynamics and the importance of sectoral composition, the OP decomposition is silent on within-industry dynamics and thus on the role of firm heterogeneity. To investigate which sets of firms impact the changes in aggregate markups and markdowns, we apply a modification of the standard Foster et al. (2001) decomposition implemented by Yeh et al. (2022). To be precise, for each industry j, we decompose the changes in the weighted harmonic averages of markups and labor wedges as follows

$$\begin{aligned}\triangle \breve{X}_{jt} = & \sum_{i,j\in\mathcal{I}_{jt}} \tilde{s}_{it-1}\triangle\breve{x}_t + \sum_{i,j\in\mathcal{I}_{jt}} \triangle\tilde{s}_{it}(\breve{x}_{it-1} - \breve{X}_{t-1}) + \sum_{i,j\in\mathcal{I}_{jt}} \triangle\tilde{s}_{it}\triangle\breve{x}_{it} \\ & + \sum_{i,j\in\mathcal{E}_{jt}} \tilde{s}_{it}(\breve{x}_{it} - \breve{X}_{t-1}) - \sum_{i,j\in\mathcal{X}_{jt}} \tilde{s}_{it-1}(\breve{x}_{it-1} - \breve{X}_{t-1}) \\ & \equiv \text{WITHIN}_{jt} + \text{BTWN}_{jt} + \text{COV}_{jt} + \text{ENTRY}_{jt} - \text{EXIT}_{jt}\end{aligned}$$

where $\breve{x}_{it} \equiv x_{it}^{-1}$, for $\breve{x}_{it} \in \left\{ \frac{\hat{e}_{it}^{l}}{\hat{e}_{jt}^{l}} \frac{1}{\hat{\nu}_{it}\hat{\mu}_{it}}, \frac{\hat{e}_{it}^{c}}{\hat{e}_{jt}^{c}} \frac{1}{\hat{\mu}_{it}} \right\}$, and $\breve{X}_t \equiv X_t^{-1} = \sum_{i,j \in \mathcal{J}_t} \tilde{s}_{it} x_{it}^{-1} \equiv \sum_{i,j \in \mathcal{J}_t} \tilde{s}_{it} \breve{X}_{it}$, for $\breve{X}_{it} \in \{V_{it}, \mathcal{M}_{it}\}$, defines a transformation from an industry level harmonic average to an arithmetic markup or labor wedge average. The variables $\mathcal{I}_{jt}$, $\mathcal{E}_{jt}$, and $\mathcal{X}_{jt}$ represent the pool of incumbents, entrants, and exiters in industry j at time t. Thus, this decomposition enables the quantification of changes that occur within firms (WITHIN), across firms (BTWN & COV), as well as through firm entry (ENTRY) and exit (EXIT). For instance, in the context of markup, the 'WITHIN' term is a counterfactual that measures the average change in markup while holding each firm's market share constant. The 'BTWN' term maintains firms' markups while their market shares fluctuate. The 'COV' term assesses the joint shift in firms' markup and market share. The 'ENTRY' and 'EXIT' terms account for alterations in markup due to changes in the extensive margin in a specific industry. Since both of these components are relatively small, we combine them into the 'NET ENTRY' component.

Following equation (13), the markdown for each j industry is the gap between the labor wedge and the markup. Therefore, by implementing the transformation described above, we can approximate the change in industry-level markdowns as the difference between the corresponding markup and the aggregate labor wedge in that industry[25]

$$\triangle \breve{\mathcal{V}}_{jt} \approx \triangle \breve{\mathcal{M}}_{jt} - \triangle \breve{V}_{jt} \tag{17}$$

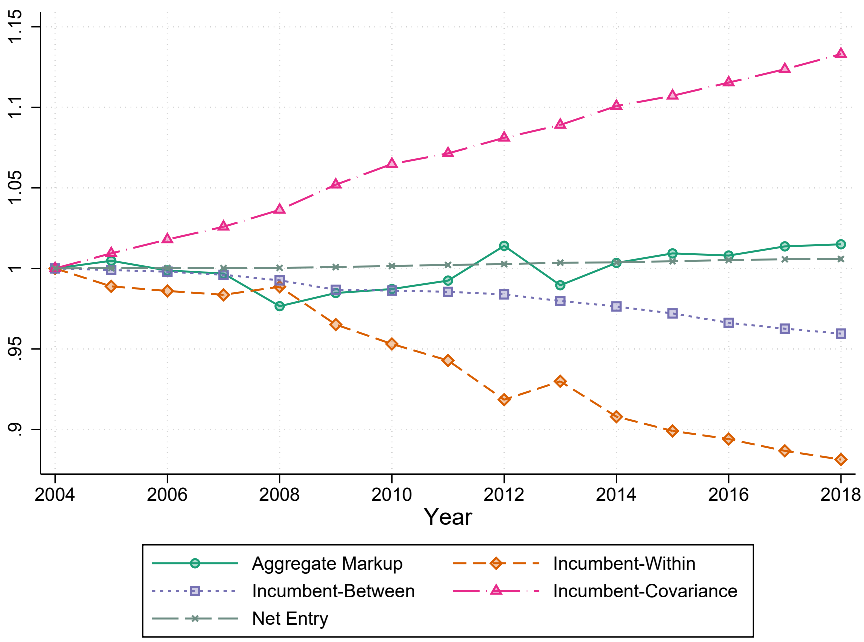
After calculating the components that are driving the changes in markup and markdown within industries, we then aggregate all industries based on their respective shares (variable input cost shares for markup and labor cost shares for markdown) to obtain the aggregate change in markup and markdown in the entire economy.[26] Figure 7 and Figure 8 illustrate this decomposition, displaying the aggregate variable

[25] For a detailed derivation, see Section O.2.4 in the online appendix of Yeh et al. (2022).

[26] The decomposition here is based on the raw components. It is a widely acknowledged fact in the literature that these raw components might be highly volatile and tend to switch signs over time, making their interpretation arduous. Therefore, as a robustness check for our decomposition, we also compute the absolute contribution of each component for aggregate markup and markdown in Appendix D. Our main message, i.e., the within and reallocation components are the main drivers of aggregate markup and markdown, remains unaffected.

input cost-weighted markup and labor cost-weighted markdown in green and three counterfactual experiments based on the decomposition beginning in 2004. We set the baseline at 2004 and then cumulatively add the changes in each of the above component terms (WITHIN, BTWN, COV, NET ENTRY).

Figure 7. FHK decomposition of aggregate markup



Note: FHK (Foster et al. (2001)) decomposition of the variable input cost-weighted aggregate markup into within, across, covariance, and net entry effect, each series is normalized to its 2004 (base) value.

For the FHK decomposition of the aggregate markup in Figure 7, the first counterfactual exercise shows the evolution of aggregate markup as if there was only the component 'WITHIN' and all other components were fixed at the level in 2004. This term has been steadily decreasing since 2004, indicating that if firms' pricing margin were the only source of variation over time, the aggregate markup would have declined by 12% over time. The second experiment focuses on the reallocation effects across firms on the aggregate markup. In this case, two forces are at play during the same time: the 'BTWN' term (which keeps markup fixed and allows the market share to vary) and the 'COV' term (which allows the markup and market share to vary simultaneously). The decline through the 'BTWN' term indicates that if changes in market shares were the only force, the aggregate markup would have declined, which aligns with the observed decline in concentration (see Figure E.1 in Appendix

E). The increase through the 'COV' term points to the fact that as firms capture market share, their markups also increase.[27] Although the 'BTWN' term slightly drives down the aggregate markup, its impact is clearly outweighed by the steady increase of the 'COV' term. These two together imply that if the only source of variation emerged from reallocation across firms within industries, the aggregate markup would have increased by 13% over time. The last experiment focuses on the extensive margin ('NET ENTRY'). This component comprises firms' entry and exit while keeping other parts fixed at the 2004 level. The figure reveals that this component is virtually flat, indicating that if the only source of variation came from the composition of firms, then the aggregate markup would have increased by 0.5% over time. Thus, although the average markup has been declining over time, the reallocation process together with firm dynamics have more than compensated for this decline, leading to the observed increase in the aggregate markup.

To compare our results with the literature, De Loecker et al. (2020) find the reallocation term is the primary driver of the rise in aggregate markup among the US public firms, whereas the within term only contributes mildly to its rise. Aoki et al. (2023) documents that the contributions of within and reallocation components are of equal magnitudes, but both are driving down the aggregate markup in Japan. Our finding that the within and reallocation terms almost operate in opposite directions is similar to the case of Spain (García-Perea et al., 2021), with a crucial difference being that the within (reallocation) term is driving up (down) the aggregate markup in Spain. These comparisons indicate a unique feature of the product market in the Lithuanian economy: although firms have experienced persistent productivity growth (Garcia-Louzao and Tarasonis, 2023), the increasing degree of competition in the market has been consistently putting pressure on the incumbents. Hence, we only observe a very mild increase in the aggregate markup.

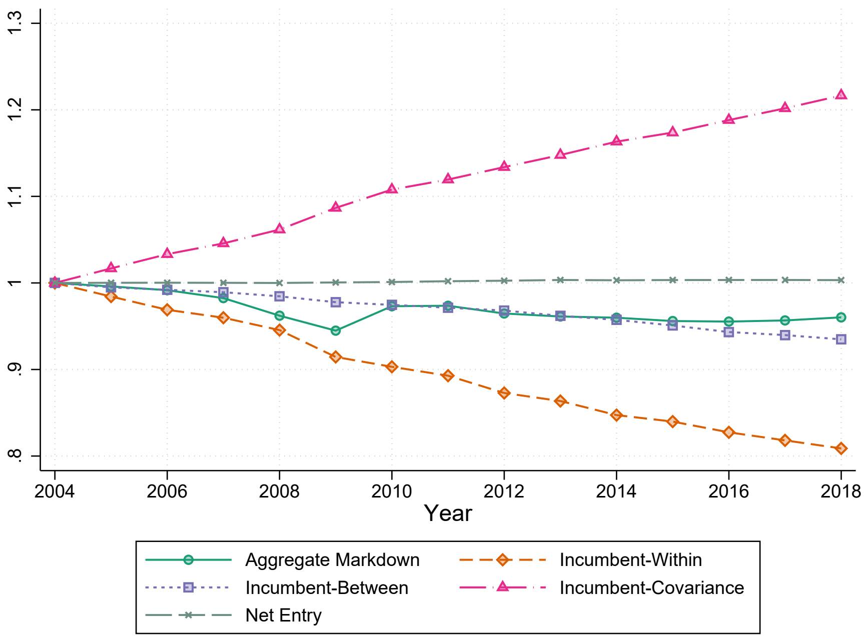
Figure 8 shows the FHK decomposition of the aggregate markdown. The first counterfactual indicates that if firms' wage setting margin were the only source of

[27] This is consistent with our micro-level regressions that indicate that firms with higher market shares have also higher markups (see Table 3).

variation over time, the aggregate markdown would have declined by 20% over time. The second experiment focuses on the reallocation effects across firms on the aggregate markdown. On the one hand, aggregate markdown would have decreased if we only look at the 'BTWN' term, as market shares based on the aggregate wage bill HHI has been steadily declining (see Figure E.1 in Appendix E). On the other hand, the 'COV' suggests that if the aggregate markdown had only been driven by firms gaining market share, then it would have increased, as markdowns are increasing in firms' market shares (see table 4). Taken together, these two terms imply that if we only look at the trends that emerged from the reallocation of market shares, the aggregate markdown would have increased by 15%. The last experiment focuses on the extensive margin ('NET ENTRY'). This component is virtually flat for the markdown, indicating that if the only source of variation came from firm entry and exit, the aggregate markdown would have increased by less than half a percentage over time. Overall, the decomposition exercise indicates that the reallocation process mitigated the large decline in aggregate markdown that would have arisen from the declining dynamics of the average markdown (20%), resulting in the observed drop of approximately 5% between 2004 and 2018.

To place these numbers into context, the reallocation and within components contribute equally to the overall rise in the aggregate markdown in the US (Yeh et al., 2022), whereas for the case of Japan (Aoki et al., 2023), the rise of aggregate markdown is mainly driven by the within component, with a slight negative impact from the within component. Among a selected number of European economies, Díez et al. (2022) find the reallocation and net entry components can explain a mild increase in aggregate markdown. Most of the economies in these studies possess different labor market conditions as compared to the case of Lithuania. Our findings that the within component is the main factor that drives down the aggregate markdown in Lithuania is consistent with the increasing degree of labor market competition in the country and compression in the dispersion of firm-specific wage components, suggesting that firms are losing wage-setting power (Garcia-Louzao and Ruggieri, 2023).

Figure 8. FHK decomposition of aggregate markdown



Note: FHK (Foster et al. (2001)) decomposition of the labor cost-weighted aggregate markdown into within, across, covariance, and net entry effect, each series is normalized to its 2004 (base) value.

6 Conclusions

This paper characterizes price markups and wage markdowns in Lithuania from 2004 to 2018. Our analysis reveals different dynamics for Lithuania's product and labor markets. Specifically, we document a 2% increase in the aggregate price markup and a slight increase in the dispersion across firms. On the other hand, we find that the aggregate wage markdown declined by 5% over the same period and that its distribution became less dispersed. Additionally, we show that the dynamics in both price markups and wage markdowns can be mostly attributed to firm heterogeneity.

The trends in competition within the product and labor markets are likely a result of the Lithuanian economy's transformation upon joining the European Union (EU) in 2004 and its zone of free movement of goods, labor, and capital (Randveer and Staehr, 2021).[28] The EU membership enabled access to new trading partners, driving foreign investment and fueling economic growth. The GDP almost doubled between 2004 and 2018, with exports and imports accounting for roughly 80 percent and 70 per-

[28] In Appendix F, we provide graphical evidence of the main macroeconomic variables that characterize the development of the Lithuanian economy after 2004.

cent, respectively, of GDP by 2018. This substantial economic growth was associated with technological progress and increased competition in the product market, mainly due to the significant entry of new firms. Our analysis reveals that this technological progress raised the average markup among firms. Nevertheless, this did not substantially increase the aggregate markup, as intensified firm competition prevented larger firms from monopolizing the market. As a consequence, Lithuania experienced a less significant increase in the aggregate markup compared to other countries.

The legal right to live and work in other EU member states caused a wave of mass emigration of Lithuanian workers, resulting in severe labor shortages. Theoretical models would predict that a lower number of workers per firm weakens employers' market power to set wages (e.g., Bagga, 2023). Therefore, it is plausible that the decline in aggregate markdowns and the compression of the distribution of firm-level markdowns can be attributed to the combination of emigration flows and firm entry. This lower margin on labor costs can also influence markups through its impact on production costs and thus on input-mix decisions. In this regard, we find that growing industries experienced increasing markups but decreasing markdowns, suggesting that the fall in labor market power may also help explain the trend in the aggregate markup. However, we do not test this directly in our context and therefore leave for further research on how product and labor market power affects input-mix decisions.

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APPENDIX

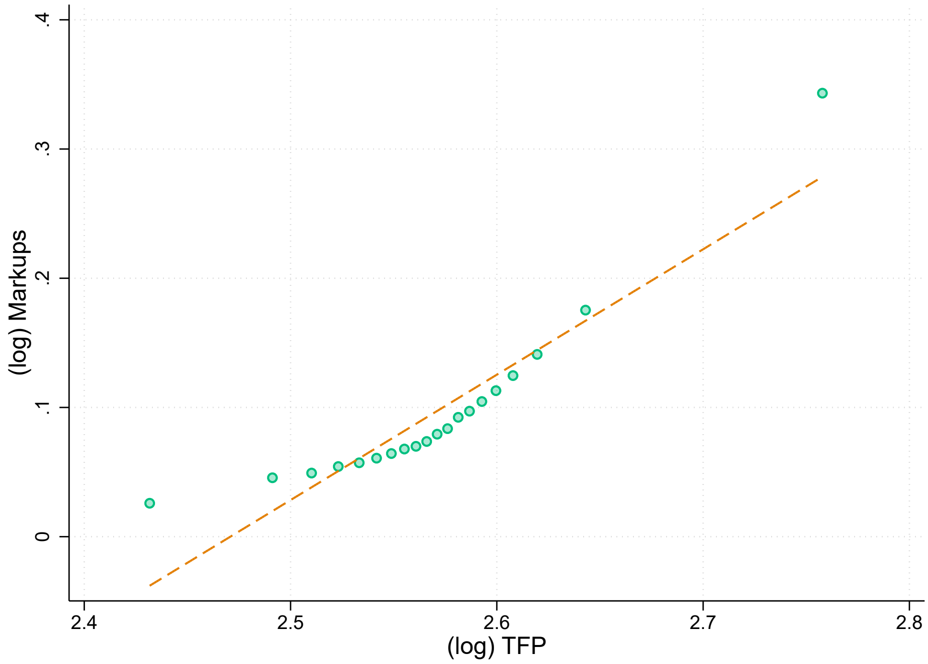
A Additional tables and figures

Table A.1. Data coverage

	Firms		Employment		
Year	LLC	Private	LLC	Private	Total
2004	81.17	39.56	90.98	79.69	55.99
2005	80.25	21.19	91.03	80.79	57.60
2006	79.53	20.17	91.28	81.50	61.47
2007	79.80	20.49	91.48	82.25	62.31
2008	79.49	21.85	91.46	82.67	61.65
2009	80.74	29.02	91.49	83.45	58.58
2010	80.75	29.85	91.22	84.47	58.59
2011	80.82	28.23	91.28	85.47	60.79
2012	81.38	27.03	91.28	86.00	62.52
2013	82.15	27.33	91.34	86.60	64.79
2014	81.51	26.33	91.14	86.84	66.33
2015	81.61	25.96	90.96	87.05	67.36
2016	81.70	25.70	91.30	87.15	67.62
2017	82.40	25.10	91.28	87.94	69.07
2018	82.84	25.29	91.45	88.38	69.00

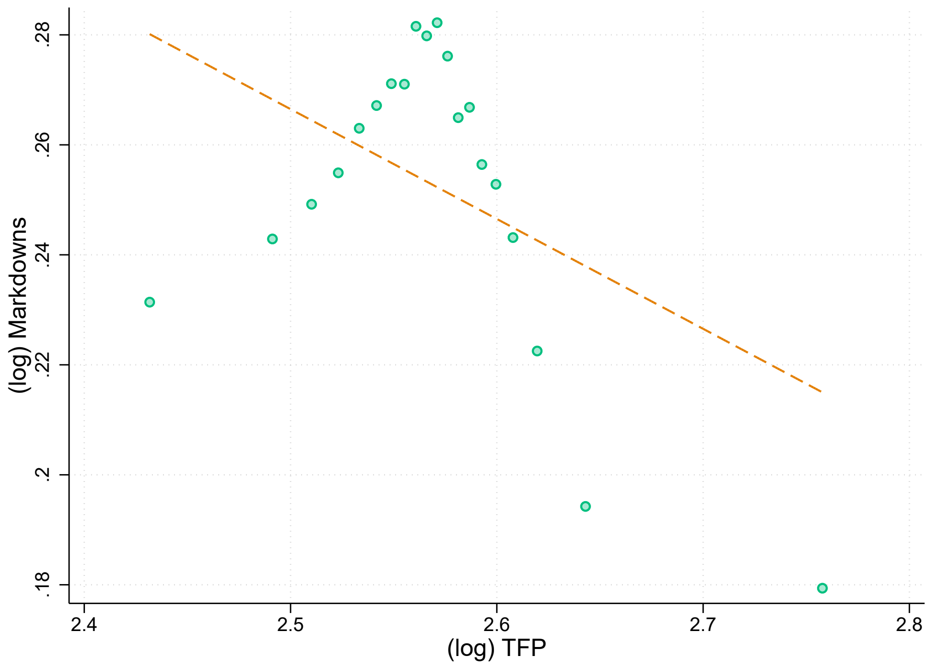
Source: Statistics Lithuania. Note: The table reports the percentage of firms and employment captured in our main data source (without imposing any restriction) relative to different populations. LLC stand for limited liability companies. Private firms adds to LLC individual enterprises and natural persons as employers. Total employment refers to wage-employment in the private sector and public administration but excludes self-employment.

Figure A.1. Correlation between markups and TFP



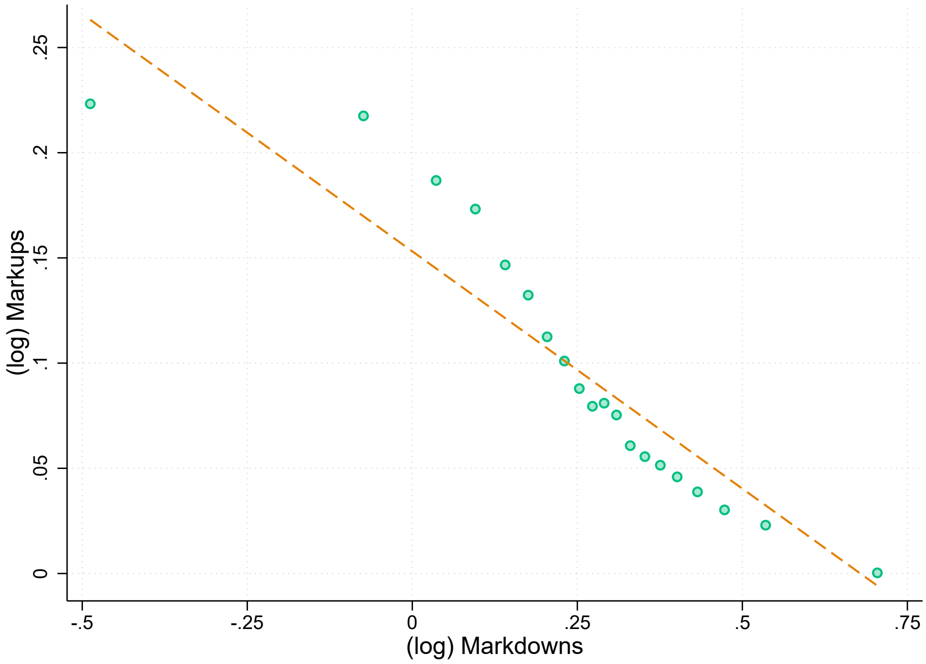
Note: Binned scatter plot from firm-level regressions of (log) markups on (log) TFP controlling for year and industry fixed effects.

Figure A.2. Correlation between markdowns and TFP



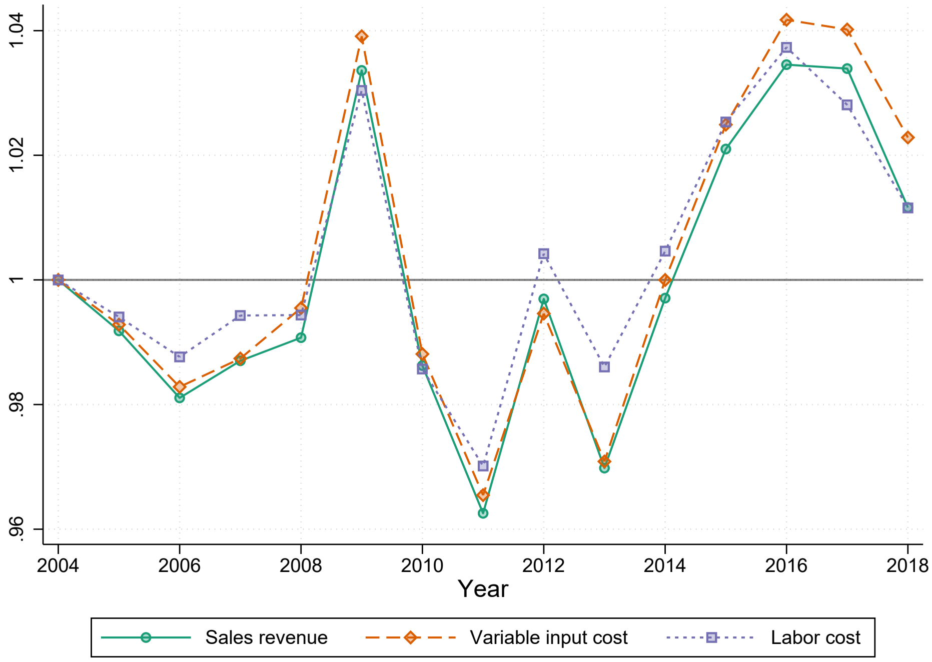
Note: Binned scatter plot from firm-level regressions of (log) markdowns on (log) TFP controlling for year and industry fixed effects.

Figure A.3. Correlation between markups and markdowns



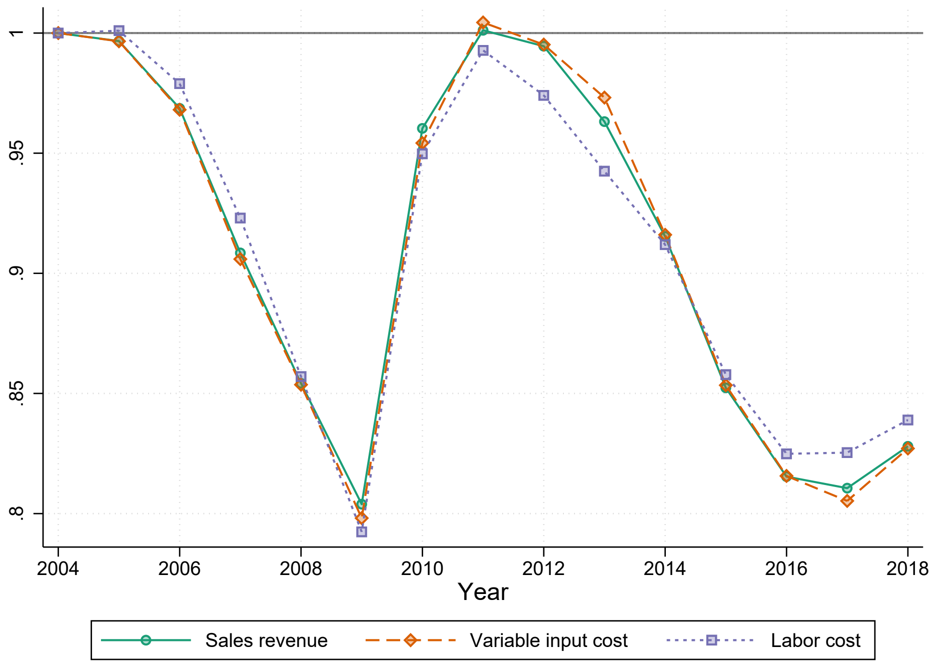
Note: Binned scatter plot from firm-level regressions of (log) markups on (log) markdowns controlling for year and industry fixed effects.

Figure A.4. Aggregate markups using Cobb-Douglas



Note: Aggregate markup based on a Cobb-Douglas production function. The aggregate markup is computed as specified in subsection 5.1. Each line corresponds to alternative NACE2-level weights used in the last step of the aggregation process described in equation (12). Each series is normalized to its 2004 (base) value.

Figure A.5. Aggregate markdowns using Cobb-Douglas

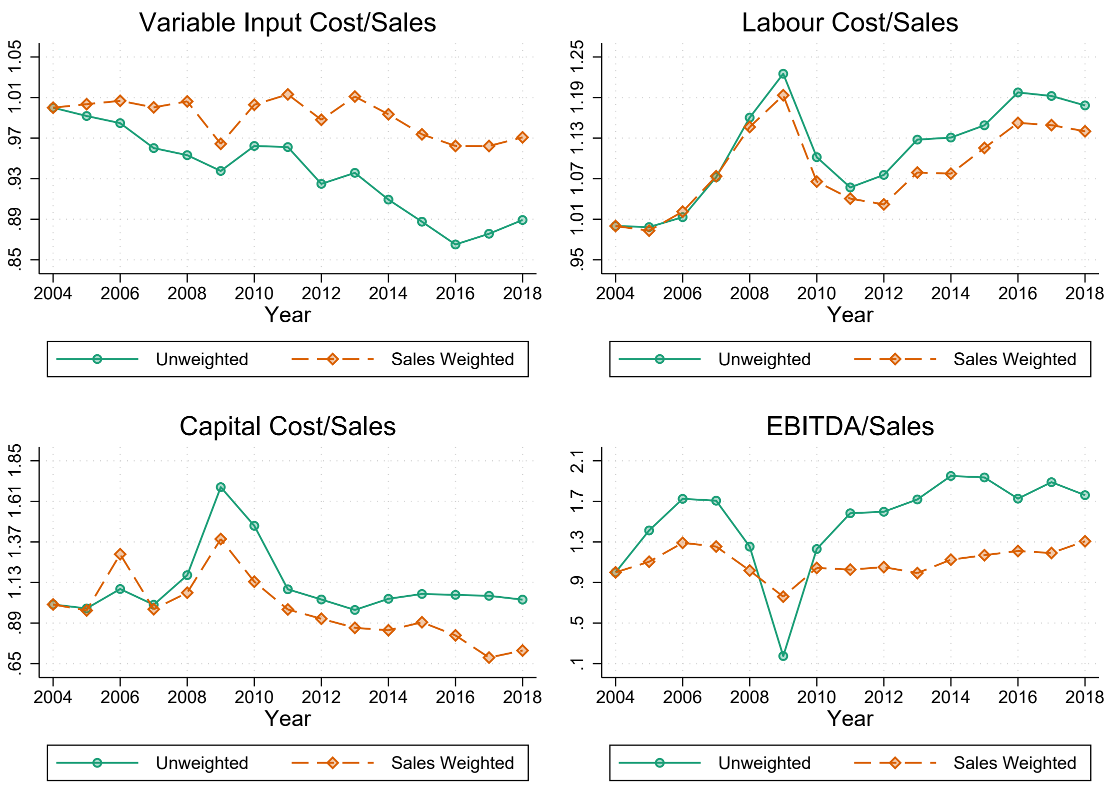


Note: Aggregate markdown based on a Cobb-Douglas production function. The aggregate markdown is computed as specified in subsection 5.1. Each line corresponds to alternative NACE2-level weights used in the last step of the aggregation process described in equation (12). Each series is normalized to its 2004 (base) value.

B Cost structure and profit rates

In this section, we document the dynamics of cost structure and profitability of Lithuanian firms in our balanced sheet data. between 2004 and 2018. We compute variable input costs as the cost of any input that is directly affected by the level of output, such as the purchase of materials, energy, electricity, and other goods and services used in production. Additionally, labor costs, consisting of the firms' wage bill, are annually available. Capital costs, encompassing interest payments, depreciation, and amortization, are also observable throughout our sample. We prioritize these factors since they are the most significant for our production function estimation process.

Figure B.1. Input cost shares and profit margins



Note: Each series is normalized to its 2004 (base) value.

Figure B.1 provides a first look at cost structures and profit rates by firm size. The sales-weighted average variable cost share accounts for between 65% and 70% of total sales. Compared to the level in 2004, the sales-weighted average variable cost share has declined around 5% over the period of 2004–2018. However, the drop is much larger (around 10%) if we calculate the series without weighting it by sales, indicating that larger firms allocate greater resources to inputs relative to their sales than smaller firms.

The labor cost share accounts for approximately 20% of the firm's sales. Normalizing the series to its 2004 level, we observe that the unweighted series consistently exceeds the weighted series, suggesting that small firms allocate a higher percentage of their sales toward labor costs than larger firms. This is in contrast to the relatively lower variable input cost shares that small firms face. With regards to the capital cost share, it amounts to between 4% and 9% of total sales, regardless of the size of the firm. The normalized series suggests that large firms allocate less capital spending as a percentage of sales compared to small firms. The labor and capital cost shares have both significantly increased during the period of the financial crisis, implying that firms experienced a decline in output and a rise in financial expenses simultaneously.

Finally, the profit margin is determined by calculating earnings before interest, taxes, depreciation, and amortization (EBITDA) as a proportion of sales. The sales-weighted profit margin averages around 12% of sales across the sample, whereas the unweighted series consistently falls below the weighted series and drops to almost zero during periods of crisis. This suggests that smaller firms typically retain a smaller portion of their sales as profit. The unweighted series showed a greater decline than the weighted series during the crisis, indicating that small firms experienced a sharper decrease in profits than large firms.

C Variance decomposition of firm-level markups and markdowns

In this section, we decompose the variance into their components (e.g., elasticities and input shares) in order to better understand the driving forces behind the overall dispersion and its evolution over time. Based on equation (7), the logarithm of firm-level markup is additively separable into the following two components

$$\ln(\hat{\mu}) = \ln(\hat{e}^c) - \ln(\hat{\alpha}^c)$$

and one can decompose the variance of $\hat{\mu}$ into the variance of its components output elasticity with respect to variable inputs, $\hat{e}^c$, and the cost share of revenue of such input, $\hat{\alpha}^c$, as follows

$$var(\ln(\hat{\mu})) = var(\ln(\hat{e}^c)) + var(\ln(\hat{\alpha}^c)) - 2cov(\ln(\hat{e}^c), \ln(\hat{\alpha}^c)) \tag{C.1}$$

Similarly, the (log) markdown in equation (8) can be expressed as

$$\ln(\hat{\nu}) = \ln(\hat{e}^l) - \ln(\hat{\alpha}^l) - \ln(\hat{\mu})$$

with the variance decomposition being equal to

$$\begin{aligned} var(\ln(\hat{\nu})) &= var(\ln(\hat{e}^l)) + var(\ln(\hat{\alpha}^l)) + var(\ln(\hat{\mu})) \qquad \text{(C.2)} \\ &- 2cov(\ln(\hat{e}^l), \ln(\hat{\alpha}^l)) - 2cov(\ln(\hat{e}^l), \ln(\hat{\mu})) + 2cov(\ln(\hat{\alpha}^l), \ln(\hat{\mu})) \end{aligned}$$

with $\hat{e}^l$ and $\hat{\alpha}^l$ being the output elasticity with respect to labor and the cost share of labor, respectively.

Table C.1 presents the breakdown of each component's contribution to the variance of markups and markdowns for the chosen sub-periods. The findings uncover a significant dispersion of firms in the output elasticity of the variable input, $\hat{e}^c$, and its share

Table C.1. Variance decomposition of markups and markdowns and their components

	Period 1: 2004-2007		Period 2: 2008-2011		Period 3: 2012-2015		Period 4: 2016-2018		Change Period 1 to 4	
	Component	Share	Component	Share	Component	Share	Component	Share	Component	Share
Markups, $var(\hat{\mu})$	0.020	-	0.021	-	0.022	-	0.022	-	0.002	
$var(\hat{e}^c)$	0.145	7.19	0.155	7.44	0.169	7.62	0.176	7.93	0.031	15.06
$var(\hat{\alpha}^c)$	0.191	9.46	0.207	9.94	0.227	10.25	0.231	10.39	0.040	19.39
$-2 \times (\hat{e}^c, \hat{\alpha}^c)$	-0.316	-15.65	-0.341	-16.39	-0.373	-16.87	-0.385	-17.32	-0.070	-33.45
Markdowns, $var(\hat{\nu})$	0.090	-	0.084	-	0.082	-	0.083	-	-0.007	
$var(\hat{e}^l)$	0.473	5.25	0.429	5.13	0.421	5.16	0.397	4.77	-0.076	11.07
$var(\hat{\alpha}^l)$	0.385	4.27	0.383	4.58	0.386	4.73	0.390	4.67	0.005	-0.67
$var(\hat{\mu})$	0.020	0.22	0.021	0.25	0.022	0.27	0.022	0.27	0.002	-0.30
$-2 \times (\hat{e}^l, \hat{\alpha}^l)$	-0.789	-8.74	-0.750	-8.97	-0.747	-9.15	-0.727	-8.72	0.062	-8.99
$-2 \times (\hat{e}^l, \hat{\mu})$	-0.030	-0.33	-0.029	-0.34	-0.035	-0.43	-0.031	-0.38	-0.001	0.20
$2 \times (\hat{\alpha}^l, \hat{\mu})$	0.031	0.34	0.029	0.35	0.034	0.42	0.033	0.39	0.002	-0.30

Note: Variance decomposition of (log) firm-level markups and markdowns based on the equations (C.1) and (C.2), respectively. The markups and markdowns distributions are winsorized by their components at the 2% of the tails of the industry distributions.

of total sales, $\hat{\alpha}^c$, despite the apparently low variance of markups. These components exhibit a significant (negative) correlation that offsets each term's individual contribution to dispersion since they contribute to the markups in opposing directions. It is critical to note that although each component's contribution has remained stable over time, the markups' dispersion has increased by approximately 10% between 2004-2007 and 2016-2018.

Markdowns exhibit significantly greater variance than markups. Markdowns' dispersion was primarily explained by the variance in the output elasticity of labor, $\hat{e}^l$, and the share of labor costs in total sales, $\hat{\alpha}^l$, but also by their covariance. As found in the US by Yeh et al. (2022), the influence of markups on markdown dispersion is quantitatively minimal, both directly and indirectly through covariances with the elasticity and the labor share. Additionally, markdowns have declined in variance by about 8% over time, in contrast to the evolution of markup dispersion. The recent decrease in markdown dispersion can be mainly attributed to the reduction in the elasticity dispersion. Additionally, the decline was also influenced by a weaker correlation between the labor share and the elasticity.

D FHK decomposition

The decomposition in Figure 7 and Figure 8 is based on the raw components. It is a widely acknowledged fact in the literature that these raw components are highly volatile and tend to switch signs over time, making their interpretation arduous. In light of this, we follow the works of Foster et al. (2001) and Yeh et al. (2022) to present the absolute contributions of each component, thereby facilitating a better quantitative evaluation of its role. Firstly, we calculate the contribution of each component of the decomposition to the overall change in markup or markdown for each industry j. Formally,

$$Contribution_{jt} = \frac{\mathcal{S}_{jt}}{\triangle \breve{\mathcal{X}}_{jt}} \tag{D.1}$$

for $\mathcal{S}_{jt} \in \{\text{WITHIN}_{jt}, \text{BTWN}_{jt}, \text{COV}_{jt}, \text{ENTRY}_{jt}, \text{EXIT}_{jt}\}$ and $\triangle \breve{\mathcal{X}}_{jt}$ stands for change in the industry-level markup ($\triangle \breve{\mathcal{M}}_{jt}$) or markdown ($\triangle \breve{\mathcal{V}}_{jt}$). To compute the economy-wide markup and markdown, we aggregate each of the contributions using as weights the share of sales in each industry j in period t. The Table D.1 displays the outcomes.

This decomposition in absolute terms shows that movements in aggregate markdown have a slightly different composition than movements in aggregate markup. Specifically, the 'WITH-IN' component contributes to 42-61% of the change in aggregate markup but only 30-43% of the change in markdown. The 'BTWN' and 'COV' terms contribute to 32-52% of the change in markup but 50-60% of the change in markdown. The 'NET ENTRY' accounts for about 2%-3% more of the change in markup than of the change in markdown. Although each term has somewhat of a different contribution to the change in aggregate markup and markdown, our main message in Section 5.3 is preserved: the within term and the reallocation term are the main drivers of the aggregate dynamics of markup and markdown, whereas the net entry margin only plays a minimal role.

Table D.1. FHK decomposition of $\triangle\breve{\mathcal{M}}$ and $\triangle\breve{\mathcal{V}}$

YEAR		WITHIN$_t$	BTWN$_t$	COV$_t$	NET ENTRY$_t$
2004-2005	$\triangle\breve{\mathcal{M}}$	.4650742	.1252619	.3352425	.0744214
2004-2005	$\triangle\breve{\mathcal{V}}$	.4066923	.1698726	.3467556	.0766795
2005-2006	$\triangle\breve{\mathcal{M}}$	.4850272	.1659523	.2887696	.0602509
2005-2006	$\triangle\breve{\mathcal{V}}$	.3780702	.2110318	.3445636	.0663344
2006-2007	$\triangle\breve{\mathcal{M}}$	.4631569	.1799457	.3065708	.0503266
2006-2007	$\triangle\breve{\mathcal{V}}$	.3698707	.2034289	.3594872	.0672132
2007-2008	$\triangle\breve{\mathcal{M}}$	.4151051	.1497795	.3985676	.0365477
2007-2008	$\triangle\breve{\mathcal{V}}$	.4049329	.1709103	.3790989	.045058
2008-2009	$\triangle\breve{\mathcal{M}}$	.4578807	.1768675	.3314287	.0338231
2008-2009	$\triangle\breve{\mathcal{V}}$	.4345075	.1960765	.3280939	.041322
2009-2010	$\triangle\breve{\mathcal{M}}$	.5944189	.1241065	.2484364	.0330382
2009-2010	$\triangle\breve{\mathcal{V}}$	.3781852	.1704756	.3887028	.0626363
2010-2011	$\triangle\breve{\mathcal{M}}$	.5231664	.1665873	.2644581	.0457882
2010-2011	$\triangle\breve{\mathcal{V}}$	.2977659	.2503613	.3799997	.0718731
2011-2012	$\triangle\breve{\mathcal{M}}$	.6064498	.1172567	.2399041	.0363893
2011-2012	$\triangle\breve{\mathcal{V}}$	.4320962	.1628907	.3369592	.068054
2012-2013	$\triangle\breve{\mathcal{M}}$	.5970976	.1226586	.2069177	.0733261
2012-2013	$\triangle\breve{\mathcal{V}}$	.3479369	.2166436	.360283	.0751364
2013-2014	$\triangle\breve{\mathcal{M}}$	.5601512	.1281307	.2720097	.0397083
2013-2014	$\triangle\breve{\mathcal{V}}$	.3993053	.1749348	.3492352	.0765246
2014-2015	$\triangle\breve{\mathcal{M}}$	.5828778	.1593191	.2072655	.0505376
2014-2015	$\triangle\breve{\mathcal{V}}$	.3563723	.2394447	.3204545	.0837285
2015-2016	$\triangle\breve{\mathcal{M}}$	.4304571	.204906	.3200096	.0446273
2015-2016	$\triangle\breve{\mathcal{V}}$	.3404908	.225148	.3754818	.0588793
2016-2017	$\triangle\breve{\mathcal{M}}$	.4906588	.1700201	.2762544	.0630667
2016-2017	$\triangle\breve{\mathcal{V}}$	.336309	.194534	.3798772	.0892798
2017-2018	$\triangle\breve{\mathcal{M}}$	.4845289	.151114	.3256906	.0386665
2017-2018	$\triangle\breve{\mathcal{V}}$	.353519	.1846737	.4022603	.0595469

Note: Markups and markdowns are estimated at two-digit NACE2 level with a translog specification for total sales. Each component is denoted in absolute values and normalized by the sum of absolute values for each component. The table reports the variable input-weighted mean across all industries for markup and wage bill-weighted mean across all industries for markdown.

E Concentration ratios

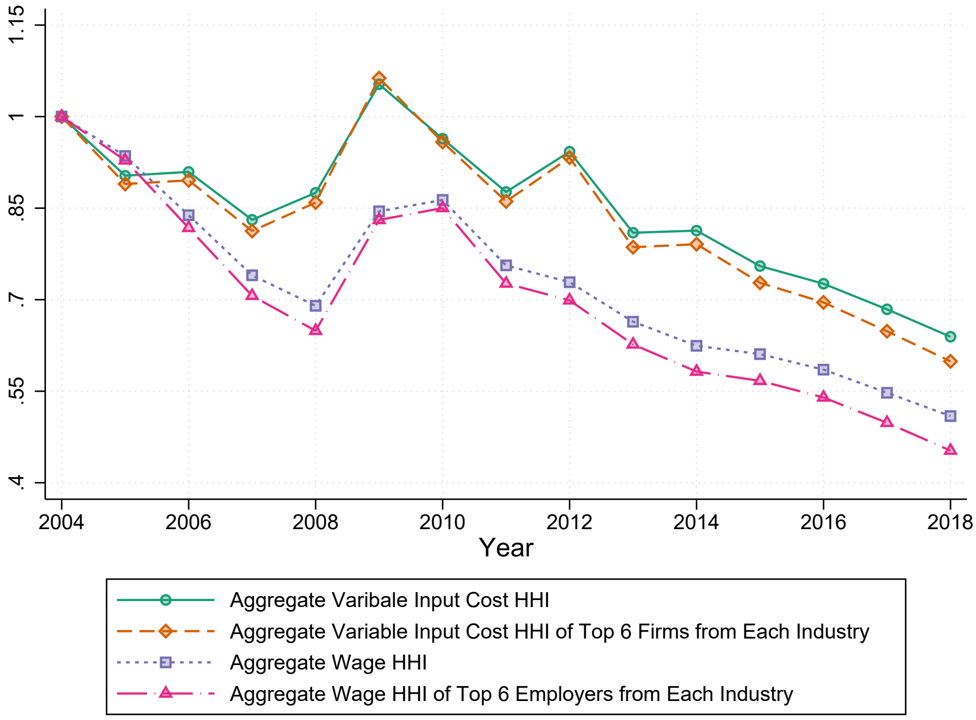
In this section, we document some concentration measures are commonly used to gauge market competition.[29] Here, we calculate two sets of concentration ratios: (i) the HHI at the industry level, and (ii) the concentration ratio for the six largest companies within a specific industry

$$\text{HHI}_{jt} = \sum_{i}^{N_j} \tilde{x}_{ijt}^2, \quad \text{HHI Top6}_{jt} = \sum_{i=1}^{6} \tilde{x}_{ijt}^2 \tag{E.1}$$

where $\tilde{x}_{ijt}$ stands for either the variable input cost or wage bill share of firm i in industry j at time t. After aggregating these industry-level indices by their corresponding industry share, we display them in Figure E.1. All these measures suggest that both variable input cost and wage bill concentration have declined throughout our sample period. This pattern may be due to a decrease in economy-wide HHI or a composition effect where industries with lower HHI are having larger market shares. Therefore, we further decompose these aggregate HHIs in the spirit of Olley and Pakes (1996) in Figure E.2.

[29] A higher concentration ratio can result from higher entry barriers imposed by incumbents or from market leaders' capital investments and innovation (Covarrubias et al., 2020)

Figure E.1. Aggregate HHI based on input costs

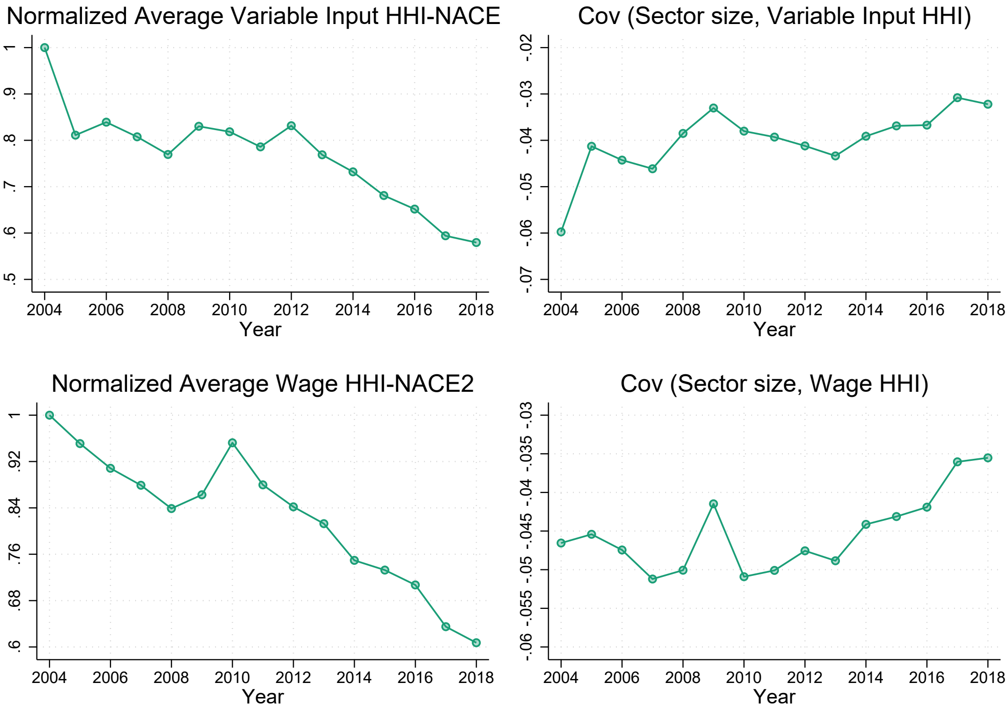


Note: Normalized aggregate Herfindahl-Hirschman Index based on each firm's input cost or wage bill share. Each series is normalized to its 2004 (base) value.

The findings indicate that the covariance between sector size and aggregate HHI remains consistently below zero throughout our sample. This reflects that sectors with higher (lower) HHI, on average, represent a smaller (larger) share of overall variable input cost (wage bills). Notably, the variable input cost HHI covariance term shows a gradual shift towards being less negative, suggesting that sectors with higher HHI progressively gained weight over time. We observe the same pattern for the covariance term between wage bill HHI and sector size. However, these trends are influenced mainly by the long-term decrease in average variable input cost or wage bill HHI at the industry level, indicating a decline in variable input cost and wage bill concentration across various industries[30].

[30] One could argue that there is a discrepancy with the slight increase in aggregate markup and markdown demonstrated in Section 5.2. Nevertheless, it is important to emphasize that HHI does not always indicate market power in the case of differentiated products. Additionally, as highlighted in De Loecker et al. (2020), a precise knowledge of what constitutes a market with information on all firms in that market is required for a proper concentration measure.

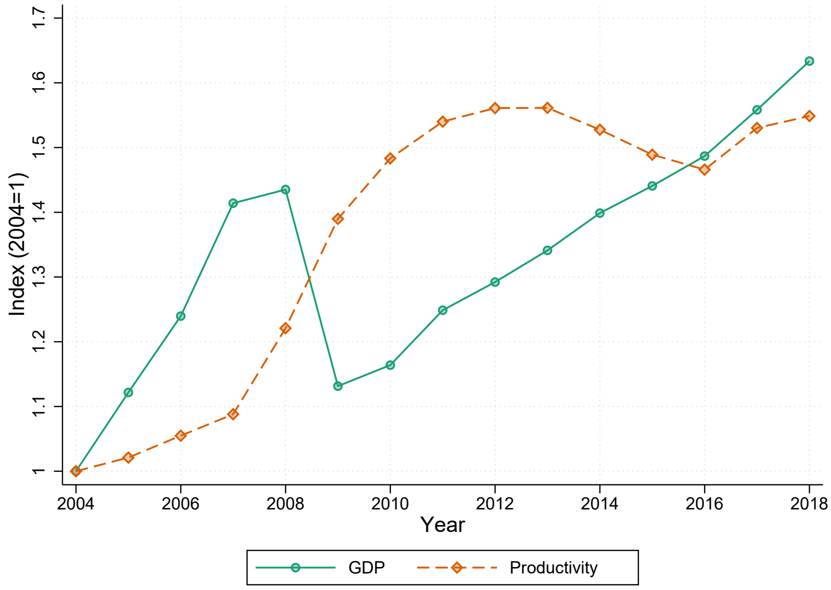
Figure E.2. OP Decomposition of Aggregate HHI



Note: OP (Olley and Pakes (1996)) decomposition for variable input cost and wage HHI at two-digit NACE2 level, with mean normalized to its 2004 (base) value.

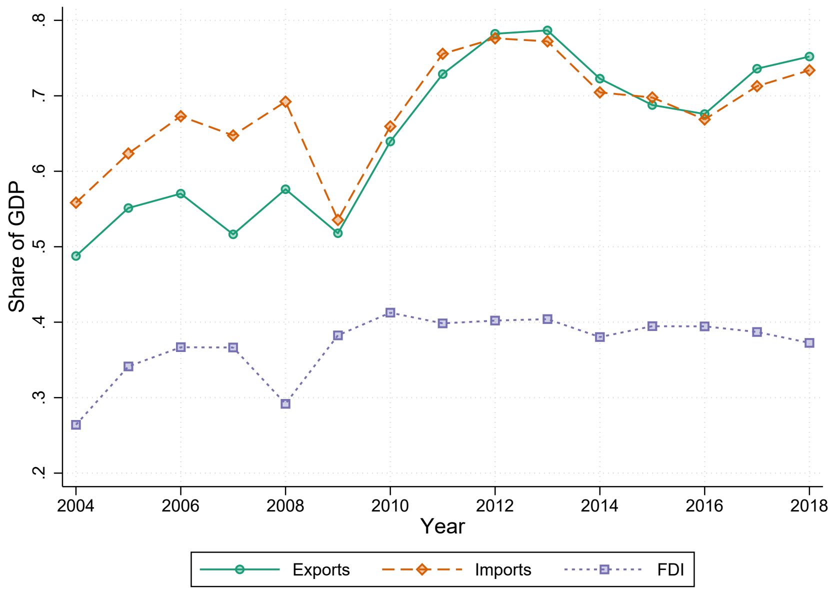
F Macroeconomic trends: Graphical evidence

Figure F.1. Economic growth



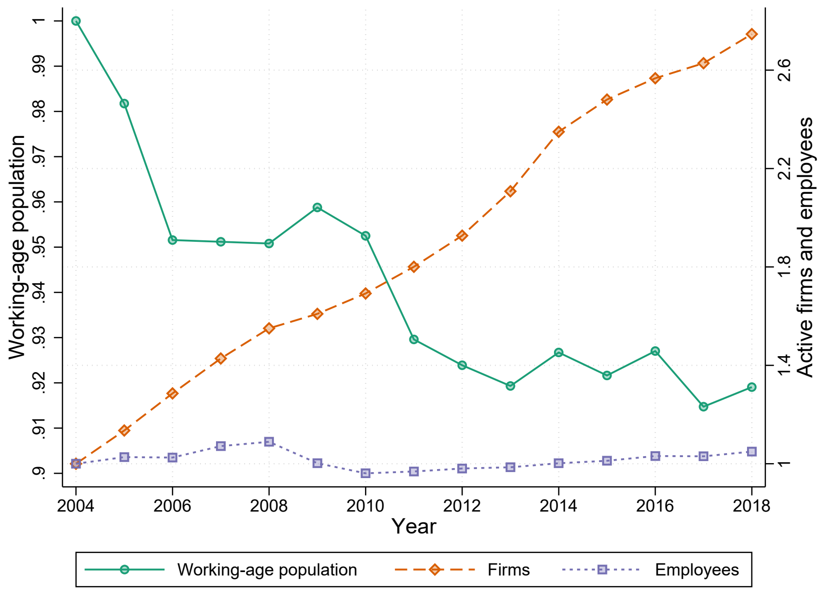
Source: Statistics Lithuania and own calculations.
Note: The figure shows Lithuania's economic growth between 2004 and 2018, measured by gross domestic product (GDP) and gross value added per worker (productivity). The series are normalized to their value in 2004.

Figure F.2. Openness



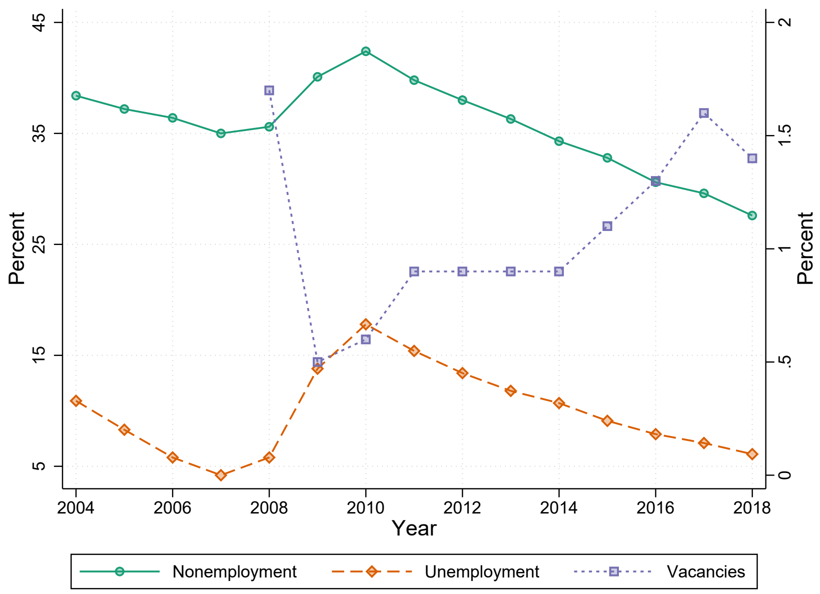
Source: Statistics Lithuania and own calculations.
Note: The figure shows the openness of the Lithuanian economy between 2004 and 2018, considering imports, exports, and foreign direct investment (FDI) as a percentage of GDP.

Figure F.3. Working-age population, firms, and employees



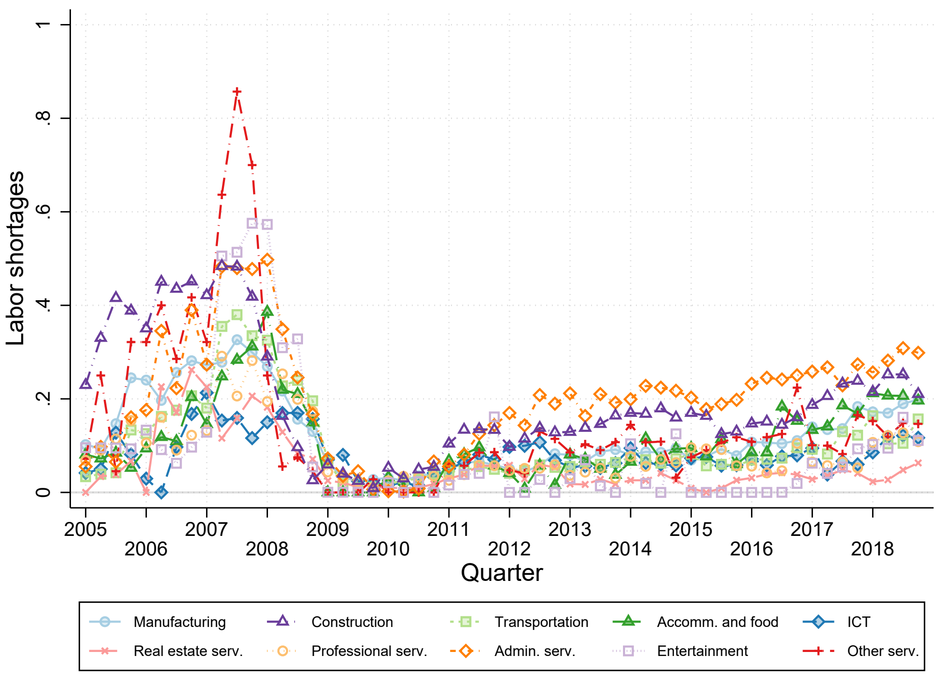
Source: Statistics Lithuania and own calculations. Note: The figure shows the evolution of the working-age population together the number of active enterprises and employees (rhs) in the Lithuanian economy between 2004 and 2018. The series are normalized relative to their value in 2004.

Figure F.4. Labor supply and demand



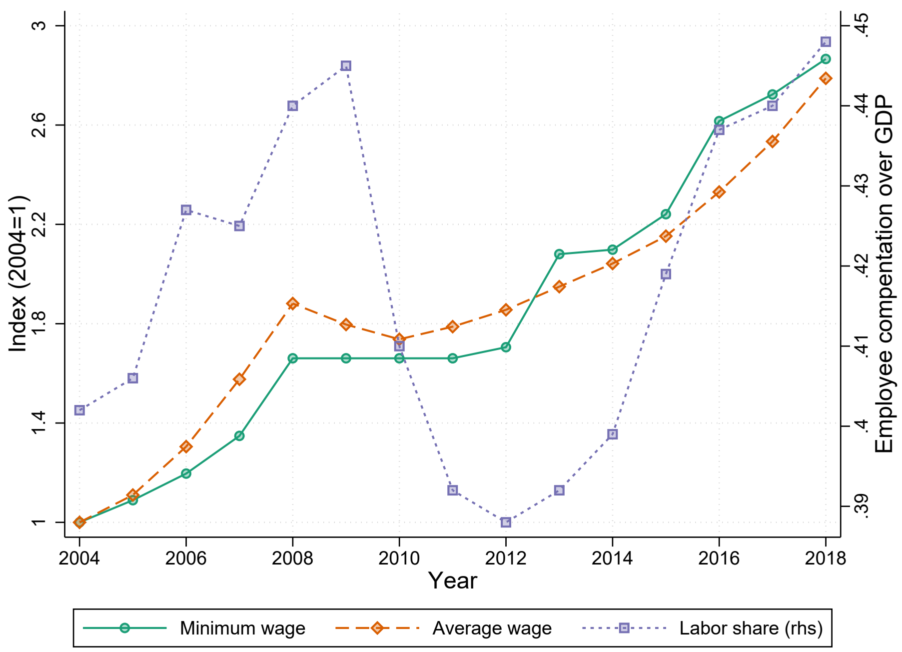
Source: Statistics Lithuania and own calculations.
Note: The figure shows the labor supply (nonemployment and unemployment) and labor demand (job vacancies) in Lithuania between 2004 and 2018. Nonemployment is the share of the total working-age population without a job. Unemployment refers to the ratio of jobless workers over the labor force. Job vacancy rate data is only available since 2008.

Figure F.5. Labor shortages



Source: EU Business and Consumer Surveys and own calculations.
Note: The figure shows the evolution of labor shortages faced by Lithuanian companies between 2005 and 2018 across broad sectors. Labor shortage refers to the proportion of companies that report the shortage of workforce as the main factor limiting production.

Figure F.6. Workers' remuneration



Source: Statistics Lithuania and own calculations.
Note: The figure shows the evolution of the statutory minimum wage and average wages in Lithuania between 2004 and 2018, as well as the share of GDP allocated to employees' remuneration. Labor share is the ratio of total employee compensation over GDP. The minimum and average wages series are normalized to their value in 2004.