# Labor Market Competition and Inequality*


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**Abstract**

We exploit a novel opportunity to study the dynamics of wage inequality and labor market competition over the course of economic development. Our context is Lithuania, where two decades of sustained growth and labor market tightening coincided with a substantial decline in wage inequality. We first fit a two-way fixed-effects model with worker and firm heterogeneity and document that the compression of the variance of firm fixed effects has been the main source of the fall in inequality. Guided by a standard dynamic monopsony model, we then estimate firms' labor supply elasticities and show that labor market competition has increased over the same period. Finally, we construct a shift-share instrument and provide evidence that new job opportunities created by the accession to the European Union in 2004 contributed to the fall in inequality through their impact on labor market competition in Lithuania.



**Keywords:** Wage inequality, Firm heterogeneity, Monopsony, Transition economy

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# 1 Introduction

Income inequality shapes the economic and political debate around the world. Although returns to capital, tangible or intangible, affect the distribution of income at the top, for millions of individuals around the globe, what matters is how their labor is rewarded in the market (Hoffmann et al., 2020). While it is well documented that labor earnings differ across workers with different skills, occupations, or genders, more recent literature has emphasized that firms —i.e., where individuals work, is a critical determinant of income gaps (Abowd et al., 1999; Card et al., 2013; Song et al., 2019; Criscuolo et al., 2020; Kline, 2024), especially in developing economies (Engbom and Moser, 2022; Pérez Pérez and Nuno-Ledesma, 2023; Bassier, 2023).

Standard textbook models of monopsony predict that imperfect labor market competition allows firms to pay different wages to workers with similar skills: when labor supply curves are far from perfectly elastic, firms have market power and set wages below their competitive levels (Manning, 2003). This might result in a degree of wage dispersion above the level predicted by a model of perfect competition. In this paper, we exploit a unique opportunity to study how changes in the dispersion of earnings among employees relate to changes in labor market competition among firms over the course of development.

We implement our analysis in the Lithuanian economy, which provides a useful laboratory for several reasons. First, Lithuania experienced sustained economic growth supported by its accession to the European Union (Grassi, 2024). Between 2000 and 2020, real GDP per capita increased by more than 120 percent, leading the country to transition from a low-income to a high-income economy. Second, in contrast to the experience of many other countries, wage inequality declined, with a reduction in the variance of wages of approximately 20 log points in about two decades. Third, integration into the EU single market contributed to both an influx of new businesses and a substantial decline in the working-age population, driven by the free movement of labor and improved job opportunities abroad for Lithuanian workers. Together, these two forces translated into a significant decline in the number of employees per firm.

We proceed with our analysis as follows. We begin by documenting the role of firm-specific components in wage inequality. Using Social Security data, we fit two-way fixed effects models to separate worker and firm fixed effects and quantify their contributions to inequality. We show that worker and firm heterogeneity explain about two-thirds of the cross-sectional wage dispersion in Lithuania. More importantly, we quantify that the sharp reduction in wage dispersion is mostly driven by the compression of firm fixed effects, which accounts for between 60 and 90% of the overall decline. Moreover, we document that the compression of firm wage premia was not due to structural change or minimum wage policy.

Guided by a standard model of dynamic monopsony, we then estimate the elasticity of firm labor supply —akin to labor market competition. We do so by identifying the workers' elasticity of separations with respect to the estimated firm-specific wage components, conditional on workers' observables. This is informative about the degree of firms' monopsony power because it captures how the firm's labor supply would respond to changes in the component of pay driven by arbitrary employer-set differences, rather than reflecting permanent differences in skills or transitory shocks to workers' job prospects. We document that the elasticity of labor supply has increased by about 0.36 percentage points over the past two decades, corresponding to 25% of the baseline estimate. While the increase in competition mimics the reduction in employer market power, as measured by firm-level wage markdowns from production function estimates, it is not driven by changes in labor market concentration or worker segmentation.

Finally, we analyze whether increased labor market competition contributed to the decline in wage inequality. For this purpose, we leverage variation across sectors and over time, together with a shift-share instrument that captures sectoral changes in employment opportunities for Lithuanian workers abroad following the 2004 EU accession. Specifically, we combine real labor compensation growth in pre-2004 EU member states over 2000–2020 with the pre-existing distribution of Lithuanian migrants across those destinations in 2000. The instrument aims to isolate changes in outside options as the catalyst for higher labor market competition among Lithuanian firms. We find that, absent the increase in labor market competition triggered by EU accession, overall wage inequality would have been between 13 and 27 percent higher.

Our paper contributes to several strands of the literature. A large body of research highlights the role of firms in shaping the earnings distribution of developed countries (see Card et al., 2018, for a recent review of the literature). Some of these studies exploit overlapping sub-periods to examine changes in wage components, i.e., firms and workers heterogeneity, over time and their contribution to inequality dynamics (e.g., Card et al., 2013; Song et al., 2019; Babet et al., 2023; Silva et al., 2022). With the increasing availability of linked employer-employee data worldwide, new evidence suggests that firms tend to explain a larger share of wage dispersion in developing countries (Alvarez et al., 2018; Pérez Pérez and Nuno-Ledesma, 2023; Bassier, 2023). We contribute to this literature by examining changes in firm-driven wage dispersion across different stages of a country's development and documenting a downward gradient in firms' contribution to inequality.

Evidence on the contribution of firm-specific components to wage dispersion has sparked interest in the role of imperfect competition in the labor market (Manning, 2021; Ashenfelter et al., 2022; Card, 2022). Numerous papers have focused on estimating separations-based labor supply elasticities to quantify the degree of employer labor market power (see the meta-analysis by Sokolova and Sorensen, 2021). Within this line of work, Hirsch et al. (2018) finds a procyclical labor supply elasticity in Germany, suggesting that employers' market power increases during recessions. Webber (2022) shows that labor supply elasticities in the U.S. have declined since the 1990s and that this decline accelerated during the Great Recession. Our paper contributes to this literature by documenting how the firm labor supply elasticity has changed over time in a country experiencing high economic growth and declining wage inequality.

Several studies have examined the link between imperfect labor market competition and workers' earnings. For example, Webber (2015) documents a positive relationship between the firm labor supply elasticity and workers' earnings. Autor et al. (2023) shows that labor market competition induced by the COVID-19 pandemic has boosted wage growth among low-wage workers, thereby reducing inequality in the US. Bassier (2023) documents that the variance of firm-specific wage components explains a larger share of wage dispersion in South African local markets with low labor supply elasticity. Using a structural model of market power in both product and labor markets, Deb et al. (2024) shows that less competitive market structures are characterized by higher between-firm wage inequality and finds that the decline in competition explains roughly 55% of the increase in wage inequality in the US. We complement this literature by documenting the joint dynamics of wage inequality and labor market competition during a period of economic growth. In addition, we show that the accession to the European Union in 2004 contributed to the decline in wage inequality through its impact on domestic labor market competition.

Unlike other countries, Central and Eastern European economies have experienced high wage growth and a substantial decrease in wage inequality in the last decades, mostly driven by a fall in between-firm wage inequality (Magda et al., 2021). Our paper contributes to understanding the dynamics of inequality in one of these countries. Using comprehensive, high-frequency Social Security data, we are the first to quantify the contributions of worker and firm heterogeneity to wage dispersion dynamics along a country's development path. Moreover, our evidence suggests that the 2004 EU enlargement has contributed to increased labor market competition and reduced overall wage inequality, providing a complementary explanation to minimum wage policy (Magda et al., 2021; Engbom and Moser, 2022). Our findings also reinforce the importance of addressing monopsony power in developing economies to address high levels of wage inequality (Bassier, 2023; Amodio et al., 2026).

The rest of the paper is organized as follows. Section 2 provides an overview of the developments in the Lithuanian economy in the last two decades. Section 3 outlines the conceptual framework to decompose the role of workers and firms in the variance of wages, while Section 4 describes the data used to implement the model. Section 5 quantifies the contribution of worker and firm heterogeneity to changes in inequality, whereas Section 6 documents the dynamics of labor market competition. Section 7 discusses the relationship between wage inequality and labor market competition and the role of the 2004 EU enlargement. Section 8 concludes.

# 2 Institutional background

This section provides background for the empirical analysis by discussing the most significant changes in the Lithuanian economy between 2000 and 2020.[1] In addition, it offers an overview of wage dispersion dynamics during that period.

## 2.1 Economic performance and labor market policies

**Early-stage development.** In the early 2000s, Lithuania was still consolidating its transition from a centrally planned to a market-based economy that began in 1991. GDP per capita (PPP) was approximately 15,000 USD, comparable nowadays to middle-

[1] In Appendix A, we provide graphical evidence on the dynamics of the key macroeconomic variables we discuss in this section.

income countries such as Colombia and Mexico.[2]

The privatization process of the 1990s fragmented productive assets and often transferred control to domestic shareholders with limited managerial capacity and weak access to external finance (IMF, 2003). Financial intermediation remained shallow. After the late-1990s banking crisis, the number of banks fell from 27 in 1993 to 13 by 2001, and surviving institutions adopted conservative lending practices (IMF, 2003). Capital markets were underdeveloped: corporate bond markets were virtually nonexistent, and equity financing was limited. Firms relied largely on retained earnings and lacked bank credit to finance investment.

Limited external finance constrained firm entry and expansion, dampened competition, and contributed to persistent productivity dispersion. Product markets were also only partially integrated into European and global value chains, and competitive pressure from foreign firms remained weaker than in other Central and Eastern European accession countries (Randveer and Staehr, 2021). Together, financial underdevelopment and incomplete product market integration constrained capital deepening and the reallocation of market shares toward more productive firms.

Labor market outcomes reflected these structural constraints. Employment growth was concentrated in a few sectors (finance, wholesale trade, and business services) while large parts of the economy experienced limited job creation (Rutkowski, 2003). In the early 2000s, non-employment reached nearly 40% of the working-age population and unemployment stood close to 17%, highlighting both substantial slack and weak labor demand in the aftermath of the banking crisis.

**EU integration and economic growth.** A marked shift occurred in May 2004, when Lithuania joined the European Union. Accession entailed not only political and institutional harmonization but also deep integration into European product and factor markets (Caliendo et al., 2021), which spurred economic growth (Grassi, 2024). EU structural funds financed infrastructure and institutional upgrades (Randveer and Staehr, 2021), while regulatory alignment reduced barriers to cross-border investment and trade. Access to the single market expanded Lithuania's set of trading partners and increased exposure to foreign competition. Over the subsequent two decades, exports (imports) reached roughly 80% (70%) of GDP, pointing to increased product

[2]See Figure A.10 in Appendix A for a comparison of real GDP per capita across OECD countries between 2000 and 2020.

market integration.

EU membership also introduced free movement of capital and labor. Financial integration facilitated a surge in FDI and cross-border banking activity, easing financing constraints that had previously limited firm expansion (Commission, 2006). At the same time, the accession introduced the free movement of workers. While improved access to capital supported firm growth, the right to live and work elsewhere in the EU triggered substantial emigration (Thaut, 2009; Klüsener et al., 2015). By 2020, Lithuanians residing in other EU countries accounted for roughly 10% of Lithuania's population. The scale of these flows had important labor market consequences (Zaiceva, 2014), contributing to labor shortages, upward wage pressure (Elsner, 2013), and adjustments in firm productivity (Giesing and Laurentsyeva, 2018). Moreover, the combination of large out-migration flows and increased firm entry raised the number of firms per worker, potentially intensifying competition for labor and altering wage-setting dynamics (Bagga, 2023).

Overall, over two decades, Lithuania's GDP per capita increased by more than 120% in real terms and reached 35,000 USD, a level comparable to that of other high-income countries such as South Korea and Spain.

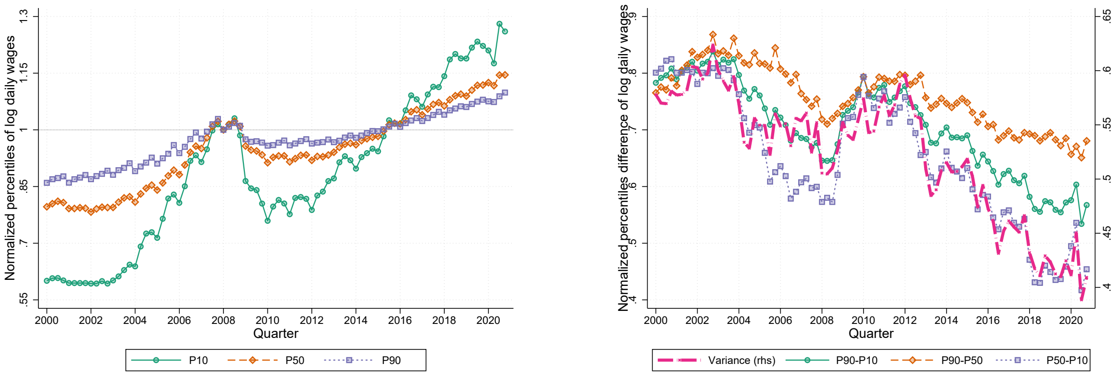
**Labor market reforms.** Minimum wage hikes were the flagship policies implemented in Lithuania to tackle inequality: between 2000 and 2020, the minimum wage increased from 160 to 607 euros, approximately a 235% increase in real terms. Available evidence suggests that this policy increased wages at the bottom of the wage distribution and spread the gains from economic growth to lower-paid workers without significantly affecting their employment prospects (Garcia-Louzao and Tarasonis, 2023), with estimates indicating that minimum wage increases between 2010 and 2019 reduced inequality by approximately one-third (Černiauskas and Garcia-Louzao, 2025).

In July 2017, two further reforms were enacted to provide more flexibility for firms and more protection for workers. A New Labor Code was introduced, which reduced statutory severance pay and simplified hiring and firing procedures.[3] The new labor code also prohibited employers from paying the minimum wage to skilled workers. In addition, a new Unemployment Insurance Law was enacted to replace the previous

[3]Despite the ambitions, changes in separation patterns induced by the reform were not substantial—prior to the reform, employers typically negotiated an agreement directly with employees, effectively avoiding large severance payments required by law.

**Figure 1:** Evolution of wage inequality

**(A)** Wage percentiles **(B)** Wage dispersion




Source: Social Security records and own calculations.
Notes: The figure shows the evolution of wage inequality among private-sector workers aged 20 to 60 from 2000 to 2020. Daily wages refer to quarterly income divided by the number of days worked in a given quarter and are expressed in real terms using the 2015 consumer price index. Panel A reports the dynamics of selected percentiles, P10, P50, and P90 of the log daily wage distribution in each quarter, expressed relative to their value in 2008Q1. Panel B reports the variance of log daily wages and the percentile differences as inequality measures. P(×)-P(·) is the difference between the specific percentiles, i.e., 90, 50, and 10, of the log daily wage distribution in a given quarter. Percentile differences are normalized using their corresponding differences in percentiles of the standard normal distribution, i.e., $\Phi^{-1}(\times) - \Phi^{-1}(\cdot)$.

(and first) law introduced in 2005. The new law made the system more generous by relaxing eligibility criteria and increasing the duration and level of benefits.

## 2.2 Stylized facts about wage dispersion in Lithuania

Figure 1 reports the dynamics of selected percentiles of the log real daily wage distribution as well as the evolution of wage dispersion based on different measures of wage dispersion, meaning the percentile difference and the overall variance of log real daily wages. To simplify the comparison among ratios, we normalized the differences across percentiles by the corresponding percentile gaps from a standard normal distribution.[4] The evidence points to a substantial long-run decline in wage inequality, regardless of the measure we look at: both the P90-P10 ratio and the variance of the log wages declined by about 20 log points. Notably, the decline in inequality was particularly pronounced at the lower end of the log wage distribution: while the P90-P50 ratio declined by only 10 log points, the P50-P10 ratio declined by nearly 40 log points.

To put these numbers in context, consider Brazil. Wage inequality, as measured by the variance of log wages, decreased by 28 log points between 1996 and 2012, and

[4] For instance, the normalized 50-10 percentile differences are the difference between percentiles 50th and 10th divided by 1.2815 ($\Phi^{-1}(0.5) - \Phi^{-1}(0.1)$, with $\Phi(\cdot)$ being the standard normal distribution).

the compression of the lower tail (P50-P10 ratio) was even higher, about 38 log points (Alvarez et al., 2018). Conversely, from 1985 to 2009, Germany experienced increases of about 16 and 18 log points in the P80-P20 and P50-P20 ratios, respectively (Card et al., 2013). Similar figures are found for the US, where the variance of log earnings increased by 19 log points between 1981 and 2013 (Song et al., 2019).

# 3 Decomposing the dynamics of wage inequality

What drove the decline in wage inequality documented in Section 2? Did firms play any role? In this section, we lay out an empirical framework to quantify the contribution of worker and firm heterogeneity to observed wage dispersion in Lithuania.

**AKM model.** To estimate worker- and firm-specific wage components, we adopt the AKM specification (Abowd et al., 1999), which is widely used in the literature that investigates the role of firms in wage setting (e.g., Card et al., 2013; Song et al., 2019). The model specifies the following additively separable function for (log) wages,

$$y_{it} = \eta_i + \psi_{j(i,t)} + X_{it}\Omega + \epsilon_{it}, \tag{1}$$

where $y_{it}$ is the (log) wage of worker $i$ in period $t$. $\eta_i$ represents worker $i$ fixed effect, and it loads any time-invariant wage-specific components of the worker, whether observable or unobservable, such as returns to formal schooling or innate ability. $\psi_{j(i,t)}$ is the fixed effect of firm $j$ where worker $i$ is employed in period $t$, meant to capture persistent wage disparities between firms, such as pay policies or rent sharing. $X_{it}$ includes time-varying covariates, like age and time effects, accounting for common life cycle and macroeconomic fluctuations that might affect wages beyond worker or firm types.[5] $\epsilon_{it}$ stands for the error term, reflecting purely transitory wage fluctuations.

In this framework, worker and firm fixed effects can only be separately identified within a set of firms and workers connected through mobility. This "connected set" emerges from workers who have switched jobs at least once. A firm belongs to the connected set if at least one of its workers was employed or will be employed in a dif-

[5] A classic identification problem arises when estimating AKM models that include age, year, and cohort effects. Since cohort effects are loaded within the person effects, it is not possible to uniquely identify the three objects separately. To address this problem, we adopt a standard strategy in the literature: we impose the age profile to be flat at age 40, use a polynomial of third-degree expressed in deviations from that value, and omit the linear term from the estimating equation (Card et al., 2018).

ferent firm within the period analyzed. The identification of the fixed effects hinges on two key interrelated assumptions. The first assumption is *exogenous mobility*: worker mobility is uncorrelated with the time-varying residual components of wages. This means that wages before or after a job switch should be, on average, the same as if there had been no switch. The second assumption is *additive separability*: there must be no interaction effect between firm type and worker fixed effects. This assumption imposes a proportional firm's markup/down for all workers.

**Variance decomposition.** To quantify the role of firms and workers in the dispersion of wages, we use the parameters from equation (1) and decompose the variance of (log) wages as follows,

$$\begin{aligned} var(y_{it}) &= var(\eta_i) + var(\psi_{j(i,t)}) + var(X_{it}\Omega) + var(\epsilon_{it}) \\ &+ 2 \cdot \left[ cov(\eta_i, \psi_{j(i,t)}) + cov(\eta_i, X_{it}\Omega) + cov(\psi_{j(i,t)}, X_{it}\Omega) \right], \end{aligned} \tag{2}$$

where a positive (negative) value of $cov(\eta_i, \psi_{j(i,t)})$ captures positive (negative) sorting effects between worker $\eta_i$ and firm $\psi_{j(i,t)}$-types.[6] In other words, the covariance term will be positive if high-wage firms hire the most productive workers, and their earnings are above those of the less productive individuals working in the same organization (Abowd et al., 1999).

A well-known problem that arises in AKM models is that a large number of firm-specific intercepts are uniquely identified by workers who change firms, leading to biased estimates of the variances of the fixed and their covariance, or the so-called *limited mobility bias* (Andrews et al., 2008, 2012; Kline et al., 2020; Bonhomme et al., 2023). Therefore, we complement the AKM approach with two alternative empirical strategies that directly address this bias.

As a first approach, we follow Bonhomme et al. (2019) (BLM, hereafter) and implement a firm clustering approach. The BLM strategy discretizes firm heterogeneity so that the support ot the firm wage effects is restricted to a finite number of firm clusters. This approach allows us to reduce the dimensionality of firm fixed effects and thus correct for mobility bias. We implement the strategy as follows. As a first step, we create the firm clusters using a *k-means* clustering algorithm (Bonhomme et al., 2022) based

[6]Under the assumption of exogeneity, the error term is uncorrelated with any of the fixed effects as well as the time-varying covariates; thus, the covariance terms are zero.

on the quantiles of the wage distribution within firms. This approach clusters firms whose latent types, as determined by the wage distribution, are most similar. Since the number of clusters must be specified before implementing the algorithm, we set it to 1,500, about 1% of the original number of firms in our sample. This number of clusters enables us to address the mobility bias that could arise in AKM estimation while capturing significant wage heterogeneity among firms (71% of total between-firm wage dispersion). In the second step, we estimate a two-way fixed effects model as in equation (1) where the firm fixed effects are now reduced to the number of clusters.

As a second approach, we apply the leave-one-out estimator proposed by Kline et al. (2020) (KSS). The KSS estimator consists of removing one unit (e.g., observations, worker-firm matches, workers' histories) at a time and re-estimating the variance components using the remaining observations. Specifically, an AKM model is estimated for each excluded unit, and the estimates are used to compute an unbiased estimator of the variance of the residuals, which characterizes the limited mobility bias itself. We implement the KSS estimator by excluding a given worker-firm match at each iteration and use the resulting estimate of the error variance to compute bias-corrected estimates of the variances of worker and firm fixed effects.[7]

# 4 Data

**Social Security records.** The main data source for our analysis is a 25 percent "de facto random" sample of workers appearing in the Social Security system at any time between 2000 and 2020.[8] The dataset has a longitudinal design with unique identifiers for each individual, together with the firm where they are employed at a given time.[9] These individuals have been tracked every month since 2010. Before that year, the frequency was quarterly because employers were required to report information on their employees only then. Thus, one can follow workers over time and across companies, which is key to estimating worker and firm permanent wage components. For each sample member, we have information on income and benefits received per period,

[7]The KSS estimator is implemented following the random projection strategy proposed by Kline et al. (2020) using the JLA algorithm.

[8]We observe all individuals in Social Security born in an odd month of each even year. We follow the labeling of DellaVigna et al. (2017), who coined this type of sampling scheme as "de facto random".

[9]Due to legal reasons, individuals do not appear in our sample until they are 18, even if they were present in the Social Security system at younger ages.

gender, age, employment status, start and end of employment, location of the firm's headquarters, industry, firm size, and total payroll measured at the end of the year.[10]

The labor income variable refers to *all* work-related income subject to Social Security contributions, including base salary and non-regular payments such as bonuses, allowances, overtime pay, commissions, or severance payments.[11] This is a broad measure of earnings, as it directly captures any payment made by the employer in a given quarter. There is an important limitation that is worth discussing. The dataset does not report hours worked. This implies that we cannot calculate hourly wages or restrict the analysis to full-time workers.[12] To mitigate this issue, we employ a daily wage, computed as quarterly income divided by days worked in the quarter and expressed in real terms using the 2015 consumer price index.

**Estimation sample.** To obtain the analysis sample, we process the original data as follows. First, we construct a quarterly panel of workers aged 20 to 60 between 2000 and 2020 employed in the private sector.[13] Second, we only consider quarterly employment observations such that a person works at least 15 days and earns at least half of the monthly minimum wage in that quarter. Third, we exclude the last observation of each job spell lasting more than 3 months (the probationary period) to avoid the influence of severance packages or other payments made at the time of contract termination (such as unused vacation time, which is not directly related to firms' wage policies) on our estimates. Finally, if a person has more than one job in a given quarter, we select the one reporting the highest earnings. These restrictions yield a final sample of 532,495 workers across 143,461 firms, totaling 16,735,572 observations from the first quarter of 2000 to the last quarter of 2020. As discussed in Section 3, identification of worker and firm fixed effects is based on job switchers and, hence, is only achieved through the so-called *largest connected set*, i.e., the largest set of firms over which workers move. The estimation sample is thus restricted to this set. The largest connected set consists of 526,536 workers across 137,783 firms and 16,638,459

[10]Unfortunately, the database does not provide education information, and the occupation variable has only been available since 2012.

[11]Given the change in Social Security contributions in 2019, we recalculate income before the 2019 reform by multiplying it by the official re-scaling factor of 1.289.

[12]Nevertheless, part-time employment is not particularly widespread in Lithuania, representing from 5 to 7% of overall wage-employment between 2000 and 2020.

[13]Our focus on the private sector is both due to the peculiarities of the wage-setting process in the public sector as well as the ability to make comparisons with the existing literature.

**Table 1:** Summary statistics

| | 2000-2020 | | 2000-2005 | | 2015-2020 | |
|---|---|---|---|---|---|---|
| | Cleaned data | Connected set | Cleaned data | Connected set | Cleaned data | Connected set |
| Wages | | | | | | |
| Mean | 2.905 | 2.909 | 2.525 | 2.539 | 3.252 | 3.278 |
| Std.Dev. | 0.779 | 0.777 | 0.764 | 0.759 | 0.679 | 0.667 |
| Firms | 143,461 | 137,783 | 64,509 | 56,698 | 78,103 | 62,387 |
| Direct movers | 296,159 | 295,942 | 124,873 | 124,425 | 124,595 | 123,530 |
| Movers | 391,670 | 391,229 | 173,540 | 172,827 | 165,418 | 163,837 |
| Workers | 532,495 | 526,536 | 330,161 | 320,625 | 333,238 | 314,337 |
| Direct moves | 815,911 | 815,539 | 218,456 | 217,821 | 233,805 | 232,016 |
| Job changes | 1,399,550 | 1,398,910 | 341,133 | 340,191 | 349,526 | 347,079 |
| Worker-quarters | 16,735,572 | 16,638,459 | 4,510,485 | 4,409,926 | 4,957,606 | 4,696,179 |

Notes: Wages refer to the (log) quarterly income divided by days worked in a given quarter and are expressed in real terms using the 2015 consumer price index. Firms stand for the unique number of employers. (Direct) movers refer to the *unique* number of workers who switched jobs at least once (between two consecutive quarters). Direct moves are job-to-job transitions, i.e., the number of worker-quarter observations when an employer change is recorded between two consecutive quarters. Job changes refer to all job changes recorded across all worker-quarter observations, regardless of whether there was a period of non-employment between the move.

observations between 2000 and 2020.

Table 1 reports descriptive statistics for the cleaned data and the largest connected set. The figures show that the largest connected set captures virtually all workers in the cleaned data (98%) and the majority of firms (95%) due to the high mobility rate. In particular, 74% of workers changed at least one employer between 2000 and 2020, and 56% made at least one job-to-job transition over the same period. Moreover, over the whole sample period, the average number of movers per firm is 9.8 (5.7 if only job-to-job transitions are counted). To put patterns of mobility in perspective, the quarterly mobility rate over the full sample period, i.e., the number of job changes divided by the total number of observations, is 8.4% (4.9% if using only job-to-job transitions), while the annual mobility rate using German data form yields a rate of 3% (Card et al., 2013) or a 9.7% rate for the US in Washington administrative data (Lachowska et al., 2020). This high degree of mobility reflects both the quarterly frequency and long time span of the data, and it improves identification in the absence of population data (Andrews et al., 2012; Babet et al., 2023; Bonhomme et al., 2023).

# 5 Firms and workers in the variance of wages

**Pooled estimates.** We are now ready to discuss the role of firm and worker heterogeneity in the variance of wages in Lithuania. Table 2 reports the variance decomposition obtained using the estimates from the AKM model in equation (1), as well as from the two alternative approaches, and using data from the entire sample period (2000-2020). Worker and firm permanent heterogeneity combined explain two-thirds of the dispersion in (log) daily wages. The estimates from the standard AKM model point to firm-specific pay policies as the most relevant component, with the dispersion of firm fixed effects accounting for about 32% of the dispersion in (log) daily wages. Permanent worker heterogeneity explains 28% of wage variance, while sorting contributes roughly 7%. As expected, the estimates from the KSS correction yield lower contributions from worker and firm fixed effects (26% and 29%, respectively) and a higher contribution from sorting (9%). The differences between AKM and KSS are not substantial in the cross-section, likely because of the high worker mobility in our data. The change is more noticeable when using the BLM clustering approach: while the contribution of firms is halved (15%), the contribution of sorting is doubled (13%) relative to the AKM estimates. As discussed in detail in Bonhomme et al. (2019), these differences tend to arise from worker segregation, which could bias the clustering approach: firms may be clustered based on a combination of their own fixed effects and their workers' fixed effects.

**Table 2:** Variance decomposition of log daily wages, 2000-2020

| | AKM | | KSS | | BLM | |
|---|---|---|---|---|---|---|
| | Component | Share | Component | Share | Component | Share |
| $Var(y)$ | 0.604 | - | 0.594 | - | 0.606 | - |
| $Var(\eta)$ | 0.165 | 0.274 | 0.156 | 0.263 | 0.204 | 0.336 |
| $Var(\psi)$ | 0.189 | 0.313 | 0.171 | 0.287 | 0.092 | 0.152 |
| $Var(X\Omega)$ | 0.089 | 0.147 | 0.089 | 0.149 | 0.066 | 0.110 |
| $Var(\epsilon)$ | 0.121 | 0.200 | 0.121 | 0.204 | 0.148 | 0.245 |
| $2 \times Cov(\eta, \psi)$ | 0.041 | 0.068 | 0.052 | 0.088 | 0.078 | 0.129 |
| $2 \times Cov(\eta, X\Omega)$ | -0.002 | -0.004 | -0.003 | -0.005 | -0.007 | -0.012 |
| $2 \times Cov(\psi, X\Omega)$ | 0.002 | 0.003 | 0.003 | 0.004 | 0.024 | 0.040 |

Notes: Variance decomposition of (log) daily wages based on equation (2). AKM uses estimates from the two-way fixed effects model following Abowd et al. (1999). BLM relies on estimates from the firm-clustering approach of Bonhomme et al. (2019), using 1,500 firm clusters. KSS is based on estimates from the leave-one-out estimator by Kline et al. (2020), excluding worker-firm matches in each iteration. The estimation sample for each method corresponds to the largest connected set of firms (or firm clusters) over which workers move during the entire sample period.

**Robustness checks.** In Appendix B, we discuss the assumptions of the two-way fixed-effect approach and show that both exogenous mobility and additive separability are satisfied. In Appendix C, we evaluate the sensitivity of the results to different model specifications and sample selection criteria. First, in Table C.1, we show that the age normalization we adopt does not affect our results. The AKM estimates are quantitatively the same under alternative specifications of the time-varying effects, such as using sex-specific effects, centering wages at their mean in each calendar time, or netting out age and time effects in a first stage and then applying the AKM model to the residuals. Second, we investigate the relative contribution of each term using different sampling restrictions. We find that restricting the sample to workers earning at least the minimum wage, or including the public sector, reduces the contribution of firms while increasing that of workers by the same proportion (Table C.2). In the first two columns of Table C.3, we allow firm fixed effects to shift every 5 years, in the spirit of dynamic wage policies (Engbom et al., 2023), while in the last two columns, we allow both worker and firm effects to vary. The results of the first exercise point to a larger contribution of firms to inequality, while the second exercise shows a larger contribution of worker-fixed effects than in the baseline specification. This difference suggests the existence of a long-run trend in the contributions of firms and workers to inequality, which we will investigate further below. Furthermore, performing the KSS estimation by leaving out either workers or observations, rather than worker-firm matches, in each iteration yields negligible changes to our findings (Table C.4). Finally, in Tables C.5 and C.6, we test the robustness of the BLM exercise using (i) a different number of firm clusters, or (ii) alternative wage definitions to classify firms. The main results remain unchanged.

**Changes over time.** Our pooled estimates indicate that workers' and firms' permanent heterogeneity, along with sorting, explain about two-thirds of wage dispersion in Lithuania. A key question is how the contribution has evolved and what role workers and firms played in the observed decline in wage inequality.

Earlier studies have assumed perfect stability of the bias over time, in which case comparing AKM estimates across periods would be informative about how firms and workers have contributed to the dynamics of inequality (e.g., Card et al., 2013; Alvarez et al., 2018; Song et al., 2019). However, recent work suggests that this may be a strong assumption in environments where mobility patterns may have changed over time (Babet et al., 2023). Given the major economic transformation that Lithuania has experienced in the last 20 years, instead of assuming perfect stability of the bias, we estimate the wage components using the three methods for four selected sub-periods of our data (2000-2005, 2005-2010, 2010-2015, and 2015-2020) and rely on these estimates to provide ranges of the contribution of firms and workers.

Table 3 reports the change in wage inequality from 2000-2005 to 2015-2020, together

**Table 3:** Decomposition of the decrease in wage inequality

| | 2000-05 to 2015-20 | | |
|---|---|---|---|
| | AKM | KSS | BLM |
| Change in $Var(y)$ | -0.131 | -0.136 | -0.123 |
| Contribution | | | |
| $Var(\eta)$ | -0.088 | -0.043 | -0.233 |
| $Var(\psi)$ | 0.898 | 0.930 | 0.639 |
| $Var(X\Omega)$ | -0.067 | -0.068 | -0.148 |
| $Var(\epsilon)$ | 0.058 | 0.059 | 0.096 |
| $2 \times Cov(\eta, \psi)$ | 0.184 | 0.109 | 0.504 |
| $2 \times Cov(\eta, X\Omega)$ | 0.036 | 0.038 | 0.121 |
| $2 \times Cov(\psi, X\Omega)$ | -0.021 | -0.024 | 0.022 |
| Counterfactual change in $Var(y)$ | | | |
| 1. Fixed variance of firm effects | -0.013 | -0.017 | -0.045 |
| 2. Fixed corr. of firm and worker effects | -0.117 | -0.150 | -0.109 |
| 3. Both 1 and 2 | 0.012 | -0.024 | 0.024 |

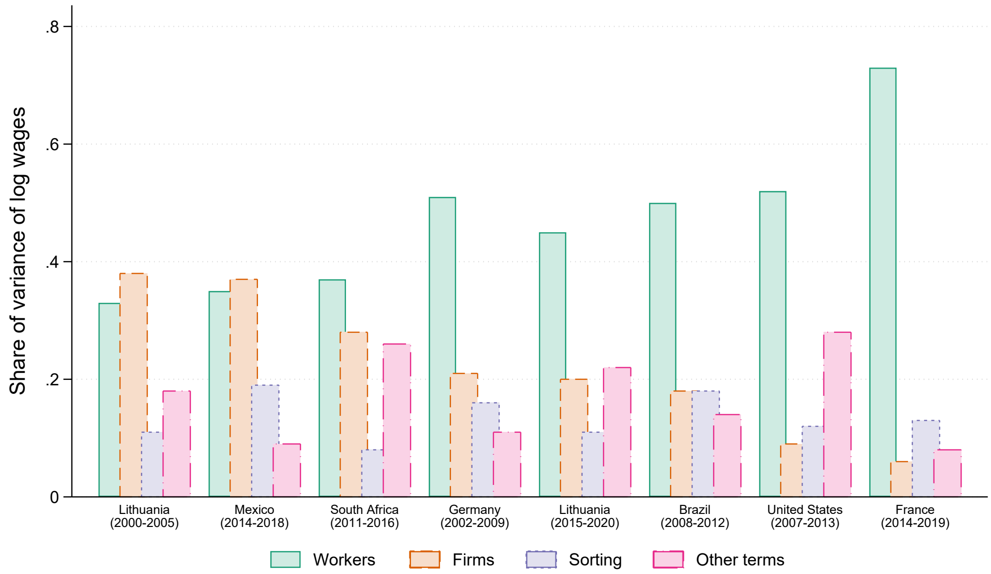
Notes: AKM, BLM, and KSS columns show the change in wage inequality along with the contribution of each component. The contribution of each component is the change in the component divided by the change in the wage variance. AKM uses estimates from the two-way fixed effects model following Abowd et al. (1999). BLM relies on estimates from the firm-clustering approach of Bonhomme et al. (2019). KSS is based on estimates from the leave-one-out estimator by Kline et al. (2020). All estimates are period-specific. The estimation sample for each method corresponds to the largest connected set of firms (or firm clusters) within which workers move in each period. Counterfactual 1 computes the change in inequality, fixing the variance of firm effects to that in the 2000-05 period, i.e., $Var_{2000-05}(\psi)$. Counterfactual 2 shows the change in wage inequality between 2000-05 and 2015-20, assuming no change in the correlation of worker and firm effects, i.e., $Cov_{2015-20} = \rho_{2000-05} \times Var_{2015-20}(\eta)^{1/2} \times Var_{2015-20}(\psi)^{1/2}$. Counterfactual 3 measures the change in inequality, allowing only the variance of worker effects to vary, i.e., we combine counterfactuals 1 and 2.

with the contribution of each component to such change.[14] To assess the role of firms and workers in the decline of inequality, we follow Card et al. (2013) and implement three counterfactual exercises. In the first counterfactual, we compute the change in inequality had the variance of firm fixed effects not changed from its value in 2000-2005. This exercise suggests that the decrease in the dispersion of firm fixed effects might explain between 64% and 93% of the reduction in inequality.[15] In the second counterfactual, we assume that the correlation between firm and worker fixed effects (sorting) did not change over time. The results indicate that sorting can explain no

[14]The results for each sub-period and estimation method are reported in Appendix C, Tables C.7, C.9, and C.10.

[15]The compression of fixed effects remains the main factor behind the decline in inequality, even when pooling all years and estimating the AKM model with dynamic effects, or when using alternative firm cluster sizes for the BLM approach (see Tables C.11 and C.12 in Appendix C, respectively).

**Figure 2:** Comparison with existing estimates around the world




Source: Social Security records (Lithuania), Song et al. (2019) (United States), Babet et al. (2023) (France), Engbom and Moser (2022) (Brazil), Card et al. (2013) (Germany), Bassier (2023) (South Africa), and Pérez Pérez and Nuno-Ledesma (2023) (Mexico), and own calculations.
Notes: The figure shows the contributions to the variance of log wages from worker and firm effects, their covariance, and other terms (residuals, life-cycle, and time effects, together with their covariances with worker and firm effects) across countries. Countries are ranked in decreasing order by the contribution of firms to wage variance. Reported contributions for Brazil, Lithuania, Mexico, and South Africa are based on KSS estimates, while those for France are based on a simplified version of the KSS estimator. Contributions in the US and Germany are obtained from standard AKM estimates.

more than 20% of the observed reduction in inequality. In our final exercise, we hold constant both the variance of firm fixed effects and sorting to examine the contribution of worker fixed effects to the decline in inequality. The figures suggest that had only the variance of worker fixed effects changed over time, the dynamics of wage dispersion might even have been reversed, and there is no scenario in which it could explain more than 15% of the actual decline.[16]

**Cross-country comparison.** We place the contribution of firm and worker wage components into perspective by comparing the experience of Lithuania with the outcomes of several countries. Figure 2 reveals that the Lithuanian economy in 2000-2005 exhibited the largest contribution of firms in explaining the variance of wages (38%), a value only comparable to Mexico in 2014-2018 (37%), and followed by South Africa in 2011-2016 (35%). The sharp decline in the contribution of firm heterogeneity over time

[16]The contribution of firms to inequality remains substantial, accounting for 80 to 85 percent of the total, even when restricting the sample to firms or to firms *and* workers observed at least once in each of the four overlapping periods. Thus, the results mostly reflect changes in pay policies among incumbents as opposed to being driven by firm entry and exit (see Table C.8 in Appendix C).

places the Lithuanian economy in 2015-2020 closer to cases of Germany in 2002-2009 and Brazil in 2010-2014, where firms explained about 20% of wage dispersion. These numbers are still above those of the United States (2007-2013) and France (2014-2019), where the dispersion of firm fixed effects accounts for less than 10% of pay dispersion.

**Structural change and labor reallocation.** Between 2000 and 2020, Lithuania underwent a profound economic transformation, and the compression of the variance of firm fixed effects may simply be the result of labor reallocation to sectors with relatively lower wage dispersion. To assess the extent to which compositional shifts in employment across sectors account for the overall reduction in the variance of firms' pay policies, we employ the decomposition proposed by Foster et al. (2001).[17]

Table C.13 in Appendix C reports the contribution of between-sector and within-sector components to the total change in the variance of firms' fixed effects, both in levels and in percent, between 2000-2005 and 2015-2020. The decomposition shows that the total change in the dispersion of firms' pay policies over time can be fully explained by changes within sectors. Changes in employment across sectors have slowed wage compression: if the sectoral composition of employment had remained fixed, the decline in the variance of firm pay policies would have been between 0.6 and 1.6 percentage points higher.

**Minimum wage and firm pay policies.** Changes in the national minimum wage were significant over the last two decades and could have compressed the cross-firm wage distribution by raising wages at the bottom. Because the decline in the dispersion of firm pay policies has occurred within each sector, we now investigate the role of changes in the national minimum wage by constructing a sector-specific measure of minimum-wage exposure for the period 2000-2005. This measure reflects the wage increase necessary to bring all workers' wages in a sector up to the minimum wage (Dustmann et al., 2021). Then, we correlate changes in the variance of firm fixed effects with the initial incidence of the minimum wage.

Figure C.4 in Appendix C shows that the decline in the dispersion of firm fixed effects was widespread and generally uncorrelated with minimum wage policy, as measured by the sectors that would be more exposed to increases in the MW.[18] In

[17]Further details are reported in Appendix C.

[18]Figure C.5 shows that the lack of correlation holds for alternative measures of minimum wage

Figure C.6 we repeat the same exercise using the P90-P10 ratio, the P50-P10 ratio, and the P90-P50 ratio. The same result emerges: the decline in the percentile difference of the firm fixed effects occurred in almost every sector and is not correlated with sectoral exposure to the minimum wage.

The lack of a clear link between minimum wage exposure and the compression of firm fixed effects should be understood in light of the observed wage dynamics. While the minimum wage rose significantly over the sample period and percentiles at the bottom of the wage distribution increased more compared to those at the top, the growth in minimum wage did not outpace the economy-wide wage growth (see Figure A.7 in Appendix A). If anything, the minimum wage "bite", that is, its position relative to the overall wage distribution, declined in almost any sector, both in terms of share as well as incidence of workers employed at minimum wages (see Figure C.3 in Appendix C). This is consistent with Černiauskas and Garcia-Louzao (2025), who show that between 2013-2019, a period when the most continuous and sizable minimum wage hikes happened in Lithuania, changes in the minimum wage could explain only about a third of the decline in overall wage inequality and roughly 42% of the compression of the lower tail.[19]

# 6 Firms, inequality, and labor market competition

In the previous section, we have shown that the sharp decline in wage inequality observed in Lithuania over the last 20 years was almost entirely due to within-sector compression of firm-specific wage components and was not correlated with minimum wage policy. What can explain these dynamics? Guided by a textbook model of dynamic monopsony, we argue in this section that changes in labor market competition can be a plausible factor behind the observed trend in inequality.

## 6.1 Theoretical framework

We consider a parsimonious dynamic monopsony model for the labor supply to the firm, in the spirit of Manning (2003) and Langella and Manning (2021). While we do

incidence based on either the share of workers whose earnings are below the minimum wage or the share of firms for which the minimum wage is at least 75% of the average wage.

[19]Figure A.8 reports the timing of changes in mandated nominal minimum wage. While it was relatively flat before accession to the EU, it increased from 200 to 300 EUR between 2007 and 2008, and from 300 to 400 EUR between 2013 and 2014.

not explicitly estimate the model in this paper, the intuition of the effect of monopsony power on wage dispersion is central to our argument.

Time is discrete. The economy is populated by heterogeneous firms, differing in their productivity, $z_{jt}$, and producing a homogeneous good with a production function with decreasing marginal returns in labor $L_{jt}$,[20]

$$y_{jt} = z_{jt} L_{jt}^{\alpha}, \quad \alpha \in (0,1).$$

Let $\Pi(L_{jt-1})$ be the discounted value of future profits from date $t$ onwards, and let $\delta \in (0,1)$ be the discount rate. Each firm post wages $w_{jt}$ to maximize $\Pi(L_{jt-1})$, defined recursively as follows:

$$\Pi(L_{jt-1}) = \max_{L_{jt}, w_{jt}} \quad z_{jt} L_{jt}^{\alpha} - w_{jt} L_{jt} + \delta \Pi(L_{jt}),, \tag{3}$$

subject to the labor supply function for firm $j$, equal to

$$L_{jt} = R(w_{jt}) + [1 - s(w_{jt})] L_{jt-1}.$$

Here $R(w_{jt})$ and $s(w_{jt})$ denote the number of workers recruited and separated, respectively, both defined as a function of wages $w_{jt}$. In what follows, we assume the following reduced-form for both recruitment and separation:

$$R(w_{jt}) = A_t w_{jt}^{\varepsilon_{Rt}} \quad \text{and} \quad s(w_{jt}) = B_t w_{jt}^{\varepsilon_{sept}},$$

where $\varepsilon_{Rt}$ and $\varepsilon_{sept}$ denote the wage elasticities of recruitment and separation, while $A_t$ and $B_t$ are common constant.[21] These two assumptions imply the following dynamics of employment:

$$L_{jt} = A_t w_{jt}^{\varepsilon_{Rt}} + [1 - B_t w_{jt}^{\varepsilon_{sept}}] L_{jt-1}. \tag{4}$$

[20]Because of the limited role of worker fixed effects and sorting in explaining the change in inequality documented in Section 5, we follow Card et al. (2018) and abstract from modeling worker-level heterogeneity. See Lamadon et al. (2022) for a discussion on the role of worker sorting.

[21]Burdett and Mortensen (1998), or alternatively Manning (2003) provide with a micro-fundation of both functions in the context of a search and matching model.

Taking the first-order condition with respect to wages, we get

$$\left[\alpha z_{jt} L_{jt}^{\alpha-1} - w_{jt} + \delta \frac{\partial \Pi(L_{jt})}{\partial L_{jt}}\right] \frac{\partial L_{jt}}{\partial w_{jt}} \frac{w_{jt}}{L_{jt}} = w_{jt}. \tag{5}$$

In a steady state with sufficiently low future discounting (i.e., $\delta \approx 1$), equation (5) can be re-arranged to show that dispersion in wage is equal to[22]

$$\text{var}_t[\log w_{jt}] \approx \frac{1}{\phi_t^2} \text{var}_t\left[\log z_{jt}\right], \tag{6}$$

where

$$\phi_t = 1 + (1-\alpha)\varepsilon_{LSt},$$

and $\varepsilon_{LSt} = \varepsilon_{Rt} - \varepsilon_{sept}$ is the overall wage elasticity of labor supply.

Equation (6) states that the dispersion in firm pay negatively correlates with the degree of labor competition, as measured by the firm's labor supply elasticity. This happens because when the labor market becomes less competitive, the labor supply curve rotates clockwise, i.e., it becomes less elastic, and a wedge opens up relative to the marginal cost of labor, which tilts even more. This wedge passes through wages, generating wage dispersion among firms with different marginal products of labor (Figure 3).[23] Guided by this result, in the rest of this section, we document how the labor supply elasticity has evolved between 2000 and 2020.

## 6.2 Estimation of the firm labor supply elasticity

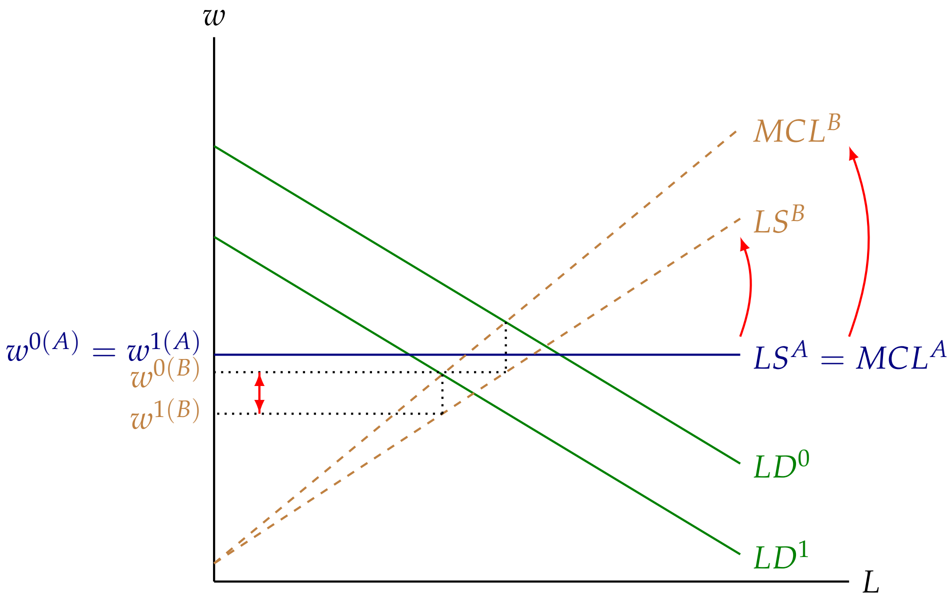
To estimate the firm labor supply elasticity, $\varepsilon_{LS}$, we follow a widely common approach and start by identifying the wage elasticity of job separation (Manning, 2003; Langella and Manning, 2021). Specifically, we relate the separation rate to the (log) wage using the following linear probability model,

$$P(s_{ijt} = 1) = \alpha + \beta \log w_{ijt} + X_{ijt}\Lambda + \xi_{ijt}, \tag{7}$$

[22]See Appendix D for a full derivation of the model solution.

[23]This prediction is valid as long as $\alpha \in (0,1)$; that is, as long as there are decreasing returns to scale in production. When $\alpha = 1$, as in standard one-worker-firm search models, a common increase in the labor supply elasticity only shifts the level of wages without affecting their dispersion. When $\alpha < 1$, however, differences in productivity translate into endogenous differences in firm size, which feed back into wages through the marginal product of labor. As labor supply elasticity rises, employment reallocates toward high-productivity firms, compressing cross-firm differences in marginal products and, hence, wages. See Armangué-Jubert et al. (2025) for a discussion.

**Figure 3:** Less elastic labor supply increases wage inequality




Notes: $w$ refers to wage. $L$ refers to employment. $MCL$ refers to the marginal cost of labor. $LS$ refers to the inverse labor supply curve. $LD$ refers to the inverse labor demand curve. Scenario "A" refers to a perfectly competitive labor market. Scenario "B" refers to a monopsonistic labor market. Indexes "0" and "1" refer to (potentially heterogeneous) employers.

where $s_{ijt}$ stands for the separation of worker $i$ from employer $j$ at quarter $t$ and $w_{ijt}$ is the corresponding wage measure.[24] $X_{ijt}$ is a vector of controls that includes *estimated* AKM worker fixed effect (capturing permanent heterogeneity across workers that can influence mobility patterns) along with indicators for age groups, gender, 2-digit industries, and time effects.

Consistent with our theoretical framework, an estimate for the separation elasticity, $\varepsilon_{sep}$, can be obtained as

$$\varepsilon_{sep} = \frac{\hat{\beta}}{\overline{s_{ijt}}} \tag{8}$$

where $\overline{s_{ijt}}$ is the average separation rate in the period. A lower-magnitude separation elasticity, arising when separations are less sensitive to wage cuts, will reflect greater employers' labor market power. Following Manning (2003), we compute the firm labor supply elasticity as $\varepsilon_{LS} = \varepsilon_R - \varepsilon_{sep} \approx -2 \times \varepsilon_{sep}$.[25] The theory of labor market monopsony suggests that the relevant elasticity governing the firm wage-setting process is the "quit" elasticity (Burdett and Mortensen, 1998; Manning, 2003). However,

[24]In Table E.1 of Appendix E, we also report estimates of the separation elasticity using a complementary log-log hazard model as in Langella and Manning (2021).

[25]Monopsonistic employers set wages based on the labor supply elasticity, which is the sum of the quit and hire elasticities. In the steady state, this can be approximated as twice the separation elasticity (Manning, 2003).

the latter may not capture the full range of workers' outside options, especially following Lithuania's accession to the EU and the resulting free mobility of workers across countries. Therefore, we examine the elasticity of total separations and employer-to-employer transitions.

It is common in the literature to estimate these elasticities using workers' wages, controlling for relevant individual characteristics that may affect mobility patterns (e.g., Hirsch et al., 2018; Bachmann et al., 2022; Webber, 2022). However, recent work by Bassier et al. (2022) emphasizes that the relevant dimensions for workers' decisions to leave their current jobs are the firm- and match-specific components of wages. We follow their approach and proxy firm wage policy using the AKM firm effect, which isolates cross-firm wage premia while holding worker permanent heterogeneity fixed. Identification, therefore, relies on cross-firm differences in wage-setting behavior, captured by the AKM premia, which are assumed not to be influenced by worker separation propensities conditional on controls.[26]

Three main conditions are required for this approach to yield credible elasticities. First, since pure sorting would mechanically induce a correlation between separations and firm premia unrelated to labor supply responses, sorting between worker and firm fixed effects must be limited. In our setting, the covariance seems not to be large: around 0.02 in AKM and at most 0.04 in BLM (Table 2). Second, separations should not mechanically affect the estimation of firm effects. Third, because AKM premia are estimated, classical measurement error may attenuate the elasticity. To address the latter two concerns, we instrument the estimated firm effects with firms' average wages computed from the end-of-year full workforce. As AKM effects are estimated from a quarterly sample of workers with a different composition, under the assumption that worker-level wage shocks embedded in the AKM estimates are orthogonal to average wages measured on the full workforce, the instrument remains correlated with true firm premia while uncorrelated with the error term, thereby mitigating biases in the spirit of Goldschmidt and Schmieder (2017) and Bassier et al. (2022).

[26]Although firm fixed effects isolate the demand-related component of wages, the resulting elasticity may still understate firms' true labor supply elasticity if observed separations do not fully capture workers' behavioral responses to wage policies (Bassier et al., 2022). To the extent that the worker-specific propensity to move, which is correlated with the firm's wage policy, shows little variability across periods, our results remain informative about changes in the elasticity over time.

### 6.3 The dynamics of labor market competition

**Firm's labor supply elasticity.** Table 4 reports the estimates of the quarterly elasticity of separation for the first and the last periods (2000-2005 and 2015-2020, respectively) together with the implied firm labor supply elasticity.[27] Three main results emerge from our estimates. First, in terms of levels, the estimated elasticities are at the lower end of the range reported in the literature (Sokolova and Sorensen, 2021). Using the estimates from Columns (1) and (2) in Panel A, a log-point drop in wages increases the overall separation by 6 percent and the employer-to-employer separation by 2.5 percent. These estimates imply a labor supply elasticity of 1.03 and 0.98, respectively, values that are consistent with what Armangué-Jubert et al. (2024) document for low-income countries. Second, the estimates are significantly higher (1.38 and 1.69) when the wage measure is net of the worker-specific wage components and is instrumented by the average wage in the firm (Columns (5) and (6) of Panel A). Finally, and crucially for our analysis, the results point to a decrease (increase) in the elasticity of separation (firm labor supply elasticity) between 2000-2005 and 2015-2020, regardless of the strategy used to estimate the response of separations to wage changes. For example, comparing our estimates in Column (5) Panel A to those in Panel B of Table 4, we observe an increase in the labor supply elasticity of roughly 0.36 percentage points.[28]

**Labor supply elasticity vs. wage markdowns.** Changes in the frequency of job transitions over the period might bias the estimates of the labor supply elasticity if these were related to structural forces other than changes in labor market competition. If, as a result of economic transformation, workers respond less to wage changes at the beginning of the period than at the end, this would explain why the estimates of the separation elasticity are initially low and rise over time. However, in Appendix E (Figure E.1), we show that although the majority of job-to-job transitions occurred within 2-digit industries, there is no clear trend over the sample period.

To further address this concern, we rely on an alternative measure of labor mar-

[27]See Table E.2 in Appendix E for estimates for the 2005-2010 and 2015-2020 sub-periods.

[28]In Appendix E, Table E.3, we check the sensitivity of the estimates to different choices of controls, i.e. i) including tenure to account for potential tenure-specific wage policies (Manning, 2003; Bachmann et al., 2022), ii) excluding worker FE, which may introduce a downward bias in the estimates because of sorting (Bassier et al., 2022), iii) including sector×municipality fixed effects to account for potential differences in amenities across industries and locations, or iv) controlling for family characteristics that may influence mobility. While the magnitude of the estimates is slightly affected, the change between periods remains quantitatively the same.

**Table 4:** Firms' labor supply elasticity

| A. 2000-2005 | Worker wage | | Firm fixed effect | | IV-Firm fixed effect | |
|---|---|---|---|---|---|---|
| | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\beta$ | -0.0601 | -0.0250 | -0.0485 | -0.0220 | -0.0800 | -0.0433 |
| | (0.0004) | (0.0003) | (0.0019) | (0.0010) | (0.0024) | (0.0014) |
| $\varepsilon_{LS}$ | 1.0329 | 0.9747 | 0.8327 | 0.8561 | 1.3746 | 1.6861 |
| | (0.0068) | (0.0104) | (0.0083) | (0.0125) | (0.0417) | (0.0556) |
| First stage F-statistic | | | | | 3,062.27 | |
| Observations | 4,149,923 | 4,149,923 | 4,149,923 | 4,149,923 | 4,149,923 | 4,149,923 |
| **B. 2015-2020** | **Worker wage** | | **Firm fixed effect** | | **IV-Firm fixed effect** | |
| | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\beta$ | -0.0773 | -0.0289 | -0.0565 | -0.0246 | -0.0979 | -0.0507 |
| | (0.0005) | (0.0003) | (0.0015) | (0.0009) | (0.0023) | (0.0013) |
| $\varepsilon_{LS}$ | 1.3693 | 1.1145 | 1.0007 | 0.9478 | 1.7340 | 1.9514 |
| | (0.0216) | (0.0220) | (0.0265) | (0.0125) | (0.0415) | (0.0519) |
| First stage F-statistic | | | | | 13,757.87 | |
| Observations | 4,404,064 | 4,404,064 | 4,404,064 | 4,404,064 | 4,404,064 | 4,404,064 |

Notes: Panel A and B estimate period-specific linear probability models as specified in Equation (8) for all quarterly separations (Sep) and employer-to-employer transitions (EE Sep) using alternative measures of wages. Worker wage columns rely on individual-level wages as the independent variable. Firm fixed effect columns use AKM effects retrieved from the estimating equation (1) separately by period. IV-firm fixed effect columns instrument period-specific firm fixed effects with the (log) average firm wage (wage bill divided by firm size). All specifications control for the estimated AKM worker fixed effects and indicators for age groups, sex, 2-digit industries, and time effects. Standard errors (in parentheses) are clustered at the level of variation of the wage measure, i.e., worker- or firm-level. $\varepsilon_{LS}$ refers to the firm's labor supply elasticity computed as: $\varepsilon_{LS} \approx -2 \times \hat{\beta}/\bar{s}$, where $\bar{s}$ is the average separation rate used as the dependent variable. Standard errors of $\varepsilon_{LS}$ are obtained using the Delta method.

ket competition: the firm-level wage markdown (Yeh et al., 2022). The optimality condition for the choice of labor input in equation (5) implies a negative relationship between the average wage markdown, $\nu_t$, defined as the ratio of the marginal product of labor and wages, and the average elasticity of labor supply.

We test if this is the case in the data using estimates of firm-level wage markdowns provided by Ding et al. (2025).[29] We compare our two measures of labor market power in Appendix F, and both suggest an increase in labor market competition: the increase in the firm's labor supply elasticity documented in Table (4) is met by a decline of more

[29] Ding et al. (2025) use Lithuanian firm balance sheet data to estimate a trans-log production function and obtain firm-level estimates of wage markdown as

$$\nu_{it} = \frac{e^{\ell}_{it}}{e^{c}_{it}} \frac{\alpha^{c}_{it}}{\alpha^{\ell}_{it}},$$

where $e^{\ell}_{it}$ is the estimated output elasticity of labor input, $e^{c}_{it}$ is the estimated output elasticity of intermediates, $\alpha^{\ell}_{it}$ is the labor share, and $\alpha^{c}_{it}$ is share of intermediate input costs in output.

than 4% in the aggregate wage markdown. In addition, Figure F.1 compares sector-specific firm-labor supply elasticities with the sector-level average wage markdowns. Consistent with the theory, firms in sectors with higher labor supply elasticity, as estimated using Social Security data, charge lower wage markdowns, as estimated using firm balance sheet data.

**Workers segmentation.** Despite the limited role of worker heterogeneity in explaining the change in inequality over time, we cannot yet rule out increased labor market segmentation in terms of characteristics such as education and skills. If worker segmentation leads to more pronounced differences in job mobility or separation behavior across labor market segments, we could observe a higher labor supply elasticity, even without changes in the underlying degree of labor market competition.

To address this concern, we replicate the estimates in Table 4 separately for high-skilled and low-skilled workers. We use the estimated AKM worker fixed effects to label workers as low- or high-skilled based on whether their fixed effects are below or above the median, respectively. The estimates indicate that the overall dynamics of labor market competition are similar across skill types: between 2000 and 2020, the labor supply elasticity based on all separations (job-to-job transitions) has increased by 0.37 (0.34) percentage points for low-skilled workers and 0.30 (0.21) percentage points for high-skilled workers (Columns (5) and (6) of Tables E.4 and E.5 in Appendix E).

**Firm granularity.** The model proposed in Section 6.1 features atomistic firms in the spirit of Card et al. (2016) and Lamadon et al. (2022). In this framework, the labor supply elasticity is constant, and it does not depend on the degree of market concentration. In contrast, when firms are granular, as in Berger et al. (2022), changes in labor supply elasticities could reflect shifts in market structure.

To understand the role of granularity, Figure E.2 in Appendix E scatters changes in the firm's labor supply elasticity against changes in wage-bill Herfindahl index across sectors over the sample period. Overall, sectors with a larger increase in the labor supply elasticity did not experience a larger decline in concentration, suggesting market structure had a limited role in explaining changes in labor market competition.[30]

[30] When firms are granular, an increase in minimum wage could also increase the average labor supply elasticity by reducing markdowns of low-paying firms. Figures E.3 and E.4 in Appendix E show that there is no direct relation between the incidence of minimum wage across sectors and the relative change in the firm's labor supply elasticity.

# 7 Inequality, competition, and the EU accession

**Reduced-form equation.** To assess whether labor market competition contributed to the decline in firm-driven inequality, we exploit cross-sector changes in the dispersion of firm fixed effects and labor supply elasticities using the following reduced-form specification[31]

$$\Delta \text{var}_{st+1}[\psi_j] = \alpha + \beta \Delta \varepsilon_{LSst+1} + X_{st+1}\Omega + v_{st+1}, \tag{9}$$

where $\Delta \text{var}_{st+1}[\psi_j]$ and $\Delta \varepsilon_{LSst+1}$ denote, respectively, the change in the variance of firm fixed effects and the change in the labor supply elasticity in sector $s$ between 2000–2005 and 2015–2020.[32] $X_{st+1}$ includes two sets of controls. The first comprises model-implied controls derived from equation (6) (see Appendix D for the full derivation). Specifically, we include the level of the labor supply elasticity in the final period and the change in the dispersion of employers' log size, which proxies for changes in firm-level productivity dispersion. The second set captures sector-level changes in institutional and market structures. We control for changes in labor market concentration, measured by the wage-bill Herfindahl–Hirschman index, and for the initial minimum-wage incidence across sectors. The former accounts for the relationship between concentration and wage dispersion (Deb et al., 2024), while the latter captures the potentially heterogeneous effects of minimum wage (Dustmann et al., 2021).[33]

**Bartik-IV.** Despite our set of controls, endogeneity concerns remain. There are several confounders, i.e., changes in TFP dispersion or sectoral demand shocks among others, which could have jointly affected wage dispersion and the elasticity of labor supply faced by firms, biasing OLS estimates. We address this issue by exploiting Lithuania's 2004 accession to the EU, which triggered a mass wave of outward mi-

[31] In practice, we re-estimate the labor supply elasticity with respect to firm-specific wages by sector for 2000–2005 and 2015–2020, and then relate sectoral changes between these periods. Importantly, rather than re-estimating the AKM model by sector, which would raise limited mobility bias concerns and substantial computational costs, we compute the sectoral variance of firm fixed effects from pooled period-specific estimates. This approach implies that the residual may not be fully orthogonal to sector-level covariates, but the actual share of variance attributable to these correlations is negligible.

[32] Berger et al. (2022) documents firm size–dependent labor supply elasticities. Incorporating this feature would imply that wage dispersion also depends on the variance of labor supply elasticities. We abstract from this margin and instead allow elasticities to vary at the sector–period level.

[33] Although we do not explicitly control for product market power, Appendix F shows that its omission is likely to bias the OLS estimate of $\beta$ downward, as changes in markups and markdowns are negatively correlated (see Figure F.3).

gration (Thaut, 2009; Klüsener et al., 2015): by 2020, more than 10 percent of Lithuania's population resided in pre-2004 enlargement EU countries. In a standard dynamic search framework (Burdett and Mortensen, 1998), access to external labor markets increases workers' reservation wages and intensifies mobility. In monopsonistic settings, stronger outside options raise the elasticity of labor supply to the firm and compress wage dispersion (Autor et al., 2023).[34] By expanding workers' outside options and increasing job opportunities for Lithuanian workers, EU accession likely contributed to higher domestic wages and lower wage inequality.[35]

We construct a sector-level measure of employment opportunities abroad following Caldwell and Harmon (2019). Formally, we build a shift-share Bartik-IV, $\Delta z_{st+1}$, as the inner product of $|\mathcal{C}|$ destination country $c$-specific shifts that are common to all sectors $s$, $\Delta w_{ct+1}$, and a sets of exposure shares that vary across sectors, $\mu_{sct_0}$, i.e.,

$$\Delta z_{st+1} = \sum_{c \in \mathcal{C}} \mu_{sct_0} \Delta w_{ct+1}$$

For each sector $s$ and EU destination country $c$ (EU members prior to 2004), we compute the shifts $\Delta w_{ct+1}$, as the log change in overall real labor compensation in country $c$ (variable "COMP" in EU-KLEMS) between the years 2015-2020 and 2000-2004.[36] The exposure shares $\mu_{sct_0}$ are constructed as the product of Lithuanian migration share in country $c$, and the sectoral employment shares in the same country, both measured in year $t_0 = 2000$;

$$\mu_{sct_0} = \frac{\#\text{migrants}_{ct_0}}{\#\text{migrants}_{t_0}} \frac{\#\text{employment}_{cst_0}}{\#\text{employment}_{ct_0}}.$$

The identification of the Bartik-IV estimate relies on sectoral employment shares observed in countries with large Lithuanian settlements prior to the EU enlargement to be i) uncorrelated with sector-specific changes in labor demand in Lithuania following the EU integration, and ii) to explain movements of the labor supply curve among

[34] Amior and Stuhler (2022) formulate a model of monopsony in which immigration induces firms to undercut native labor in destination countries when migrant labor can be purchased more cheaply.

[35] Elsner (2013) estimates that a 1 percent increase in emigration to Ireland raised the wages of stayers in Lithuania by 0.66 percent.

[36] We use changes in total real labor compensation to further capture skill composition and wage heterogeneity, thus reflecting both quantity *and* quality changes in job opportunities abroad. Total compensation is deflated using country-specific CPI on all items from FRED, Index 2015=100.

Lithuanian workers who did not migrate.[37] As migrant networks lower migration costs and improve information about labor market outcomes (Card, 2001), workers were more likely to migrate to destinations where compatriots are already present (see Figure A.6 in Appendix A), as well as more exposed to job opportunities in EU countries with large pre-existing migrant networks. Thus, through the lens of a canonical monopsony model, we expect EU integration to have increased the bargaining power of Lithuanian workers and, by so doing, their elasticity of labor supply to firms.

**Estimates.** Table 5 reports both OLS and Bartik-IV estimates of equation (9). The firm's labor supply elasticity is based on Table 4, Columns (5)-(6), where the probability of leaving the job is regressed against the IV'd firm fixed effect. Columns (1) to (3) refer to estimates based on labor supply elasticities computed using all separations, whereas Columns (4) to (6) exploit only job-to-job (J2J) transitions. Columns (3) and (6) refer to a version of the Bartik-IV where the shift is unit-specific and varies across sectors and destination countries.[38]

**Table 5:** Dispersion of firm fixed effects and firm's labor supply elasticity

| | $\Delta$ var$_{st+1}[\psi]$ | | | | | |
|---|---|---|---|---|---|---|
| | All separations | | | Only J2J separations | | |
| | OLS | Bartik-IV | Bartik-IV | OLS | Bartik-IV | Bartik-IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta\ \varepsilon_{st+1}$ | -0.0137*** | -0.0325** | -0.0600** | -0.0146*** | -0.0271** | -0.0464** |
| | (0.0047) | (0.0156) | (0.0255) | (0.0038) | (0.0130) | (0.0199) |
| Implied %$\Delta$ var[$y$] | 6.1 | 14.5 | 26.8 | 7.8 | 13.2 | 22.6 |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| No. sectors | 74 | 74 | 74 | 74 | 74 | 74 |

Notes: This table reports OLS and Bartik-IV estimates of equation (9). Columns (1) to (3) refer to estimates based on labor supply elasticities computed using all separations. Columns (4) to (6) exploit only job-to-job (J2J) transitions. Columns (3) and (6) refer to a version of the Bartik-IV where the shift is unit-specific and varies across sectors and destination countries. Controls include sector-specific change in the variance of firm size, $\Delta$var$_{st+1}[L_j]$, the elasticity of labor supply in the last period, the sector-specific minimum wage incidence in the initial period, and sector-specific change in the wage-based HHI index. Standard errors are robust.

Consistent with our theory, our estimates show the negative correlation between changes in the firm's labor supply elasticity and changes in the variance of firm fixed effects. The OLS estimates indicate that a 10 percentage-point increase in labor market competition is associated with a 1.4 percentage-point decrease in the variance of firm

[37]In Appendix H, we follow Goldsmith-Pinkham et al. (2020) and use the Rotemberg weights to assess whether all or only a subset of destination countries is responsible for the identifying variation of the Bartik-IV.

[38]See Appendix H for a definition of the shift-share IV with unit-specific shifts and further results.

fixed effects. The IV estimates are larger than the OLS estimates. A 10 percentage-point increase in the firm's labor supply elasticity is associated with a decline in the dispersion of firm fixed effects ranging from 3.3 to 6 (2.7 to 4.6) percentage points when estimated using all separations (only job-to-job transitions). Combining the IV estimates with the observed change in the firm's labor supply elasticity, our results suggest that, in the absence of changes in labor market competition, overall wage inequality would be between 13 and 27% higher.[39]

Taken together, the results indicate that changes in labor market competition were accompanied by a compression in firms' wage premia and overall wage inequality, and suggest that EU accession in 2004 contributed to this decline by reducing employer market power in Lithuania.

**Robustness checks.** In Appendix H, we discuss identification and test the robustness of the Bartik-IV estimates. In Table H.3, we report the estimates of a joint regression of the change in dispersion of firm fixed effects on both the change in the labor supply elasticity and the shift-share instrument. The latter has no residual explanatory power once changes in the labor supply elasticity are factored in, providing support for the exclusion restriction. In Tables H.4 and H.5, we show that the main results are not driven by the specific construction of the shifts. Using log changes in real compensation per employee or real hourly compensation as alternative shifts yields virtually identical second-stage estimates.

Furthermore, if labor market competition were genuinely behind changes in inequality through its *sole* effect on firm-specific wage components, we should find no correlation between changes in the labor supply elasticity and the variance of the worker-specific wage component or sorting between workers and firms over time and across industries. Estimates from placebo regressions in Table H.6 confirm this is the case: sector-specific changes in the variance of worker fixed effects (Panel A) or the covariance of worker and firm fixed effects (Panel B) are used as the dependent variable in equation (9), there is no meaningful relationship between either measure and the Bartik-IV.

[39]The change of wage inequality implied by the increase in competition is computed as $0.898 \times \sum_{s=1}^{S} \frac{L_{st}}{L_t} \hat{\beta} \Delta \varepsilon_{st+1} \times (\sum_{s=1}^{S} \frac{L_{st}}{L_t} \Delta \text{var}_{st+1}[\psi_{jt+1}])^{-1} \times 100$, where 0.898 refers to the share of change in overall wage inequality explained by the change in the dispersion of firms' fixed effects (see Table 3, Column AKM.).

# 8 Conclusions

Standard models of monopsonistic competition predict that increases in labor market competition would reduce firm-driven wage dispersion. In this paper, we characterize the dynamics of firm-driven wage dispersion and labor market competition using Social Security data for Lithuania, covering two decades of economic development and declining wage inequality.

We document a substantial decline in wage inequality between 2000 and 2020, with nearly all of it due to a reduction in the dispersion of firm-specific wage premiums. During this same period, we show that firms' labor supply elasticities also increased, consistent with higher labor market competition. To investigate the underlying causes behind these changes, we exploit the expansion of employment opportunities abroad following Lithuania's EU accession in 2004. Using a shift-share instrument, we find that greater sectoral exposure to foreign labor markets through pre-existing migrant networks reduced monopsony power following the EU integration and compressed firm-level wage dispersion. Our estimates imply that between 13 and 27% of the observed decline in wage inequality could be attributed to increased labor market competition triggered by the EU accession.

Using the words of Langella and Manning (2021), the "agenda of concern about inequality and competition remains as important as ever. We know from basic economics that markets cannot be relied on to produce levels of inequality that are fair and command political legitimacy. Economists do not often regard inequality as a market failure [...], but ordinary people do, and they are right, and we are wrong." Our paper directly speaks to this agenda.

# References

Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, 67(2):251–333.

Alvarez, J., Benguria, F., Engbom, N., and Moser, C. (2018). Firms and the decline in earnings inequality in Brazil. *American Economic Journal: Macroeconomics*, 10(1):149–189.

Amior, M. and Stuhler, J. (2022). Immigration and monopsony: Evidence across the distribution of firms. *mimeo*.

Amodio, F., Brancati, E., de Roux, N., and Di Maio, M. (2026). Labor market institutions and wage-setting power: Evidence from Latin America and the Caribbean. *Journal of Human Resources*. Forthcoming.

Andrews, M. J., Gill, L., Schank, T., and Upward, R. (2008). High wage workers and low wage firms: Negative assortative matching or limited mobility bias? *Journal of the Royal Statistical Society Series A: Statistics in Society*, 171(3):673–697.

Andrews, M. J., Gill, L., Schank, T., and Upward, R. (2012). High wage workers match with high wage firms: Clear evidence of the effects of limited mobility bias. *Economics Letters*, 117(3):824–827.

Armangué-Jubert, T., Rapone, T., and Ruggieri, A. (2025). Firm dynamics, monopsony, and aggregate productivity differences. *Review of Economic Dynamics*, page 101321.

Armangué-Jubert, T., Guner, N., and Ruggieri, A. (2024). Labor market power and development. *American Economic Review: Insights (forthcoming)*.

Ashenfelter, O., Card, D., Farber, H., and Ransom, M. R. (2022). Monopsony in the labor market: New empirical results and new public policies. *Journal of Human Resources*, 57(Supplement):S1– S10.

Autor, D., Dube, A., and McGrew, A. (2023). The unexpected compression: Competition at work in the low wage labor market. *NBER Working Paper No. 31010*.

Babet, D., Godechot, O., and Palladino, M. G. (2023). In the land of AKM: Explaining the dynamics of wage inequality in France. *INSEE Working Paper No. 2023-20*.

Bachmann, R., Demir, G., and Frings, H. (2022). Labor market polarization, job tasks, and monopsony power. *Journal of Human Resources*, 57(S):S11–S49.

Bagga, S. (2023). Firm market power, worker mobility, and wages in the US labor market. *Journal of Labor Economics*, 41(S1):S205–S256.

Bassier, I. (2023). Firms and inequality when unemployment is high. *Journal of Development Economics*, 161:103029.

Bassier, I., Dube, A., and Naidu, S. (2022). Monopsony in movers: The elasticity of labor supply to firm wage policies. *Journal of Human Resources*, 57(S):S50–s86.

Berger, D., Herkenhoff, K., and Mongey, S. (2022). Labor market power. *American Economic Review*, 112(4):1147–1193.

Bonhomme, S., Holzheu, K., Lamadon, T., Manresa, E., Mogstad, M., and Setzler, B. (2023). How much should we trust estimates of firm effects and worker sorting? *Journal of Labor Economics*, 41(2):291–322.

Bonhomme, S., Lamadon, T., and Manresa, E. (2019). A distributional framework for matched employer-employee data. *Econometrica*, 87(3):699–739.

Bonhomme, S., Lamadon, T., and Manresa, E. (2022). Discretizing unobserved heterogeneity. *Econometrica*, 90(2):625–643.

Borusyak, K., Hull, P., and Jaravel, X. (2025). A practical guide to shift-share instruments. *Journal of Economic Perspectives*, 39(1):181–204.

Burdett, K. and Mortensen, D. T. (1998). Wage differentials, employer size, and unemployment. *International Economic Review*, pages 257–273.

Caldwell, S. and Harmon, N. (2019). Outside options, bargaining, and wages: Evidence from coworker networks. *mimeo*.

Caliendo, L., Opromolla, L. D., Parro, F., and Sforza, A. (2021). Goods and factor market integration: A quantitative assessment of the EU enlargement. *Journal of Political Economy*, 129(12):3491–3545.

Card, D. (2001). Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics*, 19(1):22–64.

Card, D. (2022). Who set your wage? *American Economic Review*, 112(4):1075–90.

Card, D., Cardoso, A. R., Heining, J., and Kline, P. (2018). Firms and labor market inequality: Evidence and some theory. *Journal of Labor Economics*, 36(S1):S13–S70.

Card, D., Cardoso, A. R., and Kline, P. (2016). Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women. *The Quarterly Journal of Economics*, 131(2):633–686.

Card, D., Heining, J., and Kline, P. (2013). Workplace heterogeneity and the rise of West German wage inequality. *The Quarterly Journal of Economics*, 128(3):967–1015.

Černiauskas, N. and Garcia-Louzao, J. (2025). The earnings distribution in Lithuania: The role of the minimum wage. *Journal of Economic Inequality (forthcoming)*.

Commission, E. (2006). Enlargement, two years after. an economic success.

Criscuolo, C., Hijzen, A., Schwellnus, C., Chen, W.-H., Fabling, R., Fialho, P., Grabska, K., Kambayashi, R., Leidecker, T., Nordstrom Skans, O., et al. (2020). Workforce composition, productivity and pay: The role of firms in wage inequality. *IZA Discussion Paper No. 13212*.

Deb, S., Eeckhout, J., Patel, A., and Warren, L. (2024). Walras–Bowley lecture: Market power and wage inequality. *Econometrica*, 92(3):603–636.

DellaVigna, S., Lindner, A., Reizer, B., and Schmieder, J. F. (2017). Reference-dependent job search: Evidence from Hungary. *The Quarterly Journal of Economics*, 132(4):1969–2018.

Ding, Z., Garcia-Louzao, J., and Jouvanceau, V. (2025). The dynamics of product and labor market power: Evidence from Lithuania. *Ecnomics of Transition and Institutional Change*, 33(1):165–194.

Dustmann, C., Lindner, A., Schoenberg, U., Umkehrer, M., and vom Berge, P. (2021). Reallocation effects of the minimum wage. *The Quarterly Journal of Economics*, 137(1):267–328.

Elsner, B. (2013). Does emigration benefit the stayers? Evidence from EU enlargement. *Journal of Population Economics*, 26:531–553.

Engbom, N. and Moser, C. (2022). Earnings inequality and the minimum wage: Evidence from Brazil. *American Economic Review*, 112(12):3803–3847.

Engbom, N., Moser, C., and Sauermann, J. (2023). Firm pay dynamics. *Journal of Econometrics*, 233(2):396–423.

Foster, L., Haltiwanger, J. C., and Krizan, C. J. (2001). Aggregate productivity growth: Lessons from microeconomic evidence. In *New developments in productivity analysis*, pages 303–372. University of Chicago Press.

Garcia-Louzao, J. and Tarasonis, L. (2023). Wage and employment impact of minimum wage: Evidence from Lithuania. *Journal of Comparative Economics*, 51(2):592–609.

Giesing, Y. and Laurentsyeva, N. (2018). Firms left behind: Emigration and firm productivity. *CESifo Working Paper No. 6815*.

Goldschmidt, D. and Schmieder, J. F. (2017). The rise of domestic outsourcing and the evolution of the german wage structure. *The Quarterly Journal of Economics*, 132(3):1165–1217.

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8):2586–2624.

Grassi, B. (2024). The eu miracle: When 75 million reach high income.

Hirsch, B., Jahn, E. J., and Schnabel, C. (2018). Do employers have more monopsony power in slack labor markets? *ILR Review*, 71(3):676–704.

Hoffmann, F., Lee, D. S., and Lemieux, T. (2020). Growing income inequality in the United States and other advanced economies. *Journal of Economic Perspectives*, 34(4):52–78.

IMF (2003). Capital markets and financial intermediation in the baltic states. *Country report*, 03(115).

Kaplan, G. and Zoch, P. (2020). Markups, labor market inequality and the nature of work. *NBER Working Paper No. 26800*.

Kline, P. (2024). Firm wage effects. *Handbook of Labor Economics*, 5:115–181.

Kline, P., Saggio, R., and Sølvsten, M. (2020). Leave-out estimation of variance components. *Econometrica*, 88(5).

Klüsener, S., Stankūnienė, V., Grigoriev, P., and Jasilionis, D. (2015). The mass emigration context of Lithuania: Patterns and policy options. *International Migration*, 53(5):179–193.

Lachowska, M., Mas, A., and Woodbury, S. A. (2020). Sources of displaced workers' long-term earnings losses. *American Economic Review*, 110(10):3231–66.

Lamadon, T., Mogstad, M., and Setzler, B. (2022). Imperfect competition, compensating differentials, and rent sharing in the US labor market. *American Economic Review*, 112(1):169–212.

Lange, F. (2007). The speed of employer learning. *Journal of Labor Economics*, 25(1):1–35.

Langella, M. and Manning, A. (2021). Marshall lecture 2020: The measure of monopsony. *Journal of the European Economic Association*, 19(6):2929–2957.

Magda, I., Gromadzki, J., and Moriconi, S. (2021). Firms and wage inequality in Central and Eastern Europe. *Journal of Comparative Economics*, 49(2):499–552.

Manning, A. (2003). *Monopsony in motion: Imperfect competition in labor markets*. Princeton University Press, Princeton.

Manning, A. (2021). Monopsony in labor markets: A review. *ILR Review*, 74(1):3–26.

Pérez Pérez, J. and Nuno-Ledesma, J. G. (2023). Workers, workplaces, sorting, and wage dispersion in Mexico. *mimeo*.

Randveer, M. and Staehr, K. (2021). Macroeconomic trends in the Baltic States before and after accession to the EU. In *Does EU Membership Facilitate Convergence? The Experience of the EU's Eastern Enlargement*, pages 211–237. Springer.

Rutkowski, J. (2003). Rapid labor reallocation with a stagnant unemployment pool. the puzzle of the labor market in lithuania. *The Puzzle of the Labor Market in Lithuania (January 2003)*.

Silva, J., Leitao, M., and Montana, J. (2022). The role of firms in wage inequality dynamics. *CEPR Discussion Paper No. DP17327*.

Sokolova, A. and Sorensen, T. (2021). Monopsony in labor markets: A meta-analysis. *ILR Review*, 74(1):27–55.

Song, J., Price, D. J., Guvenen, F., Bloom, N., and Von Wachter, T. (2019). Firming up inequality. *The Quarterly Journal of Economics*, 134(1):1–50.

Thaut, L. (2009). EU integration & emigration consequences: The case of Lithuania. *International Migration*, 47(1):191–233.

Webber, D. A. (2015). Firm market power and the earnings distribution. *Labour Economics*, 35:123–134.

Webber, D. A. (2022). Labor market competition and employment adjustment over the business cycle. *Journal of Human Resources*, 57(S):S87–S110.

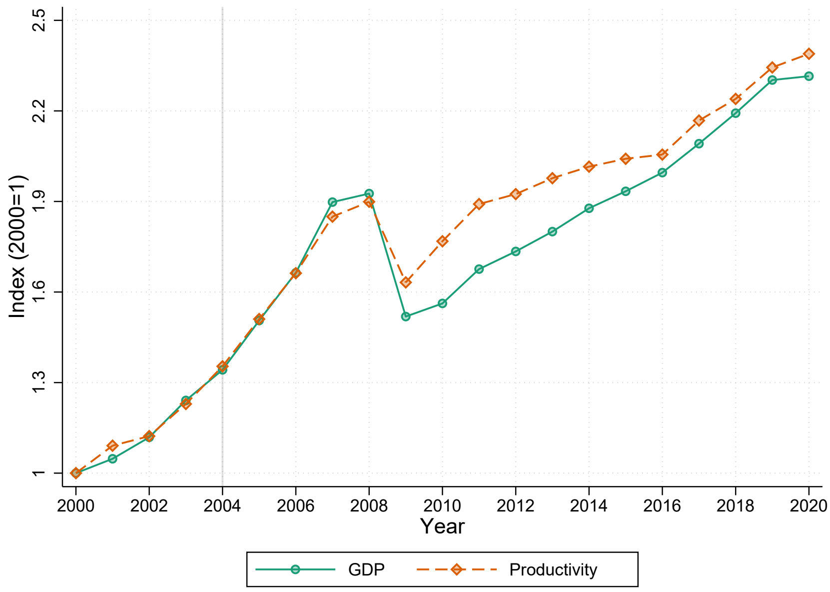
Yeh, C., Macaluso, C., and Hershbein, B. (2022). Monopsony in the US labor market. *American Economic Review*, 112(7):2099–2138.

Zaiceva, A. (2014). Post-enlargement emigration and new EU members' labor markets. *IZA World of Labor*.

# Online Appendix (not intended for publication)

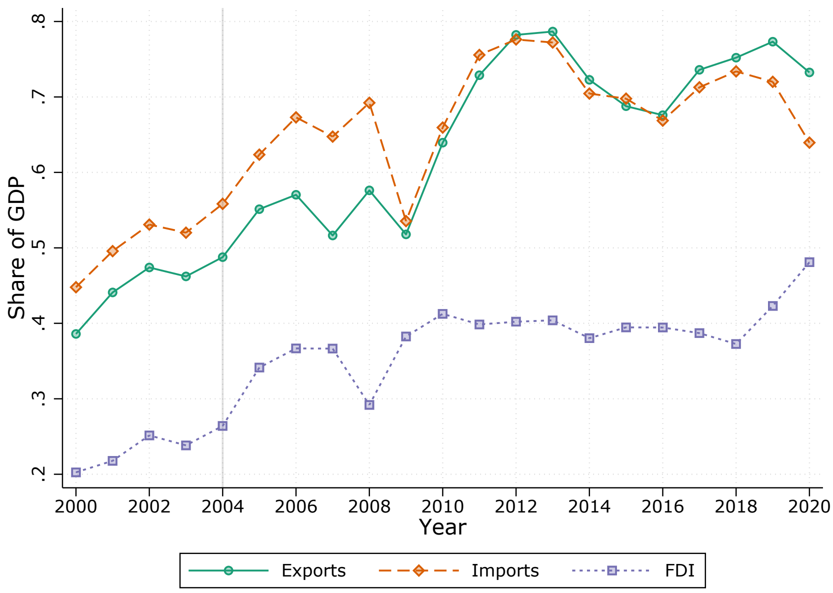
## A Institutional background: Graphical evidence

**Figure A.1:** Economic growth



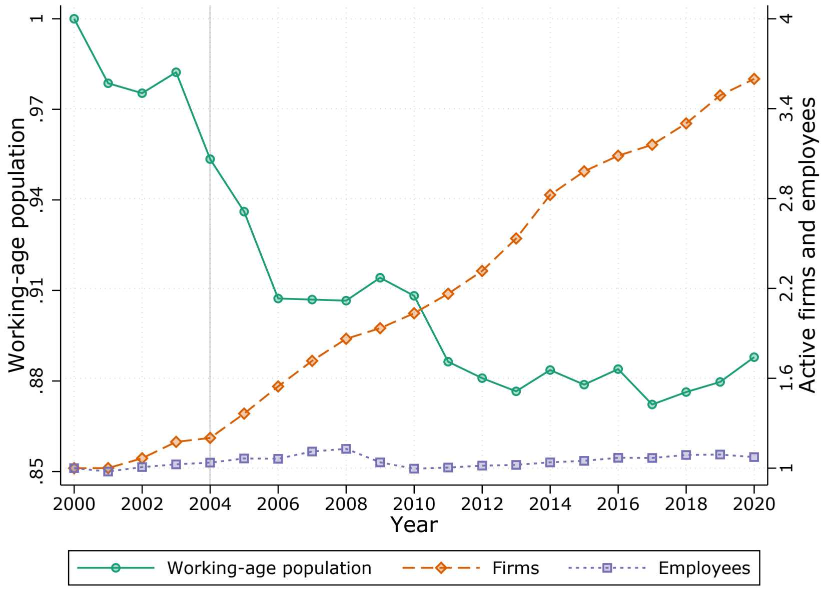

Source: Statistics Lithuania and own calculations.
Notes: The figure shows Lithuania's economic growth between 2000 and 2020, measured by gross domestic product (GDP) and gross value added per worker (productivity). The series are normalized to their value in 2000.

**Figure A.2:** Openness




Source: Statistics Lithuania and own calculations.
Notes: The figure shows the openness of the Lithuanian economy from 2000 to 2020, expressed as imports, exports, and foreign direct investment (FDI) as a percentage of GDP.

**Figure A.3:** Working-age population, firms, and employees



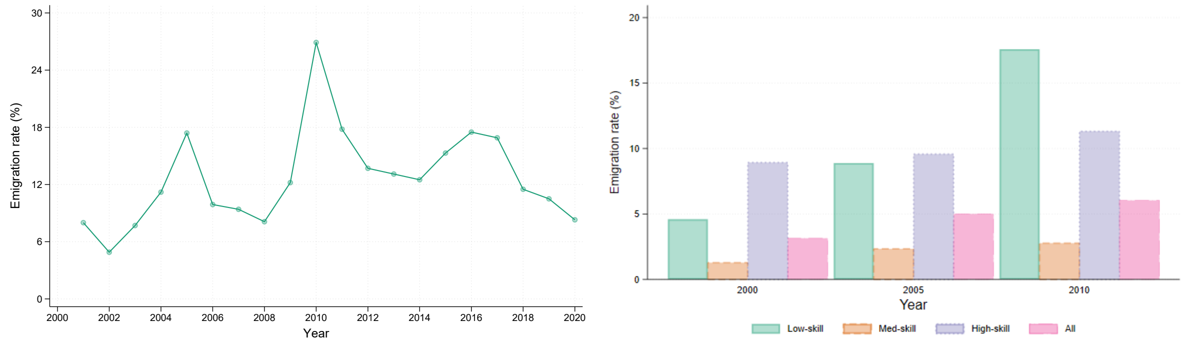

Source: Statistics Lithuania and own calculations. Notes: The figure shows the evolution of the working-age population together with the number of active enterprises and employees (rhs) in the Lithuanian economy between 2000 and 2020. The series are normalized relative to their value in 2000.

**Figure A.4:** Labor supply and demand


Source: Statistics Lithuania and own calculations.
Notes: The figure shows the labor supply (nonemployment and unemployment) and labor demand (job vacancies) in Lithuania between 2000 and 2020. 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.

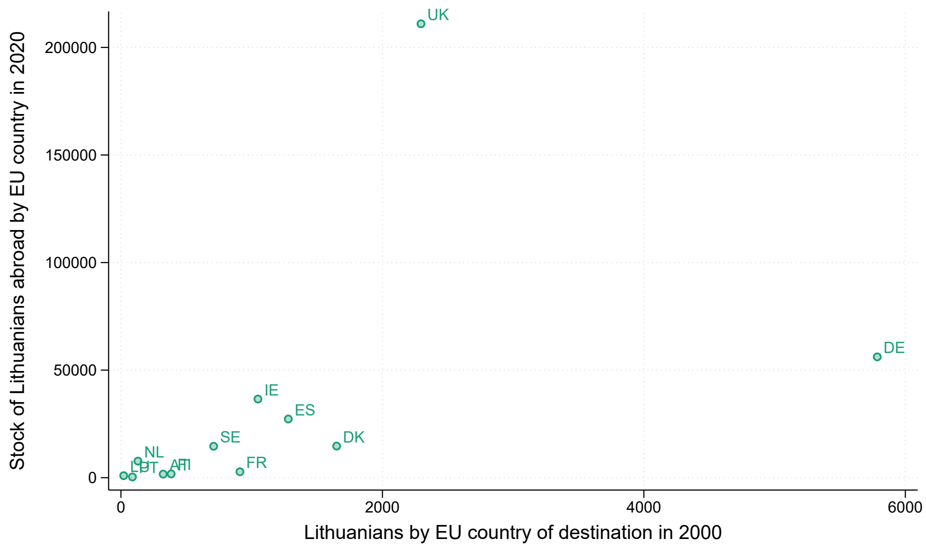
**Figure A.5:** Emigration rate over time and skill levels

**(A)** Emigration rate **(B)** Stock of emigrants by skill



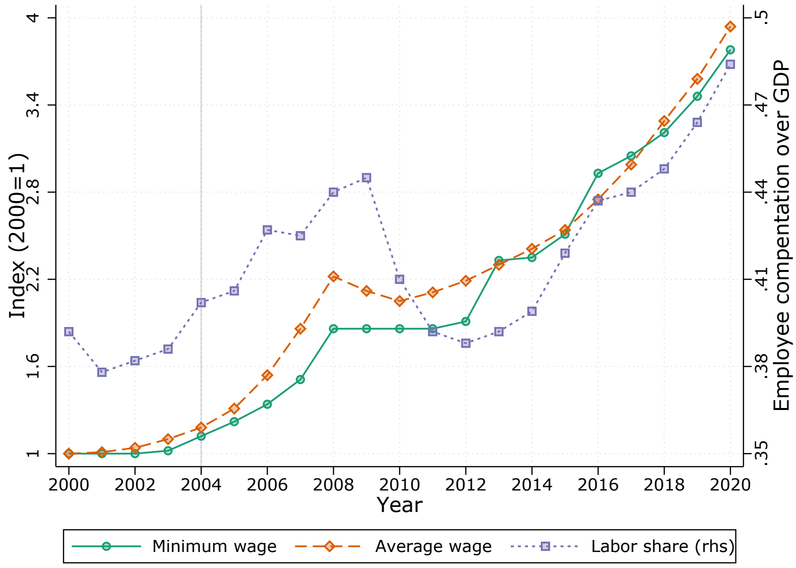

Source: Statistics Lithuania, IAB Brain Drain Data, and own calculations.
Notes: Emigration rate is the number of emigrants at the end of the year as a percentage of the Lithuanian population at the beginning of the corresponding year. Stock of emigrants by skill refers to the number of Lithuanians aged 25 and over living in Australia, Austria, Canada, Chile, Denmark, Finland, France, Germany, Greece, Ireland, Luxembourg, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom or the United States in a given year as a percentage of the pre-migration population in the destination countries of the same educational level and age in the corresponding year.

**Figure A.6:** Lithuanians in pre-2004 EU countries before and after accession



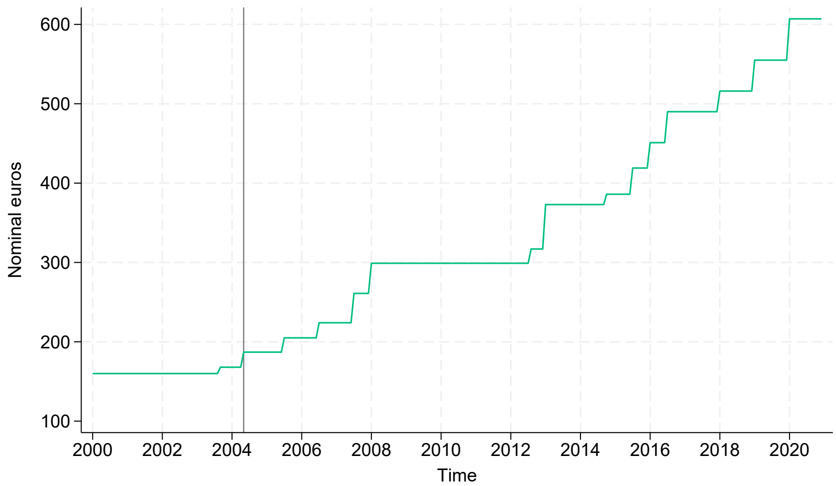

Source: Statistics Lithuania, IAB Brain Drain dataset, and own calculations.
Notes: Selected EU countries refer to economies that were part of the European Union before the 2004 enlargement, for which data are available on both foreign-born populations and EU-KLEMS.

**Figure A.7:** Workers' remuneration



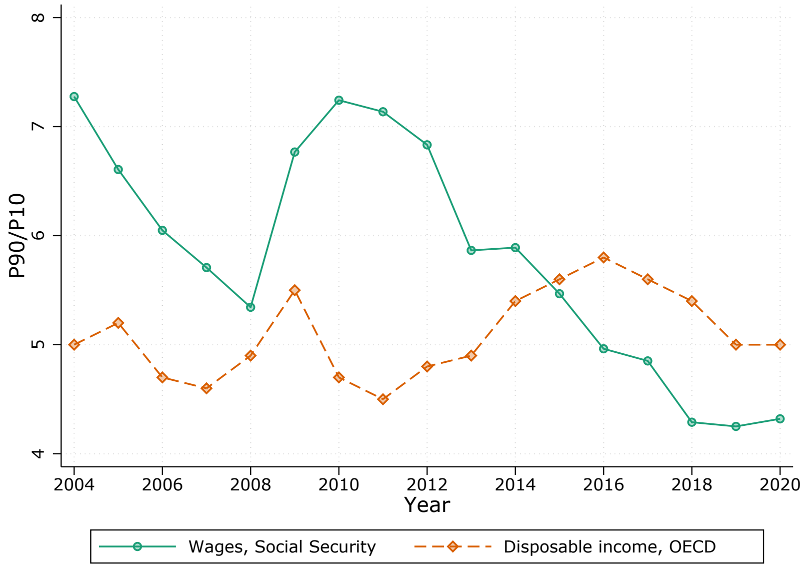

Source: Statistics Lithuania and own calculations.
Notes: The figure shows the evolution of the statutory minimum wage and average wages in Lithuania between 2000 and 2020, as well as the share of GDP allocated to employees' remuneration. Labor share is the ratio of total employee compensation to GDP. The minimum and average wage series are normalized to their 2000 values.

**Figure A.8:** Timing of minimum wage changes



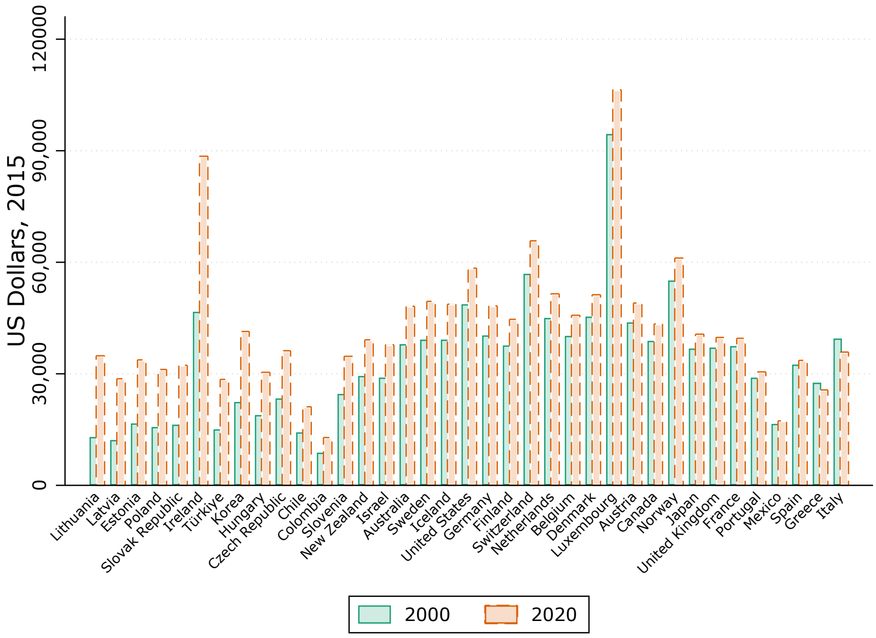

Source: Statistics Lithuania and own calculations.
Notes: The figure shows the dynamics of the nominal minimum wage in Lithuania from January 2000 to December 2020. Each step represents a minimum wage hike. The vertical line corresponds to May 2004, when Lithuania became officially part of the European Union.

**Figure A.9:** Wage vs disposable income inequality



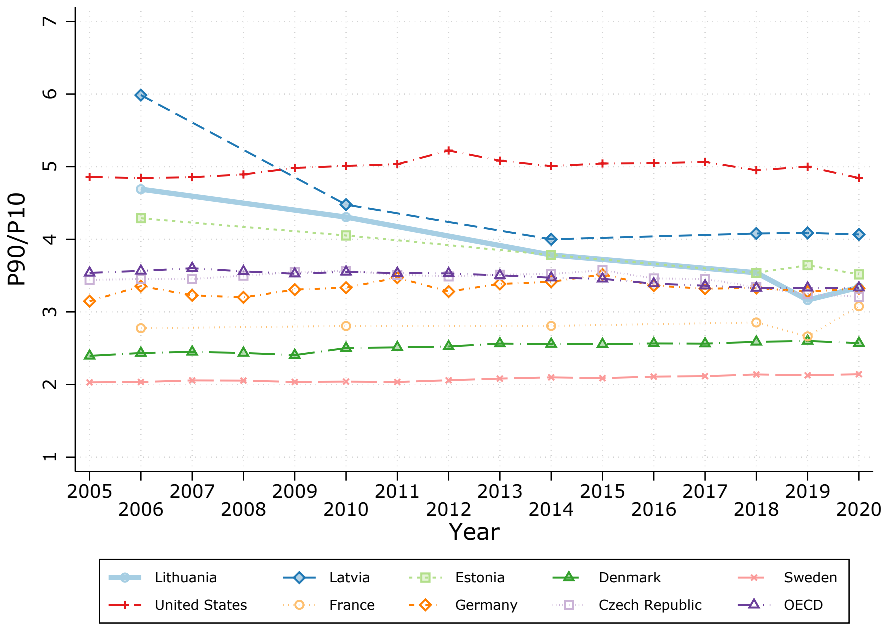

Source: Social Security records, OECD, and own calculations.
Notes: The figure compares the evolution of wage inequality and disposable income inequality. Wages refers to labor income divided by days, where labor income in the Social Security records corresponds to the insured income of workers between the ages of 20 and 60 whose primary job lasted at least 15 days and did not pay less than half the minimum wage in a quarter (see Section 4 for more details on the sample). Disposable income comes from OECD data and consists of earnings, self-employment, and capital income, and public cash transfers; income taxes and social security contributions paid by households are deducted.

**Figure A.10:** GDP per capita across selected countries, 2000 vs 2020




Source: OECD and own calculations.
Notes: The figure shows the GDP per capita of selected countries in real terms and in purchasing parity power. Selected countries are ranked in descending order by GDP per capita growth between 2000 and 2020.

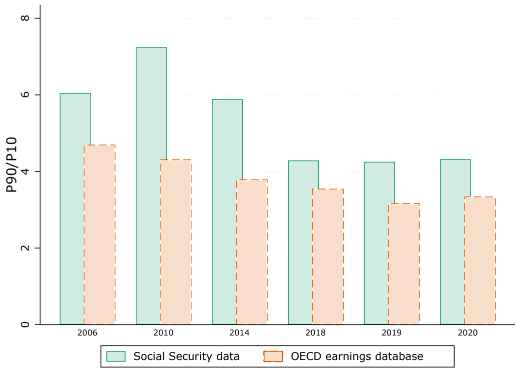
**Figure A.11:** Inequality across selected countries and time



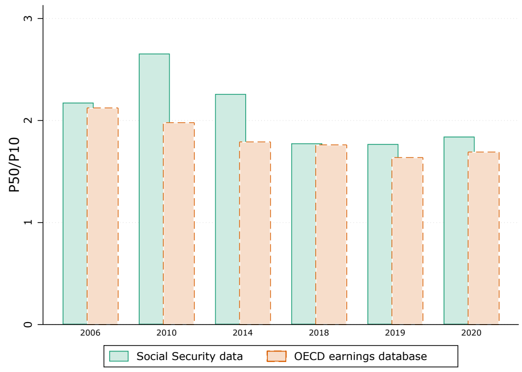

Source: OECD earnings database and own calculations.
Notes: The figure compares the evolution of gross earnings inequality across selected countries between 2005 and 2020. Inequality is measured as the ratio of the 90th percentile to the 10th percentile. Gross earnings refer to the labor income of full-time dependent employees.

**Figure A.12:** Inequality in Social Security data vs OECD earnings database

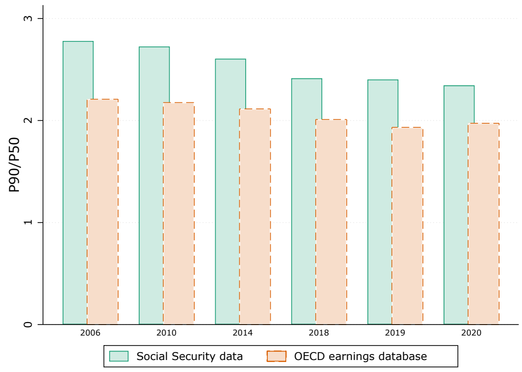
**(A)** Overall inequality




**(B)** Lower-tail inequality




**(C)** Upper-tail inequality




Source: Social Security records, OECD earnings database, and own calculations.
Notes: The figure shows the evolution of inequality in the Social Security data and in the OECD earnings database for the selected years for which information is available in the latter database. Labor income in the Social Security records corresponds to the insured income of workers between the ages of 20 and 60 whose primary job lasted at least 15 days and did not pay less than half the minimum wage in a quarter (see Section 4 for more details on the sample). Labor income in the OECD earnings database refers to the gross earnings of full-time dependent employees.

# B Validation of the two-way fixed effects model

## B.1 Exogenous mobility

One of the key assumptions for correct identification in AKM models and, in particular, of firm fixed effects implies that worker mobility among employers is exogenous, or uncorrelated with time-varying components of the residual in equation (1). Therefore, if the model specification is appropriate, workers moving from low-wage employers to high-wage employers should experience a wage increase and vice versa. Moreover, workers who move from firms with low fixed effects to firms with high fixed effects should obtain (on average) equal and opposite wage gains to workers who moved in the opposite (symmetric) direction. If, on the other hand, workers were to experience wage increases regardless of the type of job change, this would suggest the existence of specific worker-firm match effects, as workers are taking advantage of favorable specific job match opportunities.[40]

To assess the plausibility of this assumption, we follow the event-study approach proposed by Card et al. (2013) to examine how job mobility relates to employer switches and wage gains. More specifically, we focus on workers who change jobs in a given quarter but have held the previous job for at least two quarters prior to the job change and hold the new job for at least two quarters. For this group of workers, we classify their jobs according to the firm fixed effect estimated from the AKM model and track their wages over time before and after the job change.

Figure B.1 presents the results of this exercise, where we look at changes from the top to the bottom quartile of the firm fixed effects distribution. Firstly, the results suggest little evidence of transitory shocks prior to job change: wage trajectories are stable and parallel across workers, despite the expected level differences between workers employed in the highest paying firms and those working for employers at the bottom of the firm fixed effects distribution.[41] Secondly, workers who change firms but do not change employer type experience practically no wage variations. Thirdly, workers who move to high-wage firms experience (on average) wage increases, while those

[40]The existence of match effects is just one example of a possible violation of the exogenous mobility assumption. Card et al. (2018) provide extensive discussion and examples of situations where the exogenous mobility assumption may be violated.

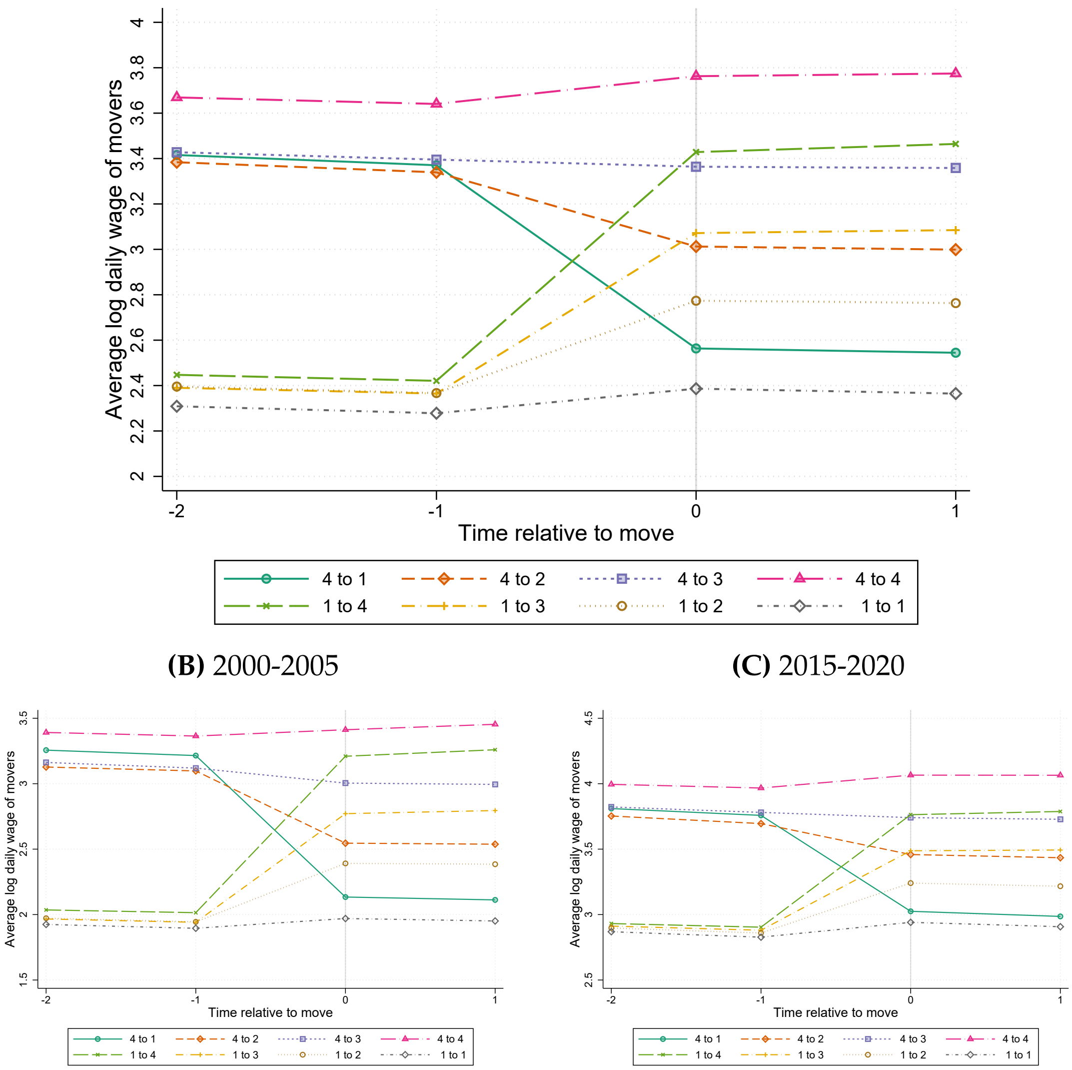
[41]If worker mobility were due to a progressive learning curve on the part of employers, one would expect wage changes to precede movements between groups of firms and these changes should be correlated with the type of movement (Lange, 2007).

who fall to the bottom of the job ladder exhibit wage losses, and these wage changes are almost symmetric (see Figure B.2). Therefore, the absence of an overall mobility premium for workers who remain in the same firm fixed effect quartile, along with wages moving in (nearly symmetric) opposite directions for workers who move along the firms' ladder, suggests that job mobility is not driven by idiosyncratic worker-firm match effects and that firm pay premia seem to be additively separable.

**Figure B.1:** Average wages of switchers by quartile of firm fixed effects

**(A)** 2000-2020

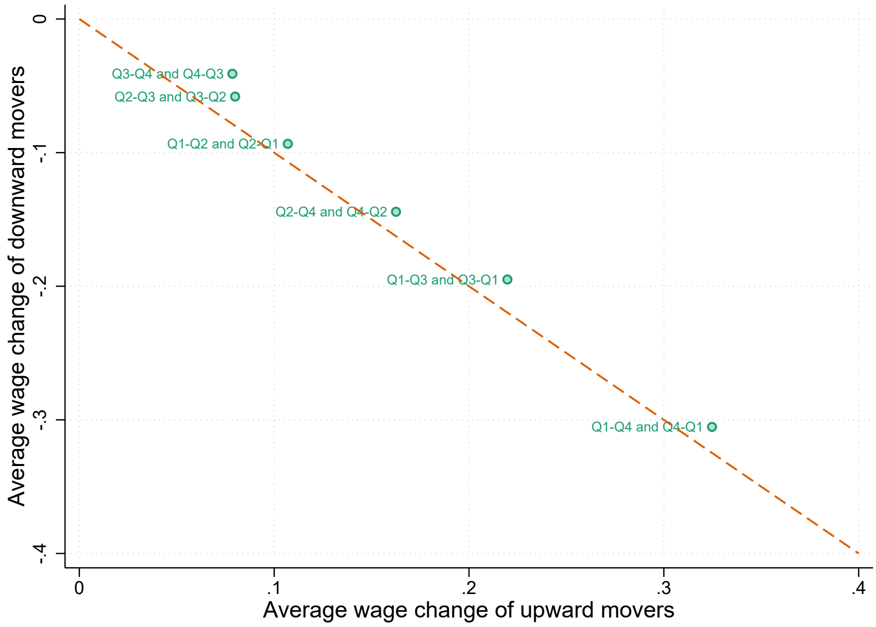
**(B)** 2000-2005 **(C)** 2015-2020



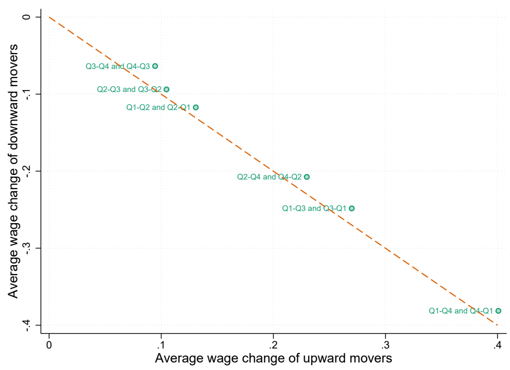

Source: Social Security records and own calculations.
Notes: Panel A shows the average daily wage of workers observed between 2000 and 2020 who changed jobs and held the old job for two or more quarters and the new job for two or more quarters, while Panel B and C report the wage dynamics of movers by sub-periods. Firms are grouped into quartiles according to period-specific AKM fixed effects estimated from the equation (1). Log daily wages are net of the time effects by removing the time-varying AKM observable component from each observation. The vertical line represents the quarter when the new job starts.

**Figure B.2:** Average wage change of switchers by quartile of firm fixed effects

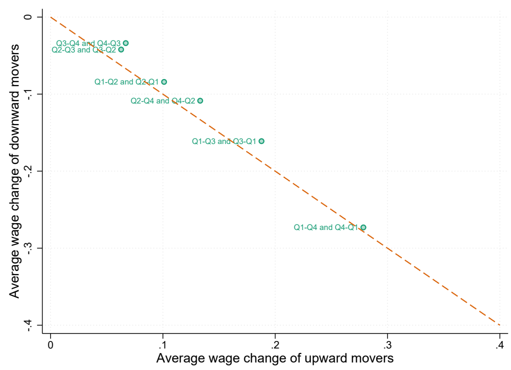
**(A)** 2000-2020




**(B)** 2000-2005




**(C)** 2015-2020




Source: Social Security records and own calculations.
Notes: Panel A shows regression-adjusted average wage changes over a 4-quarter interval for workers who switch jobs and move between the listed quartiles of firm fixed effects over the entire sample period, while Panel B and C report such average wage changes by sub-periods. Regression-adjusted average wage changes for job switchers are obtained as deviations from the actual 4-quarter interval average wage change and the predicted value using the coefficients of a model of estimated wage changes in a sample of those remaining in the same job over a given 4-quarter interval, as in Card et al. (2016). Firms are grouped into quartiles according to period-specific AKM fixed effects estimated from the equation (1).

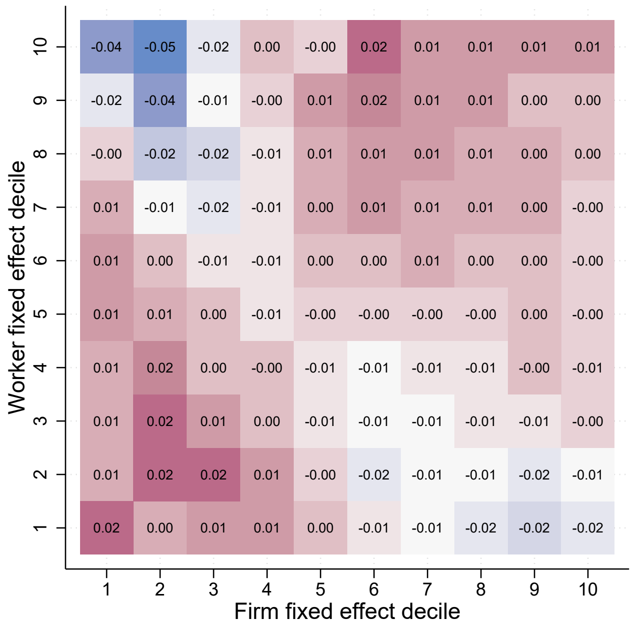
## B.2 Additive separability

The second key assumption relates to the additive separability of worker and firm effects or, in other words, the absence of match effects. Therefore, if the additive separability assumption of firm and worker permanent heterogeneity is not met, we should observe systematic differences in the residuals within the pairs defined by worker and firm fixed effects cells. To assess whether additive separability holds, in Figure B.3, we classify workers and firms into 10 groups according to their estimated fixed effects and plot the distribution of residuals across these 100 pairs. A couple of points emerge from this exercise. On the one hand, there is some evidence of misspecification for workers with the lowest value of fixed effects, as the residuals are systematically higher compared to other workers when they work in firms at the bottom of the distribution, while they are negative when they work in firms at the top. On the other hand, for firms at the bottom of the fixed effect distribution, high fixed effect workers exhibit systematically negative residuals, while the opposite is true for low fixed effect individuals. This poor fit at the bottom of both firm and worker fixed effect distributions have been found in other studies and is consistent with the existence of binding minimum wages (e.g., Alvarez et al., 2018; Card et al., 2018; Bassier, 2023). However, the magnitude of the errors is generally small, especially when compared to the wage gains from mobility described in Figure B.1, suggesting that there are no large deviations from the assumption of additive separability.

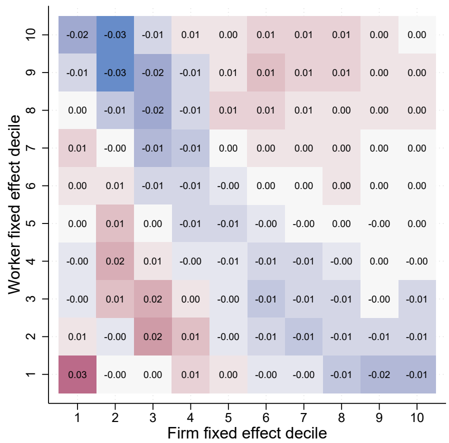
To explore the assumption of additive separability more thoroughly, we estimate the CHK match effects model (Card et al., 2013), which allows us to assess the relevance of idiosyncratic worker-firm matches in explaining the variance of wages relative to the AKM model. The idea is that if match effects are relevant, a model that features a distinct dummy variable for each worker-firm pair should fit the data much better than the AKM specification. Therefore, we estimate the equation (1) but instead of having separate fixed effects for workers and firms, we introduce a fixed effect for each pair. Table B.1 captures the results of this comparison and indicates that, although the fit of the CHK matching effects model is slightly better. However, the approximately 0.065 (0.03) increase in the adjusted R-squared of the CHK model compared to the fit of the AKM model in the full sample (in the sub-periods) suggests that the AKM model's specification of earnings as the sum of worker and firm fixed effects does not appear to be critical.

**Figure B.3:** Average residuals by deciles of worker and firm fixed effects

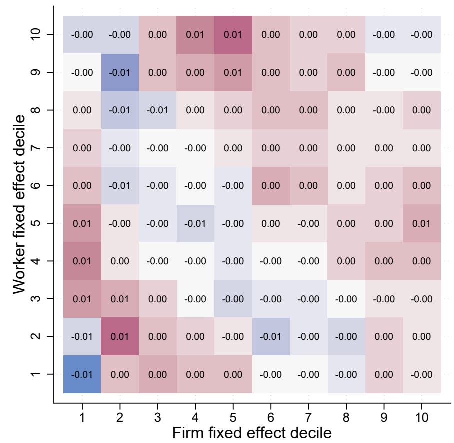
**(A)** 2000-2020




**(B)** 2000-2005




**(C)** 2015-2020




Source: Social Security records and own calculations.
Notes: Panel A shows the average of residuals by cells defined by deciles of the estimated worker and firm fixed effects from the AKM model in equation (1) using the entire sample period. Panels B and C show the average of residuals separately by sub-periods.

**Table B.1:** Additive separability vs match effects

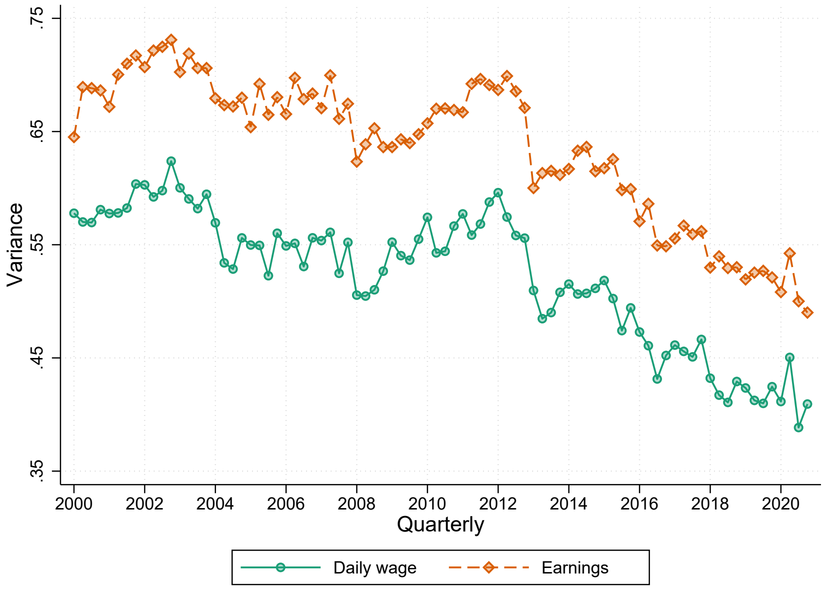
| | 2000-2020 | | 2000-2005 | | 2015-2020 | |
|---|---|---|---|---|---|---|
| | AKM | CHK | AKM | CHK | AKM | CHK |
| Adj. R-squared | 0.792 | 0.849 | 0.846 | 0.878 | 0.820 | 0.852 |
| RMSE | 0.354 | 0.302 | 0.298 | 0.267 | 0.283 | 0.262 |

Notes: AKM refers to model specification in equation (1). CHK is a match effects model where worker and firm effects are assumed not to be separable and, hence, are introduced as pair fixed effects as in Card et al. (2013). Models are estimated separately for each period.

# C Sensitivity tests and additional results on inequality

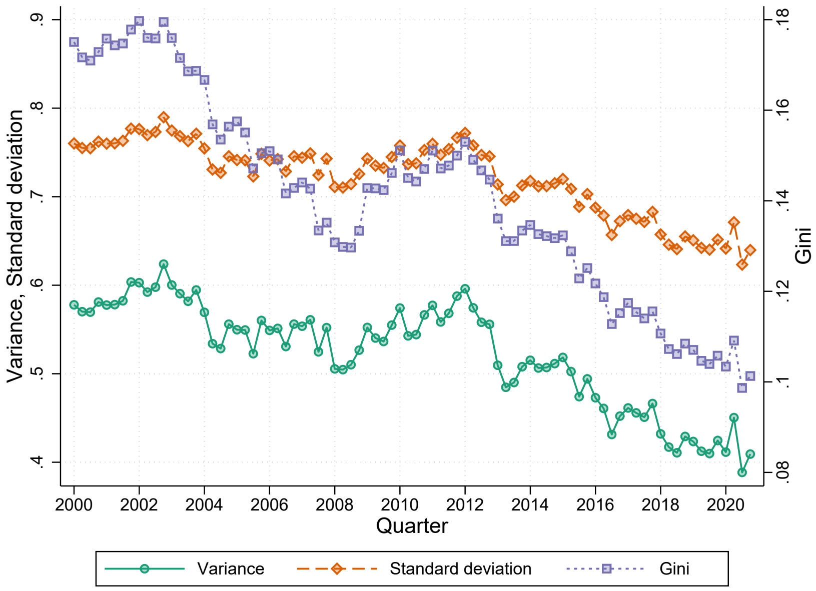
## C.1 Inequality trends in the estimation sample

**Figure C.1:** Dispersion of daily wages vs quarterly earnings




Source: Social Security records and own calculations.
Notes: The figure compares the evolution of inequality expressed in terms of the variance of (log) daily wages and total quarterly earnings.

**Figure C.2:** Wage inequality under alternative measures




Source: Social Security records and own calculations.
Notes: The figure compares the evolution of inequality using alternative indices to measure the dispersion of (log) daily wages.

## C.2 Firm-driven inequality

**Table C.1:** Variance decomposition of log daily wages for alternative AKM specifications

| | Sex-specific time effects | | Wages centered | | Residual wages | |
|---|---|---|---|---|---|---|
| | Component | Share | Component | Share | Component | Share |
| $Var(y)$ | 0.604 | - | 0.518 | - | 0.511 | - |
| $Var(\eta)$ | 0.169 | 0.280 | 0.164 | 0.317 | 0.163 | 0.318 |
| $Var(\psi)$ | 0.189 | 0.313 | 0.190 | 0.366 | 0.188 | 0.367 |
| $Var(X\Omega)$ | 0.090 | 0.149 | 0.007 | 0.013 | - | - |
| $Var(\epsilon)$ | 0.120 | 0.199 | 0.121 | 0.234 | 0.121 | 0.238 |
| $2 \times Cov(\eta, \psi)$ | 0.041 | 0.069 | 0.041 | 0.079 | 0.039 | 0.076 |
| $2 \times Cov(\eta, X\Omega)$ | -0.007 | -0.011 | -0.003 | -0.007 | - | - |
| $2 \times Cov(\psi, X\Omega)$ | 0.001 | 0.001 | -0.001 | -0.002 | - | - |

Notes: Variance decomposition of (log) daily wages based on equation (2) using the entire sample period, 2000-2020, using the AKM methodology. Sex-specific time effects column allows age profiles and year effects to vary between men and women. Wages-centered column uses as a dependent variable the deviation of individuals' wages from the average wage in a given quarter. Residual wages column relies on wages net of age and time effects as dependent variables.

**Table C.2:** Variance decomposition of log daily wages for alternative AKM samples

| | LM attachment | | MW | | Public sector | | No welfare benefits | |
|---|---|---|---|---|---|---|---|---|
| | Component | Share | Component | Share | Component | Share | Component | Share |
| $Var(y)$ | 0.617 | - | 0.395 | - | 0.564 | - | 0.608 | - |
| $Var(\eta)$ | 0.178 | 0.289 | 0.146 | 0.368 | 0.183 | 0.324 | 0.169 | 0.300 |
| $Var(\psi)$ | 0.205 | 0.332 | 0.102 | 0.257 | 0.149 | 0.264 | 0.205 | 0.364 |
| $Var(X\Omega)$ | 0.088 | 0.143 | 0.077 | 0.194 | 0.088 | 0.156 | 0.100 | 0.178 |
| $Var(\epsilon)$ | 0.117 | 0.189 | 0.068 | 0.171 | 0.115 | 0.203 | 0.099 | 0.175 |
| $2 \times Cov(\eta, \psi)$ | 0.031 | 0.050 | 0.018 | 0.044 | 0.034 | 0.060 | 0.040 | 0.072 |
| $2 \times Cov(\eta, X\Omega)$ | -0.002 | -0.004 | -0.005 | -0.013 | -0.007 | -0.012 | -0.004 | -0.007 |
| $2 \times Cov(\psi, X\Omega)$ | 0.000 | 0.001 | -0.009 | -0.022 | 0.002 | 0.004 | -0.002 | -0.003 |

Notes: Variance decomposition of (log) daily wages based on equation (2) using the entire sample period, 2000-2020, using the AKM methodology. LM attachment column considers only worker-quarter observations such that individuals work at least 75% of the quarter. MW column includes only worker-quarter observations such that individuals earn no less than the current minimum wage. Public sector column adds to the estimation sample of public administration. No welfare benefits column removes from the benchmark estimation sample worker-quarter observations when the individual collects some type of welfare benefits (e.g., sickness benefits).

**Table C.3:** Variance decomposition of log daily wages for AKM model with dynamic effects

| | Dynamic firm effects | | Dynamic worker&firm effects | |
|---|---|---|---|---|
| | Component | Share | Component | Share |
| $Var(y)$ | 0.604 | - | 0.604 | - |
| $Var(\eta)$ | 0.162 | 0.269 | 0.323 | 0.536 |
| $Var(\psi)$ | 0.282 | 0.467 | 0.179 | 0.297 |
| $Var(X\Omega)$ | 0.020 | 0.032 | 0.026 | 0.043 |
| $Var(\epsilon)$ | 0.105 | 0.175 | 0.077 | 0.128 |
| $2 \times Cov(\eta, \psi)$ | 0.042 | 0.069 | 0.015 | 0.025 |
| $2 \times Cov(\eta, X\Omega)$ | -0.006 | -0.010 | -0.018 | -0.029 |
| $2 \times Cov(\psi, X\Omega)$ | -0.001 | -0.002 | 0.001 | 0.001 |

Notes: Variance decomposition of (log) daily wages based on equation (2) using the entire sample period, 2000-2020, using the AKM methodology. Dynamic firm (worker&firm) effects allow firm (worker and firm) fixed effects to shift every 5 years. In these cases, identification comes from workers moving across firm×5-year units.

**Table C.4:** Variance decomposition of log daily wages for alternative KSS leave-out-units

| | Leave-out-observations | | Leave-out-workers | |
|---|---|---|---|---|
| | Component | Share | Component | Share |
| $Var(y)$ | 0.598 | - | 0.594 | - |
| $Var(\eta)$ | 0.157 | 0.263 | 0.156 | 0.263 |
| $Var(\psi)$ | 0.177 | 0.295 | 0.171 | 0.287 |
| $Var(X\Omega)$ | 0.089 | 0.148 | 0.089 | 0.149 |
| $Var(\epsilon)$ | 0.121 | 0.202 | 0.121 | 0.204 |
| $2 \times Cov(\eta, \psi)$ | 0.050 | 0.084 | 0.052 | 0.088 |
| $2 \times Cov(\eta, X\Omega)$ | -0.003 | -0.004 | -0.003 | -0.005 |
| $2 \times Cov(\psi, X\Omega)$ | 0.002 | 0.004 | 0.003 | 0.004 |

Notes: Variance decomposition of (log) daily wages based on equation (2) using the entire sample period, 2000-2020, using the KSS estimator proposed by Kline et al. (2020). Leave-out observations column excludes in each iteration a given worker-quarter observation to estimate the bias, while the leave-out-workers column removes the entire worker history in each iteration to estimate the bias.

**Table C.5:** Variance decomposition of log daily wages for alternative firm clusters

| | BLM 150 | | BLM 600 | | BLM 6000 | |
|---|---|---|---|---|---|---|
| | Component | Share | Component | Share | Component | Share |
| $Var(y)$ | 0.606 | - | 0.606 | - | 0.606 | - |
| $Var(\eta)$ | 0.212 | 0.350 | 0.205 | 0.337 | 0.193 | 0.318 |
| $Var(\psi)$ | 0.088 | 0.144 | 0.091 | 0.151 | 0.108 | 0.178 |
| $Var(X\Omega)$ | 0.068 | 0.112 | 0.067 | 0.110 | 0.069 | 0.113 |
| $Var(\epsilon)$ | 0.150 | 0.247 | 0.149 | 0.245 | 0.144 | 0.238 |
| $2 \times Cov(\eta, \psi)$ | 0.074 | 0.121 | 0.078 | 0.129 | 0.077 | 0.126 |
| $2 \times Cov(\eta, X\Omega)$ | -0.007 | -0.012 | -0.007 | -0.012 | -0.006 | -0.011 |
| $2 \times Cov(\psi, X\Omega)$ | 0.023 | 0.038 | 0.024 | 0.040 | 0.022 | 0.037 |

Notes: Variance decomposition of (log) daily wages based on equation (2) using the entire sample period, 2000-2020. BLM stands for two-way fixed effect estimates from the firm-clustering approach of Bonhomme et al. (2019) using three different numbers of firm clusters, i.e., 150, 600, and 6000 firm types.

**Table C.6:** Variance decomposition of log daily wages for alternative wage definitions for clustering

| | BLM w/ worker variables | | BLM w/ firm variables | |
|---|---|---|---|---|
| | Component | Share | Component | Share |
| $Var(y)$ | 0.607 | - | 0.607 | - |
| $Var(\eta)$ | 0.195 | 0.322 | 0.251 | 0.415 |
| $Var(\psi)$ | 0.103 | 0.170 | 0.074 | 0.122 |
| $Var(X\Omega)$ | 0.082 | 0.136 | 0.083 | 0.137 |
| $Var(\epsilon)$ | 0.145 | 0.238 | 0.153 | 0.252 |
| $2 \times Cov(\eta, \psi)$ | 0.078 | 0.128 | 0.044 | 0.072 |
| $2 \times Cov(\eta, X\Omega)$ | -0.004 | -0.007 | -0.007 | -0.011 |
| $2 \times Cov(\psi, X\Omega)$ | 0.008 | 0.013 | 0.009 | 0.015 |

Notes: Variance decomposition of (log) daily wages based on equation (2) using the entire sample period, 2000-2020. BLM stands for two-way fixed effect estimates from the firm-clustering approach of Bonhomme et al. (2019). BLM w/ worker characteristics column regresses (log) wages on time, age, nationality, and sex indicators and uses the residuals to classify firms. BLM w/ job-firm variables column regresses (log) wages on time, tenure, sector, and location indicators, and uses the residuals to classify firms.

**Table C.11:** Decomposition of the decrease in wage inequality: Dynamic effects

| | 2000-05 to 2015-20 | |
|---|---|---|
| | AKM Dynamic $\psi$ | AKM Dynamic $\psi$ & $\eta$ |
| Change in $Var(y)$ | -0.139 | -0.139 |
| Contribution | | |
| $Var(\eta)$ | 0.302 | -0.152 |
| $Var(\psi)$ | 0.601 | 0.906 |
| $Var(X\Omega)$ | 0.032 | 0.040 |
| $Var(\epsilon)$ | 0.107 | 0.086 |
| $2 \times Cov(\eta, \psi)$ | 0.149 | 0.197 |
| $2 \times Cov(\eta, X\Omega)$ | -0.052 | -0.070 |
| $2 \times Cov(\psi, X\Omega)$ | 0.003 | -0.005 |
| Counterfactual change in $Var(y)$ | | |
| 1. Fixed variance of firm effects | -0.059 | -0.013 |
| 2. Fixed corr. of firm and worker effects | -0.034 | -0.146 |
| 3. Both 1 and 2 | 0.050 | -0.020 |

Notes: Estimates refer to the two-way fixed effects model following Abowd et al. (1999). Column (1) allows firm fixed effects to drift every 5 years, whereas in Column (2) both firm and worker fixed effects drift every 5 years. Counterfactual 1 computes the change in inequality, fixing the variance of firm effects to that in the 2000-05 period, i.e., $Var_{2000-05}(\psi)$. Counterfactual 2 shows the change in wage inequality between 2000-05 and 2015-20, assuming no change in the correlation of worker and firm effects, i.e., $Cov_{2015-20} = \rho_{2000-05} \times Var_{2015-20}(\eta)^{1/2} \times Var_{2015-20}(\psi)^{1/2}$. Counterfactual 3 measures the change in inequality, allowing only the variance of worker effects to vary, i.e., we combine counterfactuals 1 and 2.

**Table C.7:** Variance decomposition of log daily wages by sub-periods: AKM

| | 2000-2005 | | 2005-2010 | | 2010-2015 | | 2015-2020 | |
|---|---|---|---|---|---|---|---|---|
| | Component | Share | Component | Share | Component | Share | Component | Share |
| $Var(y)$ | 0.577 | - | 0.549 | - | 0.524 | - | 0.445 | - |
| $Var(\eta)$ | 0.208 | 0.360 | 0.224 | 0.409 | 0.236 | 0.450 | 0.219 | 0.493 |
| $Var(\psi)$ | 0.241 | 0.418 | 0.196 | 0.357 | 0.192 | 0.367 | 0.123 | 0.276 |
| $Var(X\Omega)$ | 0.025 | 0.044 | 0.032 | 0.058 | 0.028 | 0.053 | 0.034 | 0.077 |
| $Var(\epsilon)$ | 0.081 | 0.141 | 0.094 | 0.172 | 0.074 | 0.142 | 0.074 | 0.166 |
| $2 \times Cov(\eta, \psi)$ | 0.037 | 0.064 | 0.019 | 0.035 | 0.012 | 0.024 | 0.013 | 0.028 |
| $2 \times Cov(\eta, X\Omega)$ | -0.015 | -0.026 | -0.016 | -0.029 | -0.020 | -0.038 | -0.020 | -0.044 |
| $2 \times Cov(\psi, X\Omega)$ | -0.001 | -0.001 | -0.001 | -0.002 | 0.001 | 0.002 | 0.002 | 0.005 |
| | | | | | | | | |
| Adj. R-squared | 0.846 | | 0.813 | | 0.845 | | 0.820 | |
| RMSE | 0.298 | | 0.321 | | 0.285 | | 0.283 | |
| N | 4,409,926 | | 4,807,353 | | 4,448,801 | | 4,696,179 | |

Notes: Variance decomposition of (log) daily wages based on equation (2) using the AKM estimates from each sub-period. AKM stands for two-way fixed effect estimates from equation (1).

**Table C.8:** Decomposition of the decrease in wage inequality: Firm and worker sets

| | 2000-05 to 2015-20 | | |
|---|---|---|---|
| | (1) Stable firms | (2) Stable firms and workers | (3) Stable firms and workers and LM attachment |
| Change in $Var(y)$ | -0.162 | -0.164 | -0.172 |
| Contribution | | | |
| $Var(\eta)$ | 0.035 | -0.103 | -0.075 |
| $Var(\psi)$ | 0.786 | 0.802 | 0.846 |
| $Var(X\Omega)$ | -0.037 | 0.074 | 0.064 |
| $Var(\epsilon)$ | 0.073 | 0.118 | 0.100 |
| $2 \times Cov(\eta, \psi)$ | 0.154 | 0.204 | 0.155 |
| $2 \times Cov(\eta, X\Omega)$ | 0.007 | -0.102 | -0.092 |
| $2 \times Cov(\psi, X\Omega)$ | -0.036 | -0.025 | -0.026 |
| Counterfactual change in $Var(y)$ | | | |
| 1. Fixed variance of firm effects | -0.034 | -0.032 | -0.032 |
| 2. Fixed corr. of firm and worker effects | -0.153 | -0.147 | -0.155 |
| 3. Both 1 and 2 | -0.010 | 0.003 | 0.002 |

Notes: Column (1) restricts our baseline sample to consider only firms that are observed at least once in each of the four overlapping periods, i.e., 2000-05, 2005-10, 2010-15, and 2015-20. Column (2) further restricts the sample to consider only firms and workers that are observed at least once in each of the four overlapping periods. Column (3), in addition to Column (2), includes individuals who are observed at least once in each of the four overlapping periods and worked at least 75% of the time. Estimates refer to the two-way fixed effects model following Abowd et al. (1999). Counterfactual 1 computes the change in inequality, fixing the variance of firm effects to that in the 2000-05 period, i.e., $Var_{2000-05}(\psi)$. Counterfactual 2 shows the change in wage inequality between 2000-05 and 2015-20, assuming no change in the correlation of worker and firm effects, i.e., $Cov_{2015-20} = \rho_{2000-05} \times Var_{2015-20}(\eta)^{1/2} \times Var_{2015-20}(\psi)^{1/2}$. Counterfactual 3 measures the change in inequality, allowing only the variance of worker effects to vary, i.e., we combine counterfactuals 1 and 2.

**Table C.9:** Variance decomposition of log daily wages by sub-periods: KSS

| | 2000-2005 | | 2005-2010 | | 2010-2015 | | 2015-2020 | |
|---|---|---|---|---|---|---|---|---|
| | Component | Share | Component | Share | Component | Share | Component | Share |
| $Var(y)$ | 0.564 | - | 0.534 | - | 0.503 | - | 0.429 | - |
| $Var(\eta)$ | 0.187 | 0.331 | 0.199 | 0.373 | 0.205 | 0.408 | 0.195 | 0.453 |
| $Var(\psi)$ | 0.215 | 0.380 | 0.163 | 0.306 | 0.149 | 0.297 | 0.088 | 0.206 |
| $Var(X\Omega)$ | 0.026 | 0.046 | 0.033 | 0.061 | 0.029 | 0.057 | 0.035 | 0.081 |
| $Var(\epsilon)$ | 0.082 | 0.145 | 0.095 | 0.178 | 0.075 | 0.149 | 0.075 | 0.174 |
| $2 \times Cov(\eta, \psi)$ | 0.062 | 0.111 | 0.052 | 0.097 | 0.055 | 0.110 | 0.048 | 0.111 |
| $2 \times Cov(\eta, X\Omega)$ | -0.015 | -0.027 | -0.017 | -0.031 | -0.021 | -0.041 | -0.021 | -0.048 |
| $2 \times Cov(\psi, X\Omega)$ | 0.000 | -0.001 | -0.001 | -0.001 | 0.002 | 0.004 | 0.003 | 0.007 |
| Observations | 4,510,485 | | 4,940,511 | | 4,677,094 | | 4,957,606 | |

Notes: Variance decomposition of (log) daily wages based on equation (2) using the KSS estimates from each sub-period. KSS refers to the leave-one-out estimator proposed by Kline et al. (2020).

**Table C.10:** Variance decomposition of log daily wages by sub-periods: BLM

| | 2000-2005 | | 2005-2010 | | 2010-2015 | | 2015-2020 | |
|---|---|---|---|---|---|---|---|---|
| | Component | Share | Component | Share | Component | Share | Component | Share |
| $Var(y)$ | 0.583 | - | 0.558 | - | 0.540 | - | 0.460 | - |
| $Var(\eta)$ | 0.249 | 0.427 | 0.258 | 0.461 | 0.279 | 0.517 | 0.277 | 0.603 |
| $Var(\psi)$ | 0.112 | 0.192 | 0.086 | 0.154 | 0.074 | 0.136 | 0.033 | 0.072 |
| $Var(X\Omega)$ | 0.022 | 0.037 | 0.032 | 0.058 | 0.030 | 0.055 | 0.040 | 0.087 |
| $Var(\epsilon)$ | 0.101 | 0.172 | 0.114 | 0.204 | 0.091 | 0.169 | 0.089 | 0.193 |
| $2 \times Cov(\eta, \psi)$ | 0.112 | 0.192 | 0.088 | 0.157 | 0.091 | 0.169 | 0.050 | 0.109 |
| $2 \times Cov(\eta, X\Omega)$ | -0.015 | -0.027 | -0.019 | -0.034 | -0.025 | -0.047 | -0.030 | -0.066 |
| $2 \times Cov(\psi, X\Omega)$ | 0.004 | 0.007 | 0.000 | -0.001 | 0.001 | 0.002 | 0.001 | 0.003 |
| Observations | 4,506,950 | | 4,939,701 | | 4,674,446 | | 4,955,309 | |

Notes: Variance decomposition of (log) daily wages based on equation (2) using the BLM estimates from each sub-period. BLM stands for two-way fixed effect estimates from the firm-clustering approach of Bonhomme et al. (2019).

**Table C.12:** Decomposition of the decrease in wage inequality: BLM clusters

| | 2000-05 to 2015-20 | | |
|---|---|---|---|
| | BLM 150 | BLM 600 | BLM 6000 |
| Change in $Var(y)$ | -0.123 | -0.123 | -0.124 |
| Contribution | | | |
| $Var(\eta)$ | -0.169 | -0.212 | -0.232 |
| $Var(\psi)$ | 0.588 | 0.630 | 0.722 |
| $Var(X\Omega)$ | -0.154 | -0.151 | -0.148 |
| $Var(\epsilon)$ | 0.101 | 0.098 | 0.085 |
| $2 \times Cov(\eta, \psi)$ | 0.482 | 0.489 | 0.433 |
| $2 \times Cov(\eta, X\Omega)$ | 0.130 | 0.123 | 0.121 |
| $2 \times Cov(\psi, X\Omega)$ | 0.022 | 0.024 | 0.019 |
| Counterfactual change in $Var(y)$ | | | |
| 1. Fixed variance of firm effects | -0.051 | -0.046 | -0.035 |
| 2. Fixed corr. of firm and worker effects | -0.110 | -0.111 | -0.110 |
| 3. Both 1 and 2 | 0.013 | 0.020 | 0.025 |

Notes: BLM 150, 600, and 6000 refer to the number of firm clusters used to reduce the dimensionality of firm fixed effects. BLM relies on estimates from the firm-clustering approach of Bonhomme et al. (2019). The estimation sample for each method corresponds to the largest connected set of firm clusters within which workers move in each period. Counterfactual 1 computes the change in inequality, fixing the variance of firm effects to that in the 2000-05 period, i.e., $Var_{2000-05}(\psi)$. Counterfactual 2 shows the change in wage inequality between 2000-05 and 2015-20, assuming no change in the correlation of worker and firm effects, i.e., $Cov_{2015-20} = \rho_{2000-05} \times Var_{2015-20}(\eta)^{1/2} \times Var_{2015-20}(\psi)^{1/2}$. Counterfactual 3 measures the change in inequality, allowing only the variance of worker effects to vary, i.e., we combine counterfactuals 1 and 2.

## C.3 Within- vs. between-sector decomposition

We follow Foster et al. (2001) and decompose the aggregate change in the variance of $\psi_j$, $\Delta\text{var}_{t+1}[\psi_j]$ as:

$$\Delta\text{var}_{t+1}[\psi_j] = \sum_{s\in\mathcal{S}} \Delta n_{st+1}\text{var}_{st}[\psi_j] + \sum_{s\in\mathcal{S}} n_{st+1}\Delta\text{var}_{st+1}[\psi_j]$$

where $n_{st+1}$ denote the employment share of sector $s$ at time $t+1$, $\text{var}_{st}[\psi_j]$ is the variance of the firm pay policies in sector $s$ at time $t$, $\Delta n_{st+1}$ is the change in employment share of sector $s$ over time, and $\Delta\text{var}_{st+1}[\psi_j]$ is the change in the variance of the firm pay policies in sector $s$ over time. The first term represents a *between-sector* component that reflects changing employment shares, weighted by the variance in the *initial* period. The second term represents a *within-sector* component based on the change in variance for a given sector $s$ between the two periods, weighted by the *final* employment shares of that sector.

Notice that the second term can broken into two separate pieces, i.e.,

$$\sum_{s\in\mathcal{S}} n_{st+1}\Delta\text{var}_{st+1}[\psi_j] = \sum_{s\in\mathcal{S}} n_{st}\Delta\text{var}_{st+1}[\psi_j] + \sum_{s\in\mathcal{S}} \Delta n_{st+1}\Delta\text{var}_{st+1}[\psi_j]$$

where the *within-sector* component is now weighted by the *initial* employment shares of each sector, while the second term represents a *cross-term* that relates changes in employment shares to changes in variance. Table C.13 reports the contributions of each term to the change in the variance of the AKM and BLM firms' fixed effects.

**Table C.13:** Sectoral decomposition

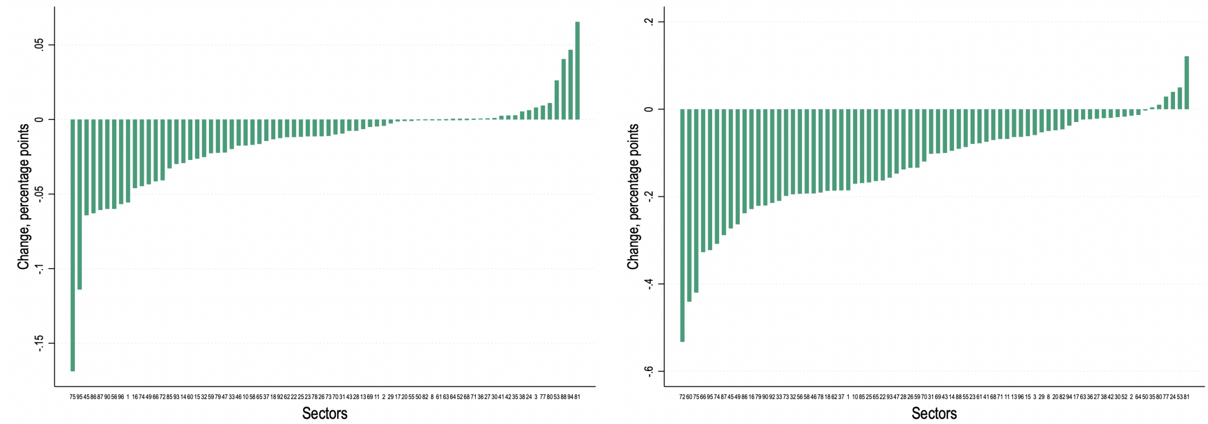
| | AKM | | BLM | |
|---|---|---|---|---|
| | Estimate | Contribution (%) | Estimate | Contribution (%) |
| | (1) | (2) | (3) | (4) |
| Change in $Var(y)$ | -0.131 | - | -0.136 | - |
| Change in $Var(\psi)$ | -0.118 | 89.8 | -0.127 | 93.0 |
| Within-sector | -0.084 | 71.2 | -0.061 | 48.0 |
| Between-sector | 0.016 | -13.5 | 0.006 | -4.7 |
| Cross-term | -0.050 | 42.3 | -0.072 | 56.7 |

Notes: Column (1) reports the observed change in wage dispersion between 2000-2005 and 2015-2020, the estimated change in AKM firm-pay policies, and its decomposition in within- and between-sector components following Foster et al. (2001). Column (2) reports the % contribution of each component.

## C.4 Role of minimum wage

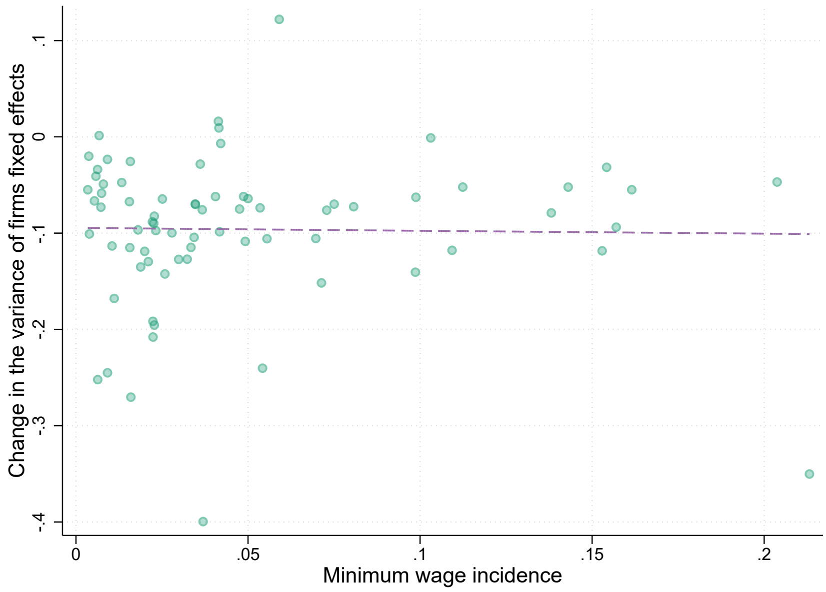
**Figure C.3:** Change in minimum wage's "bite" across sectors

**(A)** Share of minimum wage workers **(B)** Incidence of minimum wage




Source: Social Security records and own calculations.
Notes: For each sector $s$, the share of minimum wage workers is computed as the share of workers $i$ paid at most the minimum wage at time $t$. The minimum wage incidence is computed as $\frac{\sum_{i \in s} \max\{0, MW - w_{it}\}}{\sum_{i \in s} w_{it}}$ where $MW$ is the prevailing daily minimum wage, $w_{it}$ refers to the daily income of worker $i$ at time $t$. Changes in shares and incidence of minimum wage across sectors are computed between the values recorded in 2015-2020 and 2000-2005. Only sectors with at least 20 firms are included for a total of 74 sectors.

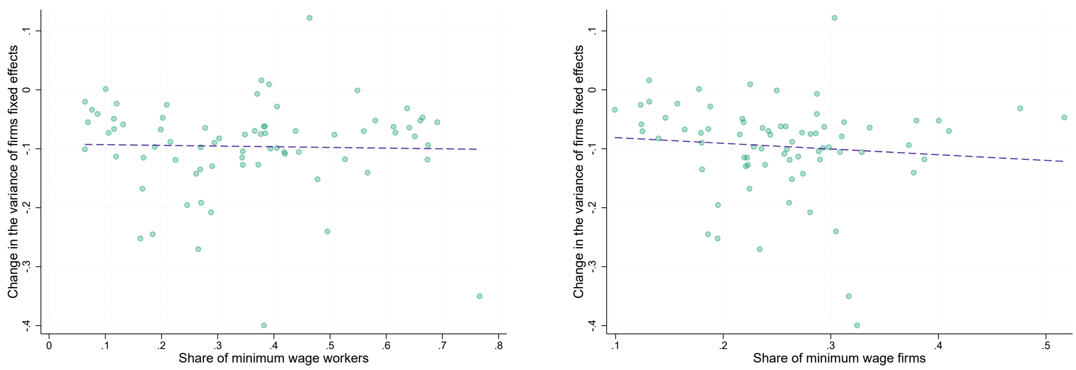
**Figure C.4:** Changes in the variance of firm fixed effects and minimum wage incidence




Source: Social Security records and own calculations.
Notes: Changes in the variance of firm fixed effects are the difference between the sector-specific variance of firm fixed effects in 2015-2020 and that in 2000-2005. Minimum wage incidence refers to the bite of the minimum wage across sectors in the initial period, 2000-2005. For each sector $s$, the minimum wage incidence is computed as $\frac{\sum_{i \in s} \max\{0, MW - w_{it}\}}{\sum_{i \in s} w_{it}}$ where $MW$ is the prevailing daily minimum wage, $w_{it}$ refers to the daily income of worker $i$ at time $t$. Only sectors with at least 20 firms are included for a total of 74 sectors.

**Figure C.5:** Changes in the variance of firm fixed effects and the minimum wage

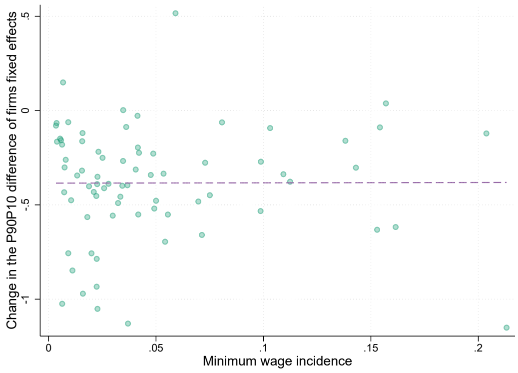
**(A)** MW incidence based on workers **(B)** MW incidence based on firms



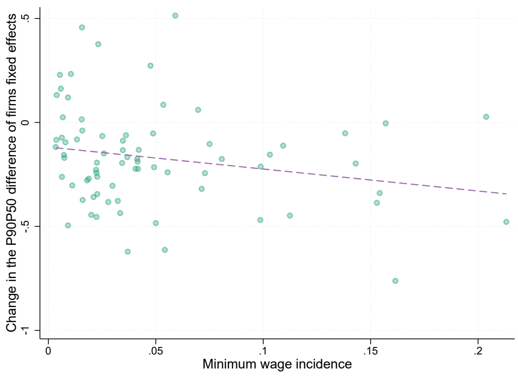

Source: Social Security records and own calculations.
Notes: Changes in the variance of firm fixed effects is the difference between the sector-specific variance of firm fixed effects in 2015-2020 and that in 2000-2005. Minimum wage incidence refers to the bite of the minimum wage across sectors in the initial period. In Panel A, the share of minimum wage workers is the sector-specific share of workers whose earnings are at or below the current minimum wage. In Panel B, the share of minimum wage firms is the sector-specific share of firms where the minimum wage is at least 75% of the firm's average wage. Only sectors with at least 20 firms are included for a total of 74 sectors.

**Figure C.6:** Changes in the percentile difference of firm fixed effects and the minimum wage

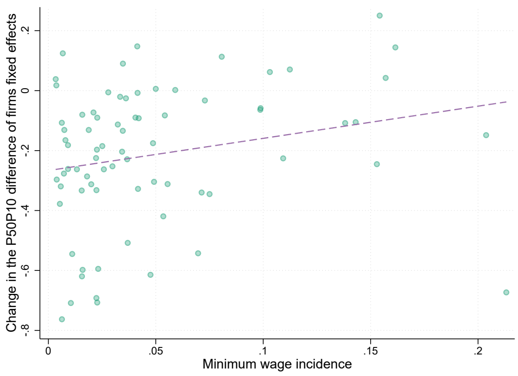
**(A)** P90-P10




**(B)** P90-P50




**(C)** P50-P10




Source: Social Security records and own calculations.
Notes: Changes in the percentile differences of firm fixed effects refer to the difference between the sector-specific percentiles of firm fixed effects in 2015-2020 and that in 2000-2005. Minimum wage incidence refers to the bite of the minimum wage across sectors in the initial period, 2000-2005. For each sector $s$, the minimum wage incidence is computed as $\frac{\sum_{i \in s} \max\{0, MW - w_{it}\}}{\sum_{i \in s} w_{it}}$ where $MW$ is the prevailing daily minimum wage, $w_{it}$ refers to the daily income of worker $i$ at time $t$. Only sectors with at least 20 firms are included for a total of 74 sectors.

# D Model derivation

We start from the first-order condition with respect to wages, which is equal to

$$\left[\alpha z_{jt}L_{jt}^{\alpha-1} - w_{jt} + \delta\frac{\partial\Pi(L_{jt})}{\partial L_{jt}}\right]\frac{\partial L_{jt}}{\partial w_{jt}}\frac{w_{jt}}{L_{jt}} = w_{jt},$$

and it corresponds to equation (5) in the main text. Differentiating the firm value function in equation (3) of the main text with respect to employment, we obtain that

$$\frac{\partial\Pi(L_{jt-1})}{\partial L_{jt-1}} = \left[\alpha z_{jt}L_{jt}^{\alpha-1} - w_{jt} + \delta\frac{\partial\Pi(L_{jt})}{\partial L_{jt}}\right]\frac{\partial L_{jt}}{\partial L_{jt-1}}.$$

Using the envelope condition in steady state, we can solve for $\frac{\partial\Pi(L_{jt})}{\partial L_{jt}}$

$$\frac{\partial\Pi(L_{jt})}{\partial L_{jt}} = \frac{\left[\alpha z_{jt}L_{jt}^{\alpha-1} - w_{jt}\right]\frac{\partial L_{jt}}{\partial L_{jt-1}}}{1-\delta\frac{\partial L_{jt}}{\partial L_{jt-1}}}.$$

Substituting it back to the first order condition (5), we get

$$\left[\alpha z_{jt}L_{jt}^{\alpha-1} - w_{jt}\right]\left(1 + \frac{\delta\frac{\partial L_{jt}}{\partial L_{jt-1}}}{1-\delta\frac{\partial L_{jt}}{\partial L_{jt-1}}}\right)\frac{\partial L_{jt}}{\partial w_{jt}}\frac{w_{jt}}{L_{jt}} = w_{jt},$$

which simplifies to

$$\frac{\alpha z_{jt}L_{jt}^{\alpha-1} - w_{jt}}{w_{jt}} = \left(1-\delta\frac{\partial L_{jt}}{\partial L_{jt-1}}\right)\frac{1}{B_t w_{jt}^{\varepsilon_{sept}}\left[\varepsilon_{Rt}-\varepsilon_{sept}\right]},$$

where we used the fact that, in steady state:

$$\left(\frac{\partial L_{jt}}{\partial w_{jt}}\frac{w_{jt}}{L_{jt}}\right) = B_t w_{jt}^{\varepsilon_{sept}}\left[\varepsilon_{Rt}-\varepsilon_{sept}\right].$$

From the law of motion of employment (equation (4)), we know that

$$\frac{\partial L_{jt}}{\partial L_{jt-1}} = 1 - B_t w_{jt}^{\varepsilon_{sept}},$$

which implies that

$$\frac{\alpha z_{jt} L_{jt}^{\alpha-1} - w_{jt}}{w_{jt}} = (1 - \delta + \delta B_t w_{jt}^{\varepsilon_{sept}}) \frac{1}{\left(B_t w_{jt}^{\varepsilon_{sept}} [\varepsilon_{Rt} - \varepsilon_{sept}]\right)}.$$

For low enough future discounting (i.e., $\delta \approx 1$), the condition above can be written as follows

$$\frac{\alpha z_{jt} L_{jt}^{\alpha-1} - w_{jt}}{w_{jt}} \approx \frac{1}{[\varepsilon_{Rt} - \varepsilon_{sept}]}.$$

The degree of monopsony power is then given by the elasticity of the labor supply curve facing the firm. Re-arranging terms, we get:

$$w_{jt} \approx \frac{1}{\left(1 + \frac{1}{[\varepsilon_{Rt} - \varepsilon_{sept}]}\right)} \alpha z_{jt} L_{jt}^{\alpha-1}.$$

Taking logs,

$$\log w_{jt} \approx \log z_{jt} - (1 - \alpha) \log L_{jt} - \log \left(1 + \frac{1}{[\varepsilon_{Rt} - \varepsilon_{sept}]}\right) + \log \alpha.$$

Since, in a steady state, firm-level employment is equal to

$$L_{jt} = \frac{R(w_{jt})}{s(w_{jt})} = \frac{A_t}{B_t} w_{jt}^{\varepsilon_{Rt} - \varepsilon_{sept}},$$

then the equation for log wages becomes

$$\log w_{jt} \approx \log z_{jt} - (1 - \alpha)[\varepsilon_{Rt} - \varepsilon_{sept}] \log (w_{jt}) + C_t,$$

where $C$ is a market constant, possibly time-varying, and equal to:

$$C_t = (1 - \alpha) \log \left(\frac{A_t}{B_t}\right) - \log \left(1 + \frac{1}{[\varepsilon_{Rt} - \varepsilon_{sept}]}\right) + \log \alpha.$$

The equation above allows us to solve for log wages and to compute log wage dispersion equal to

$$\begin{aligned}\text{var}_t[\log w_{jt}] &\approx \left(\frac{1}{1+(1-\alpha)[\varepsilon_{Rt}-\varepsilon_{sept}]}\right)^2 \text{var}_t\left[\log z_{jt}\right] \\ &\approx \left(\frac{1}{1+(1-\alpha)\varepsilon_{LSt}}\right)^2 \text{var}_t\left[\log z_{jt}\right]\end{aligned} \tag{10}$$

which is the equation (6) in the main text. Notice also that, in steady state:

$$\log L_{jt} = \log A_t - \log B_t + \varepsilon_{LSt} \log w_{jt}.$$

Using the solution for wages, that is,

$$\log w_{jt} = \frac{1}{1+(1-\alpha)\varepsilon_{LSt}}[\log z_{jt} + C_t],$$

we can back out the firm-level productivity as a function of observed firm size:

$$\log z_{jt} = \frac{1+(1-\alpha)\varepsilon_{LSt}}{\varepsilon_{LSt}} \log L_{jt} - C_t - \frac{1+(1-\alpha)\varepsilon_{LSt}}{\varepsilon_{LSt}}[\log A_t - \log B_t]$$

which implies:

$$\text{var}_t[\log z_{jt}] = \left(\frac{1+(1-\alpha)\varepsilon_{LSt}}{\varepsilon_{LSt}}\right)^2 \text{var}_t[\log L_{jt}] \tag{11}$$

Plugging equation (11) into equation (10), we get:

$$\text{var}_t[\log w_{jt}] \approx \left(\frac{1}{1+(1-\alpha)\varepsilon_{LSt}}\right)^2 \left(\frac{1+(1-\alpha)\varepsilon_{LSt}}{\varepsilon_{LSt}}\right)^2 \text{var}_t[\log L_{jt}] = \left(\frac{1}{\varepsilon_{LSt}}\right)^2 \text{var}_t[\log L_{jt}]$$

where (log) wage inequality is expressed as a function of (log) firm size dispersion.

Taking changes between two different periods, we get:

$$\Delta\text{var}_{t+1}[\log w_{jt}] = \left(\frac{1}{\varepsilon_{LSt+1}}\right)^2 \text{var}_{t+1}\left[\log L_{jt}\right] - \left(\frac{1}{\varepsilon_{LSt}}\right)^2 \text{var}_t\left[\log L_{jt}\right],$$

and using a linear approximation around $\varepsilon_{LSt} = 1$, we can write:

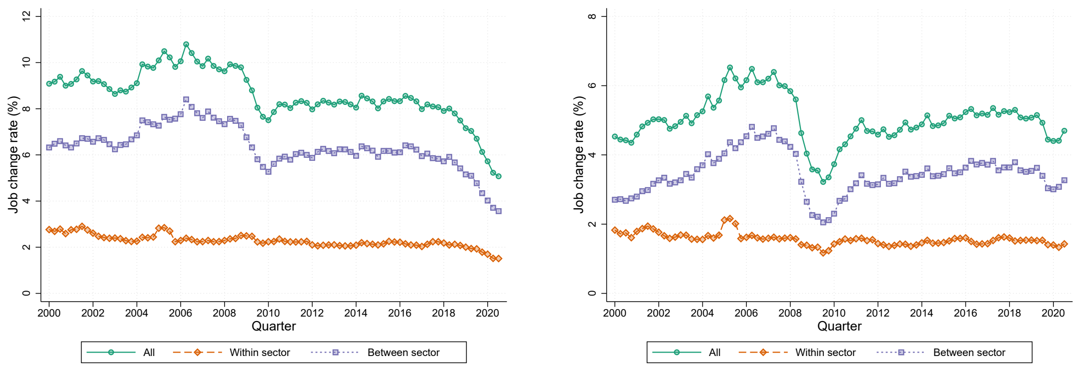
$$\Delta\text{var}_{t+1}[\log w_{jt}] \approx -2\text{var}_{t+1}[\log L_{jt}]\Delta\varepsilon_{LSt+1} + 3\Delta\text{var}_t[\log L_{jt}] - 2\varepsilon_{LSt+1}\Delta\text{var}_{t+1}[\log L_{jt}]$$

which is the equation we estimate in Section 7.

# E Sensitivity tests and additional results on firm's labor supply elasticity

**Figure E.1:** Job changes between and within sectors, 2000-2020

**(A)** All job changes **(B)** Direct job changes




Source: Social Security records and own calculations.
Notes: All job changes in Panel A include all individuals who changed jobs between 2000 and 2020. Direct job changes in Panel B refer to individuals who changed within two consecutive quarters. Within sector represents job changes that did not involve a change in the 2-digit industry, while between sector captures individuals who change jobs *and* 2-digit industries.

**Table E.1:** Separation elasticity under complementary log-log model

| A. 2000-2005 | Worker wage | | IV-Firm fixed effect | |
|---|---|---|---|---|
| | Sep | EE Sep | Sep | EE Sep |
| $\varepsilon_{sep}$ | -0.5550 | -0.4747 | -0.6712 | -0.7611 |
| | (0.0034) | (0.0046) | (0.0366) | (0.0481) |
| Observations | 4,149,923 | 4,149,923 | 4,149,923 | 4,149,923 |
| B. 2015-2020 | Worker wage | | IV-Firm fixed effect | |
| | Sep | EE Sep | Sep | EE Sep |
| $\varepsilon_{sep}$ | -0.6692 | -0.5086 | -0.8459 | -0.8666 |
| | (0.0037) | (0.0050) | (0.0203) | (0.0224) |
| Observations | 4,404,064 | 4,404,064 | 4,404,064 | 4,404,064 |

Notes: Panel A and B estimate period-specific complementary log-log models for the binary outcome of having any type of separation (Sep) and an employer-to-employer transition (EE Sep) using alternative measures of wages. Worker wage columns rely on individual-level wages as the independent variable. In the IV-firm fixed effects, we follow a two-stage approach to instrument the period-specific AKM firm fixed effects retrieved from estimating equation (1). In the first stage, we regress the firm's FE on the (log) average firm wage together with indicators for age group, sex, 2-digit industry, time effects, and the estimated AKM worker fixed effects. In the second stage, the complementary log-log model is estimated using the value predicted in the first stage as the wage measure. All specifications control for estimated AKM worker fixed effects along with indicators for age groups, sex, 2-digit industries, and time effects.

**Table E.2:** Firm labor supply elasticity, 2005-2010 and 2010-2015

| A. 2005-2010 | Worker wage | | Firm fixed effect | | IV-Firm fixed effect | |
|---|---|---|---|---|---|---|
| | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\beta$ | -0.0675 | -0.0246 | -0.0494 | -0.0199 | -0.0680 | -0.0352 |
| | (0.0004) | (0.0003) | (0.0014) | (0.0008) | (0.0021) | (0.0011) |
| $\epsilon_{LS}$ | 1.1104 | 0.9268 | 0.8139 | 0.7528 | 1.1184 | 1.3281 |
| | (0.0177) | (0.0195) | (0.0238) | (0.0297) | (0.0347) | (0.0399) |
| First stage F-statistic | | | | | 10,105.15 | |
| Observations | 4,561,130 | 4,561,130 | 4,561,130 | 4,561,130 | 4,561,130 | 4,561,130 |

| B. 2010-2015 | Worker wage | | Firm fixed effect | | IV-Firm fixed effect | |
|---|---|---|---|---|---|---|
| | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\beta$ | -0.0694 | -0.0274 | -0.0570 | -0.0257 | -0.0852 | -0.0458 |
| | (0.0004) | (0.0003) | (0.0015) | (0.0009) | (0.0022) | (0.0012) |
| $\epsilon_{LS}$ | 1.2788 | 1.1370 | 1.0510 | 1.0654 | 1.5703 | 1.9003 |
| | (0.0234) | (0.0259) | (0.0278) | (0.0378) | (0.0406) | (0.0485) |
| First stage F-statistic | | | | | 12,205.60 | |
| Observations | 4,181,332 | 4,181,332 | 4,181,332 | 4,181,332 | 4,181,332 | 4,181,332 |

Notes: Panel A and B estimate period-specific linear probability models as specified in Equation (8) for all quarterly separations (Sep) and employer-to-employer transitions (EE Sep) using alternative measures of wages. Worker wage columns rely on individual-level wages as the independent variable. Firm fixed effect columns use AKM effects retrieved from estimating equation (1) separately by period. IV-firm fixed effect columns instrument period-specific firm fixed effects with the (log) average firm wage (wage bill divided by firm size). All specifications control for the estimated AKM worker fixed effects along with indicators for age groups, sex, 2-digit industries, and time effects. Standard errors (in parentheses) are clustered at the level of variation of the wage measure, i.e., worker- or firm-level. $\varepsilon_{LS}$ refers to the firm's labor supply elasticity computed as: $\varepsilon_{LS} \approx -2 \times \hat{\beta}/\bar{s}$, where $\bar{s}$ is the average separation rate used as the dependent variable. Standard errors are obtained using the Delta method.

## **Table E.3:** Separation semi-elasticity with different set of controls

| A. 2000-2005 | Worker wage | | | | | | | | IV-Firm fixed effect | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep |
| $\beta$ | -0.0475 | -0.0209 | -0.0622 | -0.0269 | -0.0598 | -0.0249 | -0.0647 | -0.0191 | -0.0627 | -0.0379 | -0.0815 | -0.0472 | -0.0794 | -0.0431 | -0.0989 | -0.0460 |
| | (0.0004) | (0.0003) | (0.0004) | (0.0003) | (0.0004) | (0.0003) | (0.0003) | (0.0002) | (0.0022) | (0.0014) | (0.0023) | (0.0015) | (0.0024) | (0.0014) | (0.0024) | (0.0014) |
| Observations | 4,149,923 | 4,149,923 | 4,149,923 | 4,149,923 | 4,149,923 | 4,149,923 | 4,149,923 | 4,149,923 | 4,149,923 | 4,149,923 | 4,149,876 | 4,149,876 | 4,149,923 | 4,149,923 | 4,149,923 | 4,149,923 |
| **B. 2015-2020** | **Worker wage** | | | | | | | | **IV-Firm fixed effect** | | | | | | | |
| | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep |
| $\beta$ | -0.0684 | -0.0254 | -0.0795 | -0.0298 | -0.0766 | -0.0288 | -0.0750 | -0.0222 | -0.0851 | -0.0457 | -0.1062 | -0.0666 | -0.0969 | -0.0503 | -0.1394 | -0.0601 |
| | (0.0004) | (0.0003) | (0.0005) | (0.0003) | (0.0005) | (0.0003) | (0.0004) | (0.0002) | (0.0021) | (0.0013) | (0.0025) | (0.0015) | (0.0023) | (0.0013) | (0.0026) | (0.0015) |
| Observations | 4,404,064 | 4,404,064 | 4,404,064 | 4,404,064 | 4,404,064 | 4,404,064 | 4,404,064 | 4,404,064 | 4,404,064 | 4,404,064 | 4,404,024 | 4,404,024 | 4,404,064 | 4,404,064 | 4,404,064 | 4,404,064 |
| Tenure FE | Y | Y | N | N | N | N | N | N | Y | Y | N | N | N | N | N | N |
| Sector×Municipality FE | N | N | Y | Y | N | N | N | N | N | N | Y | Y | N | N | N | N |
| Family controls | N | N | N | N | Y | Y | N | N | N | N | N | N | Y | Y | N | N |
| AKM worker type | Y | Y | Y | Y | Y | Y | N | N | Y | Y | Y | Y | Y | Y | N | N |

Notes: Panel A and B estimate period-specific linear probability models as specified Equation (8) for all separations (Sep) and employer-to-employer separations (EE Sep) using alternative measures of wages. Worker wage columns rely on individual-level wages as the independent variable. IV-firm fixed effects columns instrument period-specific AKM firm fixed effects with the (log) of firms' average wage in that period. Tenure is a set of indicators for each year of tenure with the current employer. Sector×Municipality FE are pair fixed effects for each combination of sector and firm headquarters location. Family controls include indicators for marital status (single, married, divorced) and whether the individual has children or not. AKM worker refers to worker permanent heterogeneity estimated from model (1). All specifications control for age, sex, and 2-digit industry fixed effects.

**Table E.4:** Firm labor supply elasticity: Workers with AKM FE below median

| A. 2000-2005 | Worker wage | | Firm fixed effect | | IV-Firm fixed effect | |
|---|---|---|---|---|---|---|
| | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\beta$ | -0.0674 | -0.0235 | -0.0552 | -0.0241 | -0.0856 | -0.0451 |
| | (0.0007) | (0.0004) | (0.0029) | (0.0013) | (0.0036) | (0.0018) |
| $\epsilon_{LS}$ | 0.9520 | 0.8651 | 0.7798 | 0.8872 | 1.2093 | 1.6626 |
| | (0.0092) | (0.0148) | (0.0413) | (0.0462) | (0.0514) | (0.0665) |
| First stage F-statistic | | | | | 2,328.86 | |
| Observations | 2,074,976 | 2,074,976 | 2,074,976 | 2,074,976 | 2,074,976 | 2,074,976 |
| **B. 2015-2020** | **Worker wage** | | **Firm fixed effect** | | **IV-Firm fixed effect** | |
| | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\beta$ | -0.0875 | -0.0271 | -0.0730 | -0.0299 | -0.1036 | -0.0538 |
| | (0.0007) | (0.0005) | (0.0021) | (0.0011) | (0.0036) | (0.0019) |
| $\epsilon_{LS}$ | 1.3317 | 1.0121 | 1.1122 | 1.1173 | 1.5776 | 2.0090 |
| | (0.0112) | (0.0178) | (0.0317) | (0.0428) | (0.0550) | (0.0695) |
| First stage F-statistic | | | | | 9,975.29 | |
| Observations | 2,202,037 | 2,202,037 | 2,202,037 | 2,202,037 | 2,202,037 | 2,202,037 |

Notes: Panel A and B estimate period-specific linear probability models as specified Equation (8) for all quarterly separations (Sep) and employer-to-employer transitions (EE Sep) using alternative measures of wages. The models are estimated in the sample of workers with AKM worker FE at or below the median of the period-specific distribution. Worker wage columns rely on individual-level wages as the independent variable. Firm fixed effect columns use AKM effects retrieved from estimating equation (1) separately by period. IV-firm fixed effect columns instrument period-specific firm fixed effects with the (log) average firm wage (wage bill divided by firm size). All specifications control for the estimated AKM worker fixed effects along with indicators for age groups, sex, 2-digit industries, and time effects. Standard errors (in parentheses) are clustered at the level of variation of the wage measure, i.e., worker- or firm-level. $\varepsilon_{LS}$ refers to the firm's labor supply elasticity computed as: $\varepsilon_{LS} \approx -2 \times \hat{\beta}/\bar{s}$, where $\bar{s}$ is the average separation rate used as the dependent variable. Standard errors are obtained using the Delta method.

**Table E.5:** Firm labor supply elasticity: Workers with AKM FE above median

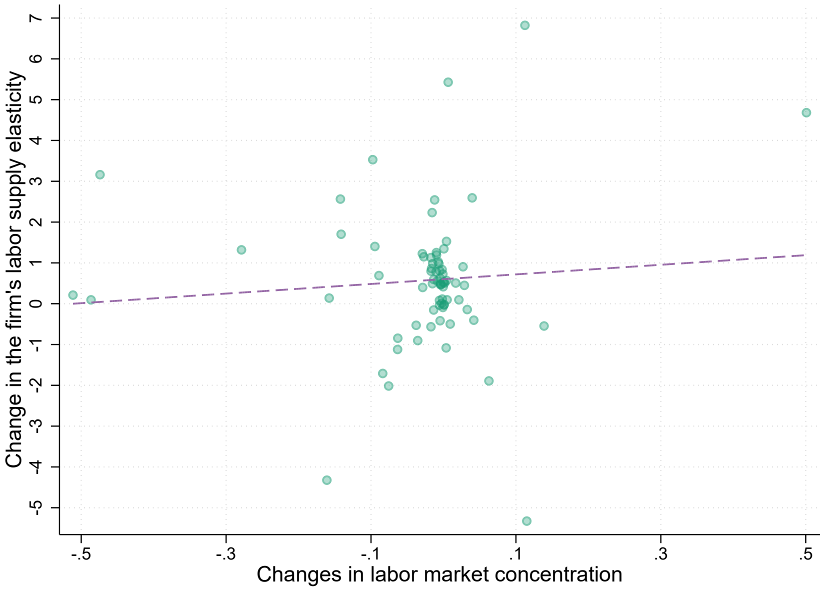
| A. 2000-2005 | Worker wage | | Firm fixed effect | | IV-Firm fixed effect | |
|---|---|---|---|---|---|---|
| | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\beta$ | -0.0526 | -0.0249 | -0.0403 | -0.0185 | -0.0742 | -0.0405 |
| | (0.0005) | (0.0004) | (0.0015) | (0.0010) | (0.0020) | (0.0014) |
| $\epsilon_{LS}$ | 1.1529 | 1.0236 | 0.8842 | 0.7613 | 1.6261 | 1.6690 |
| | (0.0108) | (0.0148) | (0.0332) | (0.0425) | (0.0430) | (0.0570 ) |
| First stage F-statistic | | | | | 3,576.39 | |
| Observations | 2,074,947 | 2,074,947 | 2,074,947 | 2,074,947 | 2,074,947 | 2,074,947 |

| B. 2015-2020 | Worker wage | | Firm fixed effect | | IV-Firm fixed effect | |
|---|---|---|---|---|---|---|
| | Sep | EE Sep | Sep | EE Sep | Sep | EE Sep |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\beta$ | -0.0668 | -0.0293 | -0.0417 | -0.0193 | -0.0910 | -0.0474 |
| | (0.0006) | (0.0004) | (0.0014) | (0.0010) | (0.0021) | (0.0014) |
| $\epsilon_{LS}$ | 1.4158 | 1.1625 | 0.8840 | 0.7665 | 1.9285 | 1.8814 |
| | (0.0134) | (0.0175) | (0.0301) | (0.0394) | (0.0449) | (0.0562) |
| First stage F-statistic | | | | | 10,122.45 | |
| Observations | 2,202,027 | 2,202,027 | 2,202,027 | 2,202,027 | 2,202,027 | 2,202,027 |

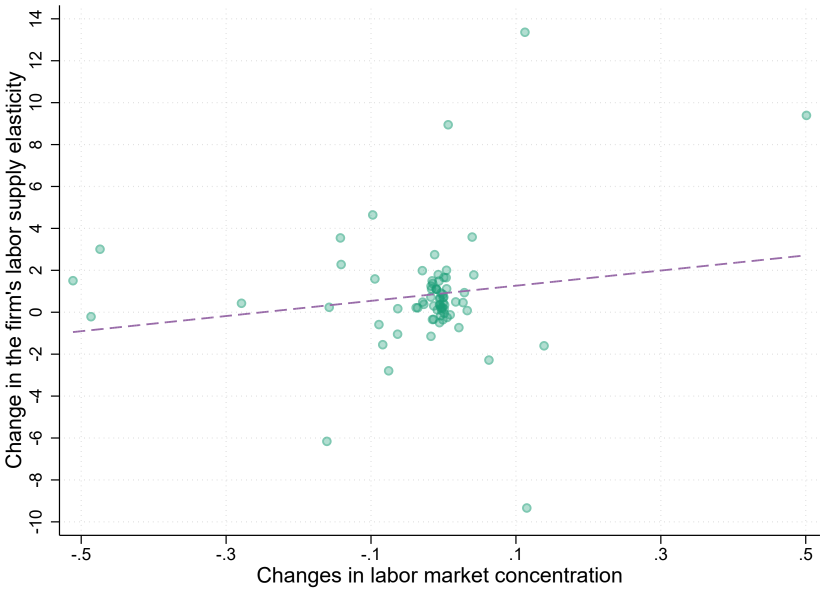
Notes: Panel A and B estimate period-specific linear probability models as specified Equation (8) for all quarterly separations (Sep) and employer-to-employer transitions (EE Sep) using alternative measures of wages. The models are estimated in the sample of workers with AKM worker FE above the median of the period-specific distribution. Worker wage columns rely on individual-level wages as the independent variable. Firm fixed effect columns use AKM effects retrieved from estimating equation (1) separately by period. IV-firm fixed effect columns instrument period-specific firm fixed effects with the (log) average firm wage (wage bill divided by firm size). All specifications control for the estimated AKM worker fixed effects along with indicators for age groups, sex, 2-digit industries, and time effects. Standard errors (in parentheses) are clustered at the level of variation of the wage measure, i.e., worker- or firm-level. $\varepsilon_{LS}$ refers to the firm's labor supply elasticity computed as: $\varepsilon_{LS} \approx -2 \times \hat{\beta}/\bar{s}$, where $\bar{s}$ is the average separation rate used as the dependent variable. Standard errors are obtained using the Delta method.

**Figure E.2:** Changes in the firm's labor supply elasticity and industry concentration

**(A)** All separations



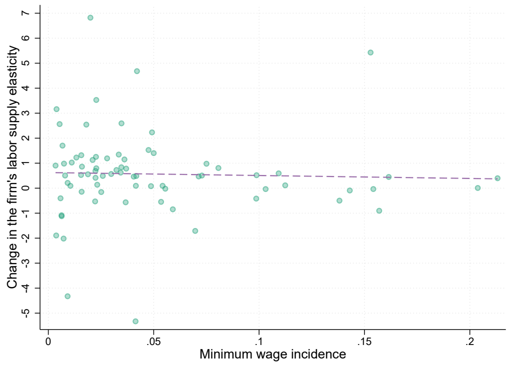

**(B)** Job-to-job



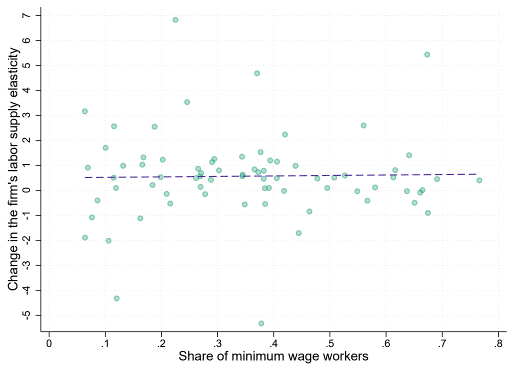

Source: Social Security records and own calculations.
Notes: Changes in the firm's labor supply elasticity are the difference in the sector-specific firm's labor supply elasticity in 2015-2020 and that in 2000-2005. Changes in industry concentration refer to differences in sector-specific wage-bill Herfindahl index between 2015-2020 and 2000-2005. Panel A relies on all separations to estimate the elasticity, whereas Panel B exploits only job-to-job transitions. There are 74 sectors.

**Figure E.3:** Changes in the firm's labor supply elasticity (all separations) and the minimum wage

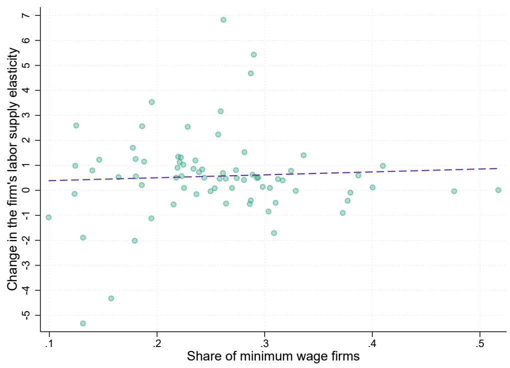
**(A)** MW incidence




**(B)** MW workers



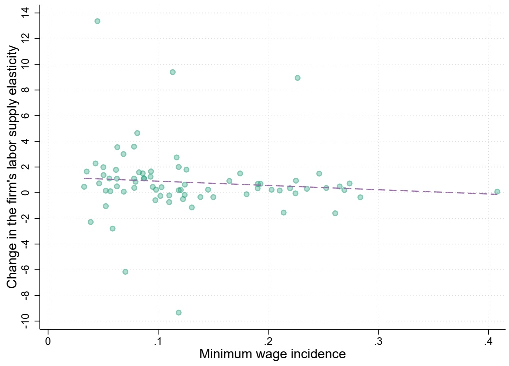

**(C)** MW firms



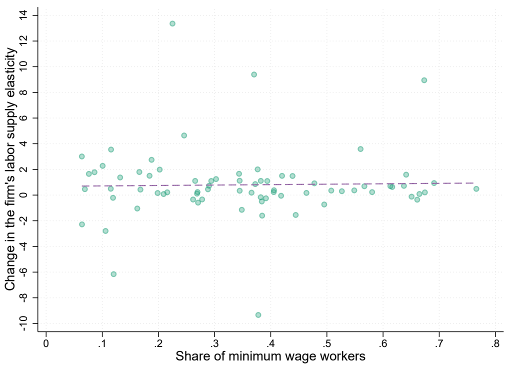

Source: Social Security records and own calculations.
Notes: Changes in the firm's labor supply elasticity are the difference in the sector-specific firm's labor supply elasticity in 2015-2020 and that in 2000-2005. The elasticity is estimated using all types of separations. In Panel A, for each sector $s$, the minimum wage incidence is computed as $\frac{\sum_{i \in s} max\{0, MW - w_{is}\}}{\sum_{i \in s} w_{is}}$ where $MW$ is the prevailing daily minimum wage, $w_{is}$ refers to the daily income of worker $i$ in sector $s$. In Panel B, the share of minimum wage workers is the sector-specific share of workers whose earnings are at or below the current minimum wage. In Panel C, the share of minimum wage firms is the sector-specific share of firms where the minimum wage is at least 75% of the firm's average wage. There are 74 sectors.

**Figure E.4:** Changes in the firm's labor supply elasticity (job-to-job transitions) and the minimum wage

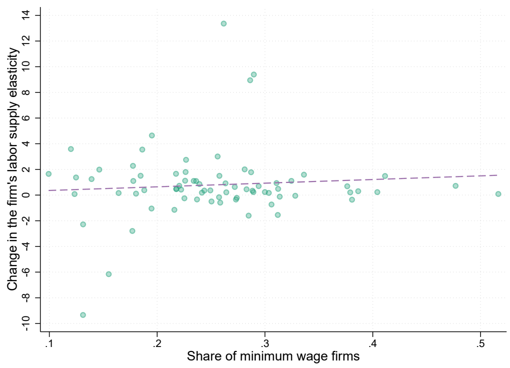
**(A)** MW incidence




**(B)** MW workers




**(C)** MW firms




Source: Social Security records and own calculations.
Notes: Changes in the firm's labor supply elasticity are the difference in the sector-specific firm's labor supply elasticity in 2015-2020 and that in 2000-2005. The elasticity is estimated using job-to-job transitions. In Panel A, for each sector $s$, the minimum wage incidence is computed as $\frac{\sum_{i \in s} max\{0, MW - w_{is}\}}{\sum_{i \in s} w_{is}}$ where $MW$ is the prevailing daily minimum wage, $w_{is}$ refers to the daily income of worker $i$ in sector $s$. In Panel B, the share of minimum wage workers is the sector-specific share of workers whose earnings are at or below the current minimum wage. In Panel C, the share of minimum wage firms is the sector-specific share of firms where the minimum wage is at least 75% of the firm's average wage. There are 74 sectors.

# F Market power evidence from firm-level data

In this section, we present supporting evidence on the dynamics of market power in Lithuania based on balance sheet data for the period 2004 and 2018. The dataset covers the population of private limited liability companies, 30-40% of all employers in Lithuania. The dataset allows us to implement a production function approach to recover firm-level price markups and wage markdowns for the set of industries covered in the dataset. We rely on estimates from Ding et al. (2025), who estimate translog production functions for firms with at least 2 employees with positive revenues and operating with variable inputs, labor, and capital. The estimation is done separately for each of those industries in the data that have at least 10 firms in each year (a total of 54 sectors). Using the estimated output elasticities along with firm-level information on inputs and sales, they derive theory-based sector-level markups and markdowns for each of the sectors as well as their economy-wide counterparts.

## F.1 Elasticity of labor supply vs wage markdown

Consider now the profit maximization problem proposed in Section 6.1. The optimality condition for the choice of the labor input implies the following relationship between the marginal product of labor $\text{MRPL}_j$ and the inverse elasticity of residual labor supply facing the firm, $\varepsilon_{LSt}^{-1}$:

$$\text{MRPL}_{jt} = w_{jt}\left(1 + \frac{1}{\varepsilon_{LSt}}\right)$$

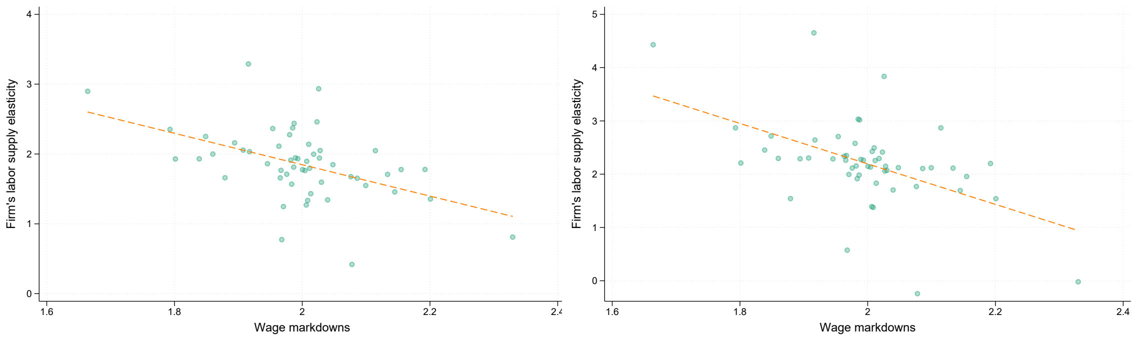
where $\varepsilon_{LSt} = \varepsilon_{Rt} - \varepsilon_{sept}$. Re-arranging terms, we can obtain an expression that links the average wage markdown $\nu_t$, defined as the ratio between the marginal product of labor and wages minus 1, to the inverse elasticity of labor supply, $\varepsilon_{LSt}^{-1}$,

$$\frac{\text{MRPL}_{jt}}{w_{jt}} - 1 \equiv \nu_t = \varepsilon_{LSt}^{-1}$$

Figure F.1 shows the negative correlation between the sector-level firm labor supply elasticity estimated from Social Security data using initial and final periods and the sector-level wage markdown estimated using balance sheet data for 2004 and 2018, controlling for period and sector fixed effects.

**Figure F.1:** Firm's labor supply elasticity and wage markdowns

**(A)** All separations **(B)** Job-to-job

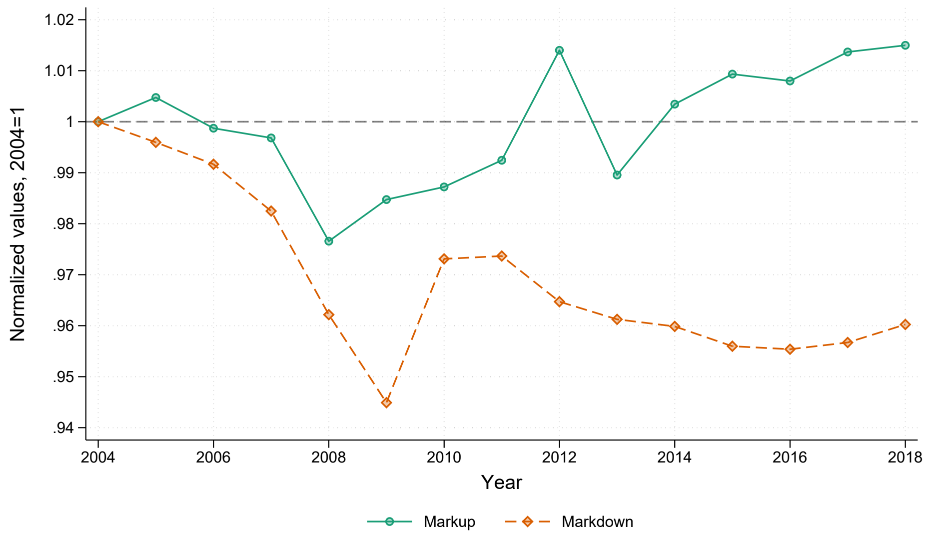



Notes: The figure shows the correlation between sector-level firm labor supply elasticity and sector-level wage markdowns, controlling for period and sector fixed effects. Firm's labor supply elasticity is based on equation (8) estimated separately by sector for the periods 2000-05 and 2015-20 using the Social Security data described in Section 4. Panel A uses all separations to estimate the elasticity, while Panel B exploits only job-to-job transitions. Markdowns refer to sector-level (log) wage markdowns calculated using firm-level estimates for 2004 and 2018. The firm-level estimates are based on a production function approach using confidential balance sheet data available for the period 2004-2018. The production function is specified as a translog and is estimated separately for each of the 54 industries for which balance sheet information is available. More details can be found in Ding et al. (2025).

## F.2 Product markups vs wage markdown

Figure F.2 shows the dynamics of aggregate markup and markdown between 2004 and 2018 in Lithuania. The data show rather opposite dynamics: while aggregate markup increased by almost 2%, aggregate markdown decreased by more than 4%.

**Figure F.2:** Aggregate markup and markdown, 2004-2018




Notes: Markups and markdowns refer to aggregate price markups and wage markdowns calculated using firm-level estimates for 2004 and 2018. The firm-level estimates are based on a production function approach using confidential balance sheet data available for the period 2004-2018. The production function is specified as a translog and is estimated separately for each of the 54 industries for which balance sheet information is available. More details can be found in Ding et al. (2025).

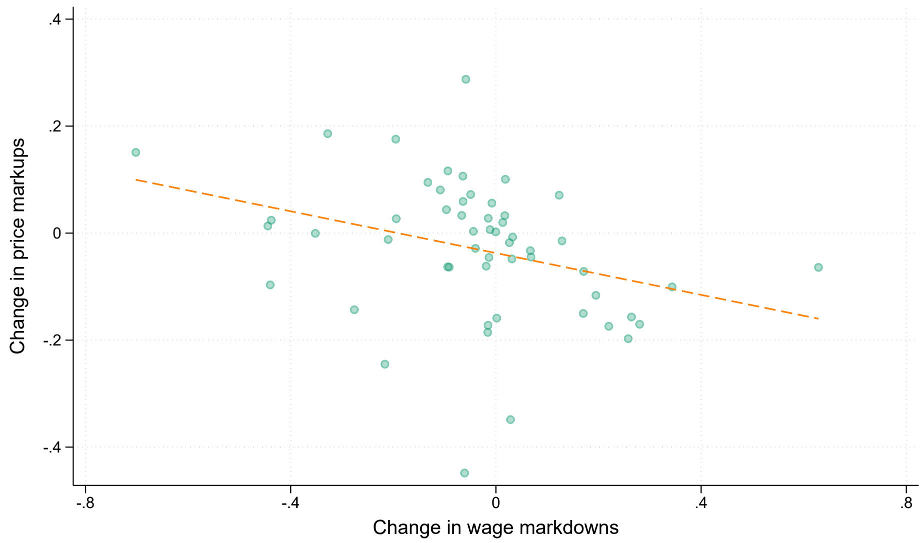
Despite the divergent dynamics over time, differences in labor market power across sectors might still correlate with differences in product market power, invalidating our inference. If this were the case, the error term in equation (9) would contain the sectoral change in product market power, $\epsilon^P_{st+1}$, i.e.

$$\Delta v_{st+1} = \gamma_0 + \gamma_1 \Delta\epsilon^P_{st+1} + \tilde{v}_{st+1}$$

which might lead to a bias in the estimate of $\beta_1$, where bias$[\beta_1] \propto \gamma_1 \text{cov}[\Delta\varepsilon_{LSst+1}, \Delta\epsilon^P_{st+1}]$.

Figure F.3 scatters the changes in industry-level markups and industry-level markdowns between 2004 and 2018. During this period, sectors experiencing a decrease in the average wage markdown have witnessed an increase in price markups, suggesting a slightly negative correlation. This implies $\text{cov}[\Delta\varepsilon_{LSst+1}, \Delta\epsilon^P_{st+1}] \neq 0$. Given the positive correlation between price markups on wage dispersion (Kaplan and Zoch, 2020), i.e., $\gamma_1 > 0$, the OLS estimates of $\beta_1$ reported in Table (5) are likely to be downward biased, and the effect of labor market competition on wage dispersion is likely to be underestimated.

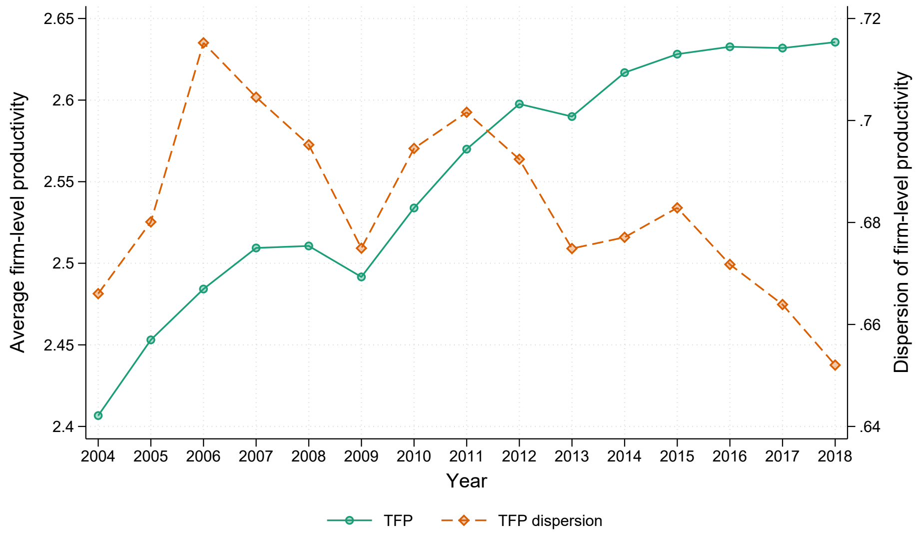
**Figure F.3:** Changes in industry-level markups and markdowns




Notes: Markups and markdowns refer to sector-level price markups and wage markdowns calculated using firm-level estimates for 2004 and 2018. The change refers to the log change in these statistics between 2004 and 2018. The firm-level estimates are based on a production function approach using confidential balance sheet data available for the period 2004-2018. The production function is specified as a translog and is estimated separately for each of the 54 industries for which balance sheet information is available. More details can be found in Ding et al. (2025).

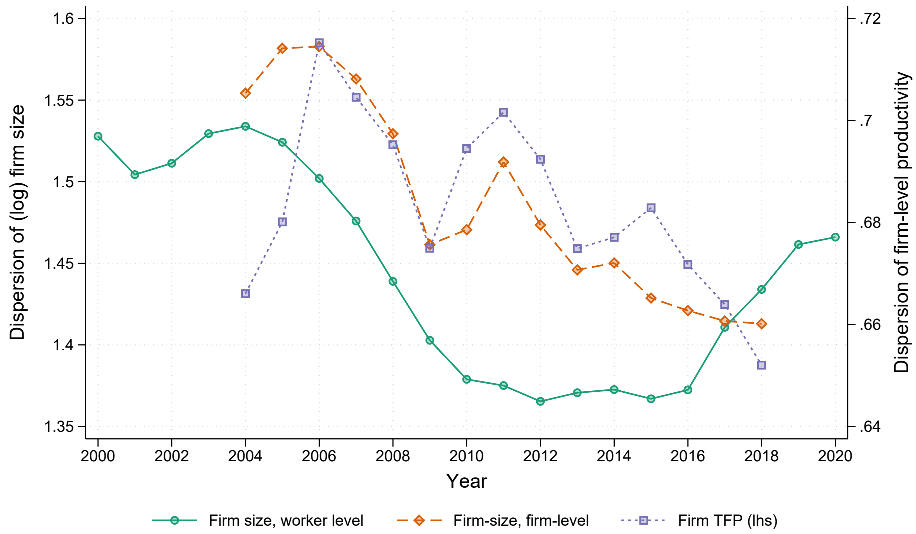
# G Dynamics of firm-level productivity

**Figure G.1:** Firm-level productivity, 2004-2018




Notes: The figure shows the evolution of the average firm-level productivity as well as the dispersion of firm-level productivity. The firm-level estimates are based on a production function approach using confidential balance sheet data available for the period 2004-2018. The production function is specified as a translog and is estimated separately for each of the 54 industries for which balance sheet information is available. More details can be found in Ding et al. (2025).

**Figure G.2:** Dispersion of firm-level productivity and firm size




Notes: The figure shows the evolution of the dispersion of firm size computed both from Social Security data (worker-level) and balance sheet data firm-level together with the dispersion firm-level productivity. The firm-level estimates are based on a production function approach using confidential balance sheet data available for the period 2004-2018. The production function is specified as a translog and is estimated separately for each of the 54 industries for which balance sheet information is available. More details can be found in Ding et al. (2025).

## H Shift-share IV validity tests

**Rotemberg weights.** Because the shift-share estimate can be seen as a pooled version of many one-at-a-time share-instrument estimates (one for each sector $c \in \mathcal{C}$), we follow Goldsmith-Pinkham et al. (2020) and use the "Rotemberg weights" to assess whether all or only a subset of these instruments drive the overall results. In panel I of Table H.1 and H.2, we report the weights for each sectoral share-instrument, $\hat{\alpha}_c$, together with their respective shift, $\Delta w_{ct+1}$, the just-identified coefficient estimates, $\hat{\beta}_c$, and their standard errors, SE[$\hat{\beta}_c$].

First, all of the weights are positive. This rules out non-convex weights of $\hat{\beta}_c$, and allows the Bartik estimate to have a LATE-like interpretation as a weighted average of treatment effects.

Second, recall that the identifying assumption of the Bartik IV requires the sectoral employment shares observed in countries with large Lithuanian settlements prior to the EU enlargement to be uncorrelated with sector-specific changes in labor demand in Lithuania following the EU integration. Inspecting the Rotemberg weights, the top three destination countries are Germany, the United Kingdom, and Denmark, and they account for about 70 percent of the overall identifying variation. The large weights on these countries are unsurprising, as these are the countries with the largest settlement of Lithuanian in 2000—equal, respectively, to 40%, 16%, and 11% of total Lithuanians living abroad.

Third, all the $\hat{\beta}_c$ are close to the Bartik estimates, which are -0.0325 when the elasticity of labor supply is computed using all separations, and -0.0271 when only J2J separations are considered. This alleviates concerns about model misspecification.

Finally, Panel II shows that the sectoral growth rates, $\Delta w_{ct+1}$ are weakly correlated with $\hat{\alpha}_c$. Hence, the growth rates provide a poor guide to understanding what variation in the data drives estimates. In contrast, $\hat{\alpha}_c$ are quite related to the variation in the sectoral shares of employment across destination countries, $\text{var}_c[\mu_{sct0}]$: the correlations are 0.5583 and 0.5219. This confirms that, in our setting, the identifying variation is across sectors with greater and smaller employment shares in countries with large Lithuanian settlements prior to the EU accession, such as Germany, the United Kingdom, and Denmark.[42]

[42] We note that in this setting there is no pre-period and so it is not possible to test for parallel pre-trends without further assumptions.

**Table H.1:** Summary of Rotemberg weights

| | All separation | | | | |
|---|---|---|---|---|---|
| I. Top Rotemberg weight countries | $\hat{\alpha}_c$ | $\Delta w_{ct+1}$ | $\hat{\beta}_c$ | SE[$\hat{\beta}_c$] | |
| DE | 0.2922 | 0.1453 | -0.0335 | 0.0180 | |
| UK | 0.2167 | 0.2150 | -0.0536 | 0.0229 | |
| DK | 0.1725 | 0.2348 | -0.0197 | 0.0123 | |
| SE | 0.1387 | 0.4639 | -0.0248 | 0.0142 | |
| IE | 0.0644 | 0.2660 | -0.0169 | 0.0327 | |
| FR | 0.0318 | 0.0823 | -0.0421 | 0.0182 | |
| ES | 0.0262 | 0.0939 | -0.0089 | 0.0297 | |
| FI | 0.0195 | 0.1874 | -0.0092 | 0.0214 | |
| AT | 0.0157 | 0.1970 | -0.0168 | 0.0243 | |
| NL | 0.0116 | 0.1479 | -0.0542 | 0.0239 | |
| LU | 0.0107 | 0.7005 | -0.0513 | 0.0259 | |
| II. Correlations | | | | | |
| | $\hat{\alpha}_c$ | $\Delta w_{ct+1}$ | $\hat{\beta}_c$ | $\hat{F}_c$ | $\text{var}_c[\mu_{sct0}]$ |
| $\hat{\alpha}_c$ | 1 | | | | |
| $\Delta w_{ct+1}$ | -0.0919 | 1 | | | |
| $\hat{\beta}_c$ | -0.1402 | -0.2507 | 1 | | |
| $\hat{F}_c$ | 0.4994 | 0.1687 | -0.4919 | 1 | |
| $\text{var}_c[\mu_{sct0}]$ | 0.5583 | -0.4338 | 0.3970 | -0.2223 | 1 |

Notes: This table reports statistics about the Rotemberg weights. Panel I lists countries according to their Rotemberg weights, $\hat{\alpha}_c$. The $\Delta w_{ct+1}$ is the national growth rate, $\hat{\beta}_c$ is the coefficient from the just-identified regression, SE[$\hat{\beta}_c$] is the robust standard errors for $\hat{\beta}_c$. Panel II reports correlations between the weights ($\hat{\alpha}_c$), the national growth ($\Delta w_{ct+1}$), the just-identified coefficient estimates ($\hat{\beta}_c$), and the first-stage F-statistic of the country-specific share ($\hat{F}_c$).

**Validity test.** If the shift-share instruments, $\Delta z_{st+1}$, were valid, they would only affect the outcome, $\Delta\text{var}_{st+1}[\psi]$ through the endogenous variable, $\Delta\varepsilon_{st+1}$. Using a reduced-form regression of $\Delta\text{var}_{st+1}[\psi]$ on $\Delta\varepsilon_{st+1}$ and shift-share $\Delta z_{st+1}$, we can test if the latter have a significant effect on $\Delta\text{var}_{st+1}[\psi]$ conditional on $\Delta\varepsilon_{st+1}$. Table H.3 reports the estimates. Conditional on $\Delta\varepsilon_{st+1}$, none of the shift-share instruments we constructed have a statistically significant effect on the change in the dispersion of firm fixed effects. This result confirms that the shift-share IV does not have any residual effect on the outcome once changes in the labor supply elasticity are factored in.

**Robustness to alternative shifts.** Following the guidelines in Borusyak et al. (2025) for the case of a share-based approach, we test the robustness of our results to two alternative specifications, where shifts are constructed using different measures. Recall that, in our benchmark specification, shifts are constructed using log changes in overall real compensation in the destination country $c$ (variable "COMP" in EU-KLEMS), between the years 2015-2020 and 2000-2005. As a robustness, we use instead either 1) log

**Table H.2:** Summary of Rotemberg weights

| | Only J2J | | | |
|---|---|---|---|---|
| I. Top Rotemberg weight countries | $\hat{\alpha}_c$ | $\Delta w_{ct+1}$ | $\hat{\beta}_c$ | SE[$\hat{\beta}_c$] |
| DE | 0.2849 | 0.1453 | -0.0284 | 0.0148 |
| UK | 0.2397 | 0.2150 | -0.0408 | 0.0168 |
| DK | 0.1640 | 0.2348 | -0.0184 | 0.0108 |
| SE | 0.1373 | 0.4639 | -0.0216 | 0.0119 |
| IE | 0.0572 | 0.2660 | -0.0132 | 0.0331 |
| FR | 0.0332 | 0.0823 | -0.0338 | 0.0144 |
| ES | 0.0267 | 0.0939 | -0.0029 | 0.0278 |
| FI | 0.0195 | 0.1874 | -0.0061 | 0.0198 |
| AT | 0.0156 | 0.1970 | -0.0116 | 0.0224 |
| NL | 0.0124 | 0.1479 | -0.0430 | 0.0187 |
| LU | 0.0094 | 0.7005 | -0.0513 | 0.0253 |

| II. Correlations | $\hat{\alpha}_c$ | $\Delta w_{ct+1}$ | $\hat{\beta}_c$ | $\hat{F}_c$ | var$_c[\mu_{sct0}]$ |
|---|---|---|---|---|---|
| $\hat{\alpha}_c$ | 1 | | | | |
| $\Delta w_{ct+1}$ | -0.0982 | 1 | | | |
| $\hat{\beta}_c$ | -0.1550 | -0.4164 | 1 | | |
| $\hat{F}_c$ | 0.5370 | 0.0223 | -0.7051 | 1 | |
| var$_c[\mu_{sct0}]$ | 0.5219 | -0.4338 | 0.4165 | -0.2310 | 1 |

Notes: This table reports statistics about the Rotemberg weights. Panel I lists countries according to their Rotemberg weights, $\hat{\alpha}_c$. The $\Delta w_{ct+1}$ is the national growth rate, $\hat{\beta}_c$ is the coefficient from the just-identified regression, SE[$\hat{\beta}_c$] is the robust standard errors for $\hat{\beta}_c$. Panel ii reports correlations between the weights ($\hat{\alpha}_c$), the national growth ($\Delta w_{ct+1}$), the just-identified coefficient estimates ($\hat{\beta}_c$), and the first-stage F-statistic of the country-specific share ($\hat{F}_c$).

changes in real compensation per employee in destination country $c$ (using variables ”COMP” and ”EMPE” in EU-KLEMS), or 2) log changes in real hourly compensation in destination country $c$ (using variables ”COMP” and ”H-EMPE” in EU-KLEMS). As in the benchmark, we use the country-$c$ domestic CPI to deflate nominal compensation and compare changes between 2015-2020 and 2000-2005.

Table H.4 compares the benchmark IV estimates in Columns (1) and (4), with the IV estimates using alternative shifts. Results are robust, both when the elasticity of labor supply is computed using all separations, as in Columns (2) and (3), or only J2J separations, as in Columns (5) and (6). This fact is reassuring because it suggests that, using the words of Borusyak et al. (2025), exploiting ”different sources of variation” gives very similar Bartik estimates.

**Bartik IV with unit-specific shifts.** We conclude our discussion by addressing the limited power of our shift-share instrument. To do so, we slightly modify the Bartik

**Table H.3:** IV validity test

| | $\Delta$ var$_{st+1}[\psi]$ | | | | | |
|---|---|---|---|---|---|---|
| | All separations | | | Only J2J separations | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta\ \varepsilon_{st+1}$ | -0.0119** | -0.0115** | -0.0117** | -0.0141*** | -0.0138*** | -0.0139*** |
| | (0.0049) | (0.0049) | (0.0049) | (0.0039) | (0.0039) | (0.0039) |
| $\Delta\ z^1_{st+1}$ | -2.348 | | | -1.695 | | |
| | (1.892) | | | (1.792) | | |
| $\Delta\ z^2_{st+1}$ | | -3.812 | | | -2.863 | |
| | | (2.628) | | | (2.471) | |
| $\Delta\ z^3_{st+1}$ | | | -2.119 | | | -1.558 |
| | | | (1.579) | | | (1.491) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| No. sectors | 74 | 74 | 74 | 74 | 74 | 74 |

Notes: $\Delta z^1_{st+1}$ refers to the benchmark shift-share instrument constructed using log changes in overall real compensation across destination countries, $c$, between the years 2015-2020 and 2000-2005, $\Delta w^1_{st+1}$ as shift. $\Delta z^2_{st+1}$ refers to a shift-share instrument constructed using log changes in real compensation per employee in destination country $c$, between the years 2015-2020 and 2000-2005, $\Delta w^2_{st+1}$, as a shift. $\Delta z^3_{st+1}$ refers to a shift-share instrument constructed using log changes in real hourly compensation in destination country $c$, between the years 2015-2020 and 2000-2005, $\Delta w^3_{st+1}$ as the shift. Controls include sector-specific change in the variance of firm size, $\Delta \text{var}_{st+1}[L_j]$, the elasticity of labor supply in the last period, the sector-specific minimum wage incidence in the initial period, and sector-specific change in the wage-based HHI index. Standard errors are robust.

IV using shifts that vary across sectors $s$ and destination countries $c$; that is,

$$\Delta z_{st+1} = \sum_{c \in \mathcal{C}} \mu_{sct_0} \Delta w_{sct+1}.$$

Borusyak et al. (2025) note that the standard econometric framework for shift-share IV nests settings where each unit is exposed to a distinct set of shifts, as proposed in this robustness check. The role of the shifts is secondary with the exogenous shares strategy, i.e., they do not affect identification, so long as the shares are exogenous. On the other hand, as noted by Goldsmith-Pinkham et al. (2020), the choice of shift may affect the power of the instrument.

Table H.5 reports first and second stage IV estimates for this robustness check. Two results emerge. First, the contribution of labor supply elasticity to changes in dispersion of firm fixed effects is greater, ranging from 15.6 to 26.8%. Second, compared to our main specification, the first-stage F-stat is now larger in magnitude and exceeds 10 for cases where the labor supply elasticity is computed using all separations.

**Table H.4:** Shift-share IV regressions

| | All separations | | | Only J2J separations | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | *First stage regression:* $\Delta\ \varepsilon_{st+1}$ | | | | | |
| $\Delta\ z^1_{ct+1}$ | 113.95*** | | | 129.76** | | |
| | (42.179) | | | (59.138) | | |
| $\Delta\ z^2_{ct+1}$ | | 163.22*** | | | 188.06** | |
| | | (57.231) | | | (81.351) | |
| $\Delta\ z^3_{ct+1}$ | | | 94.721*** | | | 108.94** |
| | | | (34.769) | | | (48.801) |
| F-stat. | 7.30 | 8.13 | 7.42 | 4.81 | 5.34 | 4.98 |
| | *Second stage regression:* $\Delta\ \text{var}_{st+1}[\psi]$ | | | | | |
| $\Delta\ \varepsilon_{st+1}$ | -0.0325** | -0.0348** | -0.0341** | -0.0271** | -0.0290** | -0.0283** |
| | (0.0156) | (0.0156) | (0.0159) | (0.0130) | (0.0128) | (0.0130) |
| Implied %$\Delta$ var$[y]$ | 14.5 | 15.5 | 15.2 | 13.2 | 14.1 | 13.8 |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| No. sectors | 74 | 74 | 74 | 74 | 74 | 74 |

Notes: $\Delta z^1_{st+1}$ refers to a shift-share instrument constructed using log changes in overall real compensation across destination countries, $c$, between the years 2015-2020 and 2000-2005, $\Delta w^1_{ct+1}$, as shift. $\Delta z^2_{st+1}$ refers to a shift-share instrument constructed using log changes in real compensation per employee in destination country $c$, between the years 2015-2020 and 2000-2005, $\Delta w^2_{ct+1}$, as a shift. $\Delta z^3_{st+1}$ refers to a shift-share instrument constructed using log changes in real hourly compensation in destination country $c$, between the years 2015-2020 and 2000-2005, $\Delta w^3_{ct+1}$ as the shift. Controls include sector-specific change in the variance of firm size, $\Delta\text{var}_{st+1}[L_j]$, the elasticity of labor supply in the last period, the sector-specific minimum wage incidence in the initial period, and sector-specific change in the wage-based HHI index. Standard errors are robust.

**Placebo regressions.** We test if the shift-share instruments have an effect on two placebo outcomes, i.e., the change in dispersion of worker fixed effects, $\Delta\ \text{var}_{st+1}[\eta]$, and the change in the covariance between worker and firm fixed effects, $\Delta\ \text{cov}_{st+1}[\psi,\eta]$. None of them is expected to be affected by our treatment. Table H.6 reports the second-stage IV estimates for this robustness exercise. We find no effect of our IV on either $\Delta\ \text{var}_{st+1}[\eta]$ or $\Delta\ \text{cov}_{st+1}[\psi,\eta]$. The estimates are very small in magnitude, and the standard errors are large, validating our hypothesis that EU enlargement served as a catalyst for increased labor market competition among firms in Lithuania, thereby reducing only the dispersion in firm fixed effects.

**Table H.5:** Shift-share IV regressions: Unit-specific shifts

| | All separations | | | Only J2J separations | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | *First stage regression:* $\Delta\ \varepsilon_{st+1}$ | | | | | |
| $\Delta\ z^1_{st+1}$ | 28.478*** | | | 36.216*** | | |
| | (8.9183) | | | (13.304) | | |
| $\Delta\ z^2_{st+1}$ | | 113.86*** | | | 123.12** | |
| | | (34.539) | | | (48.495) | |
| $\Delta\ z^3_{st+1}$ | | | 105.56*** | | | 116.75** |
| | | | (33.251) | | | (47.618) |
| F-stat. | 10.20 | 10.87 | 10.08 | 7.41 | 6.45 | 6.01 |
| | *Second stage regression:* $\Delta\ \text{var}_{st+1}[\psi]$ | | | | | |
| $\Delta\ \varepsilon_{st+1}$ | -0.0600** | -0.0444** | -0.0364** | -0.0464** | -0.0409** | -0.0321** |
| | (0.0255) | (0.0180) | (0.0162) | (0.0199) | (0.0176) | (0.0143) |
| Implied $\%\Delta$ var$[y]$ | 26.8 | 19.8 | 16.2 | 22.6 | 19.9 | 15.6 |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| No. sectors | 74 | 74 | 74 | 74 | 74 | 74 |

Notes:$\Delta z^1_{st+1}$ refers to a shift-share instrument constructed using log changes in overall real compensation in sectors, $s$, and destination country, $c$, between the years 2015-2020 and 2000-2005, $\Delta w^1_{sct+1}$, as shift. $\Delta z^2_{st+1}$ refers to a shift-share instrument constructed using log changes in real compensation per employee in sector $s$ in destination country $c$, between the years 2015-2020 and 2000-2005, $\Delta w^2_{sct+1}$, as a shift. $\Delta z^3_{st+1}$ refers to a shift-share instrument constructed using log changes in real hourly compensation in sector $s$ in destination country $c$, between the years 2015-2020 and 2000-2005, $\Delta w^3_{sct+1}$ as shift. Controls include sector-specific change in the variance of firm size, $\Delta \text{var}_{st+1}[L_j]$, the elasticity of labor supply in the last period, the sector-specific minimum wage incidence in the initial period, and sector-specific change in the wage-based HHI index. Standard errors are robust.

**Table H.6:** Second-stage IV regressions on placebo outcomes

| A. $\Delta\ \text{var}_{st+1}[\eta]$ | All separations | | | Only J2J separations | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta\ \varepsilon_{st+1}$ | -0.00251 | -0.00274 | -0.00207 | -0.00420 | -0.00403 | -0.00385 |
| | (0.0149) | (0.0145) | (0.0147) | (0.0129) | (0.0124) | (0.0127) |
| B. $\Delta\ \text{cov}_{st+1}\ [\psi, \eta]$ | All separations | | | Only J2J separations | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta\ \varepsilon_{st+1}$ | -0.0151 | -0.0130 | -0.0156 | -0.0124 | -0.0105 | -0.0127 |
| | (0.0165) | (0.0161) | (0.0164) | (0.0144) | (0.0138) | (0.0142) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| No. sectors | 74 | 74 | 74 | 74 | 74 | 74 |

Notes: Controls include sector-specific change in the variance of firm size, $\Delta \text{var}_{st+1}[L_j]$, the elasticity of labor supply in the last period, the sector-specific minimum wage incidence in the initial period, and sector-specific change in the wage-based HHI index. Standard errors are robust.