Labor Market Imperfections and Productivity Growth

Dissertation presented to obtain
the degree of Doctor in Economics

by

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Number 758

2021

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Acknowledgements

I just want to thank everybody for being so patient
And baring with me over these last couple of years
While I figure this out

– Talkin' 2 Myself –

– Eminem, 2010 –

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General Introduction

Decades of research in Labor Economics and Industrial Organization have shown that firm dynamics play a key role in shaping aggregate outcomes. Thus, understanding how firms grow and shrink, how they respond to changing market environments is crucial to understand aggregate growth, innovation, and the functioning of labor markets. Productivity, which reflects the efficiency in transforming inputs into output, has received special attention in the literature because it has a direct effect on firms', industries', and countries' performance. A key finding is that diversity is driven primarily by the differences in total factor productivity (TFP) across firms, even in narrowly specified industries (Syverson, 2011). But what are the underlying causes for the differences in TFP? Given that detailed production data have been introduced over the past decades, a wide range of literature has been developed in explaining the heterogeneity in productivity attempting to identify its key factors. These include the effect of human capital (Konings and Vanormelingen, 2015), trade openness (Pavcnik, 2002; Bernard et al., 2003; Amiti and Konings, 2007; De Loecker, 2011; De Loecker and Goldberg, 2014), IT and innovations (Bloom et al., 2012, 2013; Dhyne et al., 2020) to mention a few.

Moreover, recent access to firm-level data has characterized one distinctive feature of firms: firms are highly heterogeneous in their responses to shocks. One of the widely-recognized forces slowing down firms' responses is frictions, both on the product market and the labor market. As highlighted by Bassanini et al. (2009) and van Ark et al. (2008), the lack of convergence between the US and the EU in terms of efficiency can be, at least partly, traced back to the high level of labor market regulations in Europe. It is in this context of labor market frictions and productivity that I wrote my doctoral dissertation titled "Labor market imperfections and productivity growth".

This thesis bundles three chapters exploring the impact of labor regulations and wage dispersion on aggregate outcomes, at the firm level, in developed and emerging economies. It highlights the role of firm heterogeneity in labor market dynamics and regional aspects of inequality. The dissertation touches upon different sub-fields of economics falling in the realm of labor economics and applied industrial organization. Each chapter aims at being exhaustive in the explanation of the economic relationships under scrutiny. Although the chapters can be read independently, it is possible to see a few common features across them.

Firstly, all chapters share a single methodological approach, in particular firm-level panel data analysis techniques, in approaching the research questions posed. By building from the microeconomic actions of individual firms it highlights some of the landmarks of the path leading from microeconomic decisions to aggregate dynamics. Thus, this micro-econometric approach is important in light of increasing evidence of the presence of substantial heterogeneity in firm behavior.

The other important unifying theme underlying the chapters is the presence of labor market imperfections which hinders the aggregate productivity and employment. The standard approach in modeling the labor markets is to assume that wages are equal to the marginal product of labor. When labor markets are frictional, i.e. it takes time and effort to find employment, workers are not paid their marginal product. Manning (2011) provides an extensive discussion on the models of imperfect competition in the labor markets which allows both employers and employees to share the rents originating from the mismatch between labor supply and demand. Collective bargaining, employment protection, minimum wages, mobility, information asymmetries are some of the sources of imperfect competition in the labor markets. These imperfections can play a consequential role in determining differences in earnings, welfare, and long-term outcomes, such as productivity.

A large literature has argued the importance of employment protection policies in weakening job flows by increasing hiring and firing costs for employers (Autor et al., 2004; Bassanini et al., 2009; Criscuolo et al., 2014). Given that labor policies serve as a barrier to the reallocation of resources, it is highly likely that it affects firms' production decisions, capital to labor ratio, and, ultimately, productivity. Most of the research in this area focuses primarily on distortions in the capital market (Asker et al., 2014; Gopinath et al., 2017), which creates a gap in the empirical research that studies the effect of labor market distortions on aggregate productivity.

The first chapter of this dissertation, Chapter 1 can be positioned within this literature, more precisely, we intend to estimate the effect of labor adjustment costs and misallocation on productivity. To this end, we use a recent policy change in Belgium, leading to an increase in employment protection for blue-collar workers and a decrease in employment protection for white-collar workers. Building on Petrin and Sivadasan (2013), we use a rich data set of the universe of Belgian firms to estimate the wedge between the labor input's marginal product and its marginal cost - the gap - and use it as a measure for the lost output from inefficient allocation. Evidence shows that a firm with 90% blue-collar workers experienced after the policy change an increase in the gap of 3,120 euro relative to a firm with 10% of blue-collar workers. This is significant because given that most of the adjustment costs for labor are at the control of policymakers, it shows how policies that hinder the reallocation of inputs across firms influence aggregate efficiency.

I further explore the impact of labor market imperfections on aggregate outcomes by looking at the importance of stringent employment protection on hiring and firing behavior of the firms, and ultimately on aggregate employment dynamics. In the second chapter, Chapter 2, we hypothesize that stricter employment protection legislation constrains firms to react to market fluctuations, i.e. when the negative shock hits, firms cannot easily adjust by firing employees due to high firing costs. Following Ilut et al. (2018), the idea is depicted as a (more) convex hiring rule, which represents the mechanism that firms follow to adjust their employment. The non-linearity of the hiring rule can generate asymmetric responses of employment growth to shocks, and, hence, stimulate significant skewness and movements in the volatility. This paper argues that the institutional setting determines the shape of the hiring rule, which endogenously transforms the distribution of employment growth, and defines whether aggregate employment growth volatility is counter- or pro-cyclical. We test the hypothesis on an economy characterized by strong employment protection and high firing costs. To provide additional evidence on the shape of the hiring rule, we further test the mechanism using countries with different labor adjustment costs. We conclude that countries with more rigid labor markets are characterized by a convex hiring rule, and induce pro-cyclical volatility. The results highlight the fact that policies may shape how micro-level shocks propagate to aggregate fluctuations and are magnified.

Finally, I draw my attention back to labor market frictions and productivity. In the third chapter, Chapter 3, we study the effect of vertical intra-firm pay inequality on firm performance. To measure within-firm vertical pay inequality, we calculate the pay ratio - the wage differential between the top- and the bottom-level job occupations - using the detailed firm-level data on wages by hierarchy levels in Kazakhstan. We begin our analysis by describing the relationship between wage inequality and firm size. We observe that wage inequality increases with firm size for upper hierarchies. The observation is consistent with a theoretical model stressing the allocative efficiency of managerial positions (Gabaix and Landier, 2008; Tervio, 2008). Further, we analyze how wage inequality affects firm efficiency and profitability. After controlling for firm-specific characteristics and implementing an instrumental variable analysis approach, we report a negative effect of pay inequality on firm performance. While we are careful not to draw any causal inference, our findings support the interpretation that a differentiated pay structure is viewed as compensation for unobserved effort and individual performance. Although a higher wage dispersion may serve as a signal to attract more productive or talented workers, we find no evidence to support the idea that incentive-based pay can boost overall firm performance.

Overall, the chapters are independent of each other, and each has its own methodological limitations and concerns, which I cover in more detail in the chapters. Nevertheless, a concern that is raised in each of the chapters and is common in the productivity literature is whether the productivity measured is a true productivity shock? Given the estimation procedure we implement, the productivity measure in this dissertation resembles residual profitability rather than a true productivity estimate.

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Chapter 1

Labor Market Rigidities and Misallocation: Evidence from a Natural Experiment[1]

1.1 Introduction

Understanding how firms turn inputs into outputs has always been a key research topic in economics and management. Productivity, which measures the efficiency of this conversion, has received special attention from scholars from various fields as it directly affects the performance of firms, regions, and countries. One key finding of the literature is the extremely large degree of measured productivity dispersion between firms, i.e. some firms are substantially more productive than others, even within narrowly defined industries (Syverson, 2011).

Promoting factors that enhance the productivity of individual firms would obviously increase productivity at the aggregate level. However, there is a large potential as well for increases in aggregate productivity through the reallocation of resources. If an input is reallocated from a production unit with a low marginal product to a production unit with a high marginal product, aggregate productivity increases as more output is generated with the same amount of inputs. Several papers have shown that this reallocation component contributes to aggregate productivity growth, see for example Baily et al. (1992), Olley and Pakes (1996), Foster et al. (2001), and more recently Petrin and Levinsohn (2012) and Collard-Wexler and De Loecker (2015), among others.

A strand of literature has emerged to measure possible misallocation of resources across firms

[1]This chapter is a joint work with Prof.dr.Stijn Vanormelingen.
We gratefully acknowledge comments from participants at the 2019 IIOC Conference in Boston, EARIE 2019 in Barcelona, 2019 CAED Conference in Ann-Arbor, 2019 EEA-ESEM Conference in Manchester, Workshop on Firm Heterogeneity in Technical Change in Ghent, 15th Belgian Day for Labour Economists in Charleroi, VIVES Seminar series and ECON-CEDON Seminar series of KU Leuven.

lowering aggregate productivity. Restuccia and Rogerson (2008) suggested a neoclassical growth model to examine the impact of misallocation caused by different hypothetical shocks, such as firm-specific taxes and subsidies, on productivity. Alternatively, Hsieh and Klenow (2009) used within-sector dispersion in the marginal product of inputs as a measure of misallocation and potential productivity gains. Extending the Petrin and Levinsohn (2012) model, Petrin and Sivadasan (2013) proved that the difference in the value of the marginal product of an input and its marginal cost can be used as a measure for misallocation. More precisely, this difference is equal to a change in the aggregate output from reallocating that input's use. Altogether these seminal papers highlight the importance of allocation of resources across production units in determining the diversity in productivity and welfare across industries, countries, and time.

Inspired by these papers, a recent body of work, studying the sources of misallocation and their relation to aggregate productivity growth started off. Most of the papers focus on dispersion in the marginal revenue product of capital and distortions in the capital market. For example, Midrigan and Xu (2014) estimate the extent to which financial frictions can lead to lower aggregate productivity in India and China. Studies investigate the impact of financial crises on resource misallocation (Sandleris and Wright, 2014), internationalization (Berthou and Manova, 2016), the introduction of the euro (Gopinath et al., 2017), access to international capital markets (Varela, 2018), size-dependent policies (Guner et al., 2008; Adamopoulos and Restuccia, 2014) and market power (Asker et al., 2019). See also Restuccia and Rogerson (2013) for an overview. Others, however, have found that the so-called static misallocation as measured by the dispersion in the marginal revenue products could just reflect optimal dynamic responses of firms facing capital adjustment costs (Asker et al., 2014) or optimal investment decisions taken by multi-plant firms facing credit constraints (Kehrig and Vincent, 2018).

This paper adds to the existing literature by studying the effect of labor adjustment costs and misallocation on aggregate productivity growth in Belgium. Building on Petrin and Sivadasan (2013), we start with documenting the evolution of labor misallocation. We use firm-level production data to estimate the wedge between the labor input's marginal product and its marginal cost - the gap - and use it as a measure for the lost output from inefficient allocation. Further, we study an impact of the recent change to the labor law introduced in 2014: the harmonization of labor contracts for blue- and white-collar workers on allocative efficiency. This policy change intends to increase employment protection for blue-collar workers and reducing it for white-collar workers and allows us to evaluate the effect of labor adjustment costs on aggregate productivity growth.

This research contributes to the literature in several ways. First, it improves our understanding of how much distortions matter for aggregate productivity growth. The most recent work focuses on misallocation in the capital market (Cingano et al., 2010; David and Venkateswaran, 2019), while the project focuses on labor market distortions (Gonzalez and Miles-Touya, 2012; Cette et al., 2016). Labor market policies may cause a decline in aggregate productivity levels by distorting the way firms respond to business cycle fluctuations or changes in demand, i.e. during the downturns firms are less likely to fire and they are less likely to hire during the booms (Lagos, 2006; Autor et al., 2007; Bjuggren, 2018; Da-Rocha et al., 2019). While most of the adjustment costs for capital are likely to be outside of the control of policymakers, this is not true for labor markets. Several recent papers describe a significant slowdown in productivity growth in Europe compared to the US since 1995 (see for instance van Ark et al., 2008). As highlighted by Bassanini et al. (2009) and van Ark et al. (2008), the lack of convergence between the US and the EU in terms of efficiency can be, at least partly, traced back to the high level of labor market regulation in Europe. From this perspective, insights into the extent of misallocation of labor resources in the EU are clearly relevant. Second, so far there is little documentation on the dynamics of misallocation within countries. Instead of estimating a general measure of misallocation and subsequently calculating by how much aggregate productivity could increase by moving to a hypothetical misallocation level, this work focuses on a concrete policy measure to infer the impact of changes in distortions on performance. Moreover, given that productivity shocks are correlated with the dispersion in the marginal revenue product of input, this study creates additional knowledge in improving aggregate productivity through labor market institutions and policy changes that affect labor adjustment decisions.

The research covers all private sectors for the period 1996-2017. Results document an increase in the potential gain from labor reallocation across the Belgian economy. Furthermore, the findings indicate that the policy lowered allocative efficiency[2] for blue-collar workers relative to white-collar workers. Particularly, after the harmonization of labor contracts, the labor gap for firms with a higher share of blue-collar workers went up, relative to firms with a low share of blue-collar workers. This implies that the allocative efficiency of blue-collar labor decreased relative to white-collar labor following the harmonization of the labor contracts. Naturally, it is hard to differentiate the effect of this policy from other shocks in the economy. To clear the doubt, we perform a number of placebo tests that allow us to attribute the changes we observe to

[2] We refer to allocative efficiency in the labor market as a state where the marginal product of labor is equal to the marginal cost of labor (wage).

the harmonization of labor contracts.

The rest of the paper is organized as follows. Section 1.2 focuses on the Employment Protection Legislation of Belgium. Section 1.3 discusses the framework of Petrin and Sivadasan (2013) and, within a standard panel regression model, explores the observed changes in labor gap. Section 1.4 describes the data. Results are discussed in section 1.5. Section 1.6 concludes.

1.2 Belgian Employment Protection Legislation

Belgium is characterized as a country with strong employment protection mechanisms. Traditionally, job security is provided through the means of the advance notice periods upon dismissal and severance payments. However, the labor law in Belgium treated white- and blue-collar workers differently up till now.[3] This distinction is observed not only in their working conditions and salaries but, also, in the notice periods and benefits, which were shorter and lower for blue-collar workers.

Nevertheless, in 2011, the Belgian Constitutional Court recognized the distinction to be discriminatory and the Government had until July 8, 2013, to eliminate this discrimination. One of the paragraphs of the Law on Employment Agreement, attempting to harmonize employment status, fixed the advance notice periods upon dismissal for both types of employees.[4] As a result, the notice periods were gradually extended for blue-collar workers. For example, before the harmonization, the notice period for a blue-collar employee with 4 years of tenure was 35 days (5 weeks), while for a white-collar employee with the same tenure the notice period was 3-5 months (13-22 weeks).[5] Under the new legislation, the notice period for workers with 4 years of seniority is 15 weeks.

Changes to the notice periods have a direct impact on labor adjustment costs through compensation in lieu of notice. In a situation of dismissal without an appropriate notice period, sev-

[3] White-collar workers are employees involved in intellectual labor and blue-collar workers are manual labor.

[4] It is important to note that some narrowly defined industries are allowed to have shorter notice periods for their blue-collar workers. For some, this exemption is only temporary (temporary exemption), while for others it applies permanently (structural exemption). The reason for allowing a temporary exemption is that these sectors could potentially be seriously disrupted in employment if there is an immediate switch to the new notice periods. The structural exemption for certain blue-collar workers is compensated for by the shortage of workers in those sectors concerned and justified by the aim of maintaining the social protection of these employees. Sectors involved in the temporary exemption are the clothing and tailoring industry (JC n.109), tannery and trade in raw skins (JC n.128.01), footwear, bootmakers and custom workers (JC n.128.02), ground handling at airports (JC n.140.04), recovery of rags (JC n.142.02), weapons forged by hands (JC n.147), port of Antwerp (JC n.301.01), large retail stores (JC n.311), the diamond industry and trade (JC n.324), health establishments and services - dental prostheses (JC n.330). Sectors involved in the structural exemption are the construction industry (JC n.124), upholstery and woodworking (JC n.126) (Allen & Overy, 2014).

[5] If a worker's gross annual remuneration was less than €32,254, then the notice period was 3 months (13 weeks), and 150 days ($\approx$ 21.4 weeks), if otherwise.

erance payment is equivalent to the amount of salary that would have been received during the notice period.[6] It means that now an employer will pay 15 weeks of salary for laying-off a blue- or a white-collar worker, while before it was 5 weeks' salary for a blue-collar and 13-22 weeks' salary for a white-collar worker. Moreover, the new legislation has more adverse effects for white-collar workers with higher annual remuneration and with more than 20 years of seniority. As an illustration, consider a white-collar worker with gross annual remuneration between €32,254 - €64,508 and 20 years of seniority. Under the old regime, the employee was entitled to 632 days of advanced notification ($\approx$ 90 weeks), while the new law requires only 62 weeks of advanced notice by employer (OECD, 2013; Allen & Overy, 2014; Loyens & Loeff, 2014; American Chamber of Commerce in Belgium, nd). Therefore, the new contract seems to make blue-collar workers better-off while making white-collar workers worse-off in comparison to the previous regime.

Another step in the introduction of the unitary statute between blue- and white-collar workers was the abolition of the possibility to include a trial period clause in employment contracts.[7] For blue-collar workers, the probation period was up to two weeks (maximum 14 days). For the first seven days of the trial period, the agreement could not be broken. Between the seventh and the fourteenth days of the trial period, both employer and employee could terminate the contract immediately without a notice or/and compensation. For white-collar workers with a wage of less than €37,000 per year, the probation period was up to 6 months, and up to 12 months, if otherwise. The trial period could be terminated during the first month, but the worker was expected to continue the service until the end of the month. The notice period during the trial period was 7 calendar days. In other words, the notice period started at the earliest seven days before the end of the first month to assure that the white-collar worker is laid-off after the first month.

Contrary to this, now an employer can dismiss a worker after a period of employment of less than a month, provided that the statutory 2 weeks' notice is met, whereas, under the former regime, it was not allowed to terminate the contract of a white-collar worker during the first month of employment. In the case of dismissal after employment of, for example, 9 months, an employer will have to observe a notice period of 7 weeks, instead of 7 days. As a result, termination

[6] Compensation is calculated on the basis of worker's weekly salary. To compute a weekly salary a monthly salary is multiplied by 3 and divided by 13. For example, consider a blue-collar worker with 4 years of tenure and a monthly salary of €2,500. In case of dismissal without an assigned 15 weeks of advance notice, the employer is required to pay €8,654 ($2500 \times \frac{3}{13} \times 15 = 8653.85$) in severance payments under the new policy. While under the previous regime the severance payment would have been only €2,885 ($2500 \times \frac{3}{13} \times 5 = 2884.62$).

[7] Contracts for temporary work and contracts for students can still include a trial period.

of the contract after employment of several months involves higher dismissal costs for employers (Ajzen and Vermandere, 2014; Allen & Overy, 2014; Loyens & Loeff, 2014).

It has been argued that since the compensation would be tax-exempt, employers will not bear additional costs resulted from this harmonization of the contracts. However, many employers believe it to substantially increase the labor costs (American Chamber of Commerce in Belgium, nd), which will affect their hiring and firing behavior. It is, however, worth mentioning that only for newly hired workers as of January 1st of 2014 there will be equal treatment for the two types of the labor force. This means that the notice periods that have been accumulated before 2014 and existing trial periods, which commenced before January 1, 2014, are still valid, implying that the inequality will still be present to some extent until the existing generation of workers will completely retire.

1.3 Measuring Misallocation

The literature has developed several methods for measuring misallocation. See for example, among others, Basu and Fernald (2002), Restuccia and Rogerson (2008), Hsieh and Klenow (2009) and Asker et al. (2019), Baqaee and Farhi (2020) for more recent ones. Having considerable empirical power, flexibility, and straightforward measurement algorithm, Hsieh and Klenow (2009) has established itself as a standard empirical framework in the field. Despite being widely used and apart from some theoretical limitations (extensively covered in Foster et al., 2016; Haltiwanger et al., 2018), there are several practical issues in applying the Hsieh and Klenow (2009) method to this research question.[8] To determine aggregate productivity growth (hereinafter, APG) and to derive the reallocation terms, we build on the methodology developed by Petrin and Levinsohn (2012) and Petrin and Sivadasan (2013) and refer the interested reader to the original sources or Section 1.D for more details. We do acknowledge the fact that it has its own limitations (described in Baqaee and Farhi, 2020; Osotimehin, 2019) and it is less flexible and less straightforward compared to the Hsieh-Klenow approach. Nevertheless, we assume it serves the most for the purposes of this paper.

[8] Apart from some theoretical limitations, there are several practical issues in applying the Hsieh-Klenow method to this research question. Firstly, the measure relies on the dispersion calculations (standard deviation), which are responsive to outliers and sample selection. Another issue arises from the substitutability of inputs in the production function. Factors of production in the Cobb-Douglas function are imperfect substitutes. In calculating the dispersion for two types of labor units we would have to ignore firms that base their production on one type of labor only, i.e. selected sample of firms that constitute around 30% of the data.

1.3.1 Measuring Misallocation in a Nutshell

Assume there are N single-product firms in the economy. Each firm has a production function:

$$Q^i = Q^i(X_i, M_i, \omega_i),$$

where $X_i = (X_{i1}, ..., X_{iK})$ is a vector of K primary inputs (labor and capital), $M_i = (M_{i1}, ..., M_{iJ})$ is a vector of intermediate inputs (output of firm j) (materials) used in a production of i's firm/product and ω_i is a technical efficiency term.

The total output of firm i that goes to final demand is

$$Y_i = Q_i - \sum_j M_{ji},$$

where $\sum_j M_{ji}$ is the sum of all i's output that are used as an intermediate input in firm i and other firms j.

Aggregate productivity growth (hereinafter, APG), defined as the difference between a change in the value of aggregate demand and a change in the total expenditure on inputs, is then

$$APG(t) \equiv \sum_{i=1}^{N(t)} P_i(t) dY_i(t) - \sum_{i=1}^{N(t)} \sum_k W_{ik}(t) dX_{ik}(t), \tag{1.1}$$

where the first term refers to changes in the aggregate final demand and changes in the use of primary inputs are reflected in the second term of the right-hand side of the identity. Here, W_{ik} denotes the price of input k and X_{ik} is the amount of input k used.

Further, APG can be decomposed as:

$$\begin{aligned} APG &= \left[\sum_i P_i d\omega_i\right] + \left[-\sum_i P_i dF_i\right] + \\ &\quad \left[\sum_i \sum_k \left(P_i \frac{\partial Q_i}{\partial X_{ik}} - W_{ik}\right) dX_{ik} + \sum_i \sum_j \left(P_i \frac{\partial Q_i}{\partial M_{ij}} - P_j\right) dM_{ij}\right], \\ &= [TE] + [F] + [RE] \end{aligned} \tag{1.2}$$

where $d\omega_i$ is a change in technical efficiency and $\sum_i P_i d\omega_i$ is a gain from changes in technical efficiency, $\frac{\partial Q_i}{\partial X_{ik}}$ is a partial derivative of production function with respect to the kth primary input, $\frac{\partial Q_i}{\partial M_{ij}}$ is a partial derivative of production function with respect to the jth intermediate input and $-\sum_i P_i dF_i$ is any fixed and sunk costs. W_{ik} and P_j are input cost terms for primary and intermediate inputs, respectively. The technical efficiency term, $[TE]$,[9] is a contribution of firms producing more output holding inputs constant, while the reallocation term, $[RE]$, is a contribution of changes in input reallocation across firms to changes in final demand. The fixed cost term, $[F]$, is a combination of fixed and sunk costs.

The RE is formed of the value of marginal product (VMP) for every input (X_k) at firm i, generically given as

$$VMP_{ik} \equiv P_i \frac{\partial Q_i}{\partial X_{ik}}, \tag{1.3}$$

and includes a VMP term and input cost terms of primary and intermediate inputs for every firm.

Using labor as an example, holding total labor input constant and assuming common input costs (wages), reallocating one unit of labor from firm j to firm i (where $MP_i > MP_j$) would lead to $dL_i = 1$ and $dL_j = -1$, and will result in an increase in the value of output by

$$P_i \frac{\partial Q_i}{\partial L_i} - P_j \frac{\partial Q_j}{\partial L_j}.$$

Thus, aggregate output increases without any improvement in technical efficiency or increase in aggregate input use if an input reallocates from a firm with a low value of the marginal product to a higher one. Generally, when an input is reallocated from a firm with a small value of marginal product-input cost gap to a firm with a higher gap, the total output increases by the difference in the gaps. The reallocation term captures this increase in output.

The reallocation terms are used to measure a change in aggregate productivity growth arising from changes in the allocative efficiency term:

$$\Delta AE \equiv \int_0^1 \sum_i \sum_k \left(P_{it} \frac{\partial Q_{it}}{\partial X_{ikt}} - W_{ikt} \right) dX_{kt} + \int_0^1 \sum_i \sum_j \left(P_{it} \frac{\partial Q_{it}}{\partial M_{ijt}} - P_{jt} \right) dM_{jt}. \tag{1.4}$$

This implies that, *ceteris paribus*, the average absolute labor gap across firms is the average productivity gain from reallocating labor by one to an efficient direction at every firm.[10]

So, the gap is used as an approximation for a potential gain in productivity from adjusting the input to an efficient direction.[11]. There are two extreme cases when the reallocation term is equal

[9] where $\frac{\partial Q_i}{\partial \omega}$ is normalized to 1.

[10] Can be applied to any input.

[11] Please note that this paper focuses solely on the labor reallocation part of the APG decomposition specified in section 1.3.1. We do not know the relative importance of these contributions compared to other factors of production (like capital) or the technical efficiency and fixed costs terms. Nevertheless, the literature on the aggregate productivity growth decomposition emphasizes the importance of resource reallocation and its contribution varies by countries studied. For example, 50 percent of productivity growth is explained by the reallocation of resources across firms in the US manufacturing industry (Baily et al., 1992; Foster et al., 2001).

to zero:[12] (i) no changes in the allocation of inputs, i.e. friction and/or adjustments costs are so high, that none of the inputs are reallocated or adjusted; (ii) no input market frictions, i.e. inputs constantly reallocate across firms in response to any changes in economic conditions, so that no further output can be gained via reallocation. In fact, due to the presence of fixed costs on hiring and firing of labor, we would expect some positive level of the gap to always be present. So, in the analysis of the effect of the policy, we assume that there is always some level of misallocation which is fixed throughout. And any deviation from this fixed level is attributed to the policy change. Although, we acknowledge that this is indeed a simplified assumption.

1.3.2 Methodology: Estimating the Gap

To estimate the gap, we need to calculate the value of the marginal product and marginal cost. We utilize the average wage per FTE (full-time equivalents) directly calculated from the data as a proxy for marginal cost. To estimate the marginal product, we use the Cobb-Douglas production function:[13]

$$Q_{it} = A_{it} K_{it}^{\beta_{sp}^{k}} L_{it}^{\beta_{sp}^{l}}, \tag{1.5}$$

where Q_{it} is value-added, A_{it} is productivity/efficiency, L_{it} and K_{it} are labor and capital inputs, respectively, for firm i at time t. Elasticities of labor and capital are indexed with sp highlighting the industry and period[14] specific estimation, respectively.

Re-write the function in natural logarithms:

$$q_{it} = \beta_{sp}^{k} k_{it} + \beta_{sp}^{l} l_{it} + \underbrace{\omega_{it} + \eta_{it}}_{\varepsilon_{it}}, \tag{1.6}$$

where small letters represent log-transformation of their capital counterparts and $logA_{it} = \varepsilon_{it}$ is a productivity shock decomposed into ω_{it} as a transmitted (predictable) component and η_{it} as a measurement error.

There are a number of production function estimators at the disposal of a researcher with a panel structure of the data. We employ the approach proposed by Ackerberg et al. (2015) (here-

[12] Formally, (i) $dX_{kt} = 0$ and $dM_{jt} = 0 \ \forall k, j, t$; (ii) $P_{it} \frac{\partial Q_{it}}{\partial X_{ikt}} = W_{ikt}$ and $P_{it} \frac{\partial Q_{it}}{\partial M_{ijt}} = P_{jt} \ \forall i, k, j, t$.

[13] Given that elasticities from the Cobb-Douglas production function are industry-specific, one can argue that variation in the marginal product comes solely from a variation in output to labor ratio. To address the concern, we perform the analysis using a translog production function specification, which allows input elasticities to vary by firm and year. The results still hold.

[14] We construct industries based on NACE two-digit level specification and split the sample into 5 periods: [1996-1999], [2000-2003], [2004-2008], [2009-2013], [2014-2017], - to capture the potential differences and changes in production technology across industries and time.

after, ACF) that addresses issues in methods introduced by Olley and Pakes (1996) and Levinsohn and Petrin (2003).[15] Knowing that employment protection reforms add to adjustment costs of labor inputs, the ACF estimation method, compared to other procedures, treats labor as a state variable allowing adjustment costs to labor inputs. We estimate the production function separately by industry and certain time intervals to capture heterogeneity in production processes across industries and time, which also guarantees variation in elasticities.

From the estimates of the production function and observed levels of inputs used, the marginal product of labor is

$$\frac{\partial Q_{it}}{\partial L_{it}} = \beta^{l}_{sp}\frac{Q_{it}}{L_{it}}, \tag{1.7}$$

where Q_{it} is real output produced, measured by value-added of a firm, and L_{it} is number of employees used in firm i at time t.[16]

The value of the marginal product is, then, the multiplication of the marginal product and the firm's output price:

$$VMP^{l}_{it} = P_{it}\frac{\partial Q_{it}}{\partial L_{it}}. \tag{1.8}$$

Finally, the absolute value of the gap is the difference between the marginal product of labor and its price:

$$G^{l}_{it} = |VMP^{l}_{it} - W^{l}_{it}|, \tag{1.9}$$

where W^{l}_{it} denotes the average wage. In the economy without frictions, the marginal revenue is equalized to the marginal cost. Therefore, the gap measures the deviation from the social optimum. This gap could be due to any frictions in the market, such as firing costs, markups, taxes, and others.

To obtain the absolute real gap, we deflate the nominal value by consumer price index (CPI), to make the gap comparable over time:

$$RG^{l}_{it} = \frac{G^{l}_{it}}{CPI_t}.$$

One of the limitations of the estimation procedure is that most of the firm-level datasets report

[15] We discuss different estimation procedures in more detail in Section 1.E.

[16] Methodologies of production function estimation assume that variable inputs are chosen conditional on observing the transmitted component - ω_{it}. Therefore, we assume firms to equalize the marginal product conditional on ω_{it} to its input prices. As a result, marginal revenue conditional on $\hat{\omega}_{it}$, is given by

$$\beta^{l}_{sp}\frac{\hat{Q}_{it}e^{(\omega_{it})}}{L_{it}e^{(\varepsilon_{it})}}, \tag{1.7'}$$

where $\hat{Q}_{it}$ is output purged from the measurement error.

firm-level revenues, but not firm prices and quantities. When estimating a production function, a common approach is to deflate the revenue data with industry price deflator and estimate the production function using deflated revenues. Further, in calculating the VMP in the presence of this price measurement error, the marginal product is:

$$\beta^l_{sp}\left(\frac{P_{it}Q_{it}}{P_{st}}\right)\frac{1}{L_{it}},$$

where P_{st} is industry (NACE 2-digit) price deflator. Given that the estimate includes output price over price deflator, we multiply it back with the price deflator. As a result, we are left with the output price times the marginal product. In the presence of imperfect competition, firm-level prices deviate from the industry-level price deflators, consequently introducing an omitted output price bias. The issue could be avoided by using the information on quantities instead of sales, which is typically unavailable for researchers. Or, alternatively, one can introduce demand for output into the system, as was first suggested by Klette and Griliches (1996). Although, this approach was criticized by Ornaghi (2006). At this stage, we do not address the issue in this paper. We believe that the measurement error generated by the mismatch between industry and firm-level prices will be absorbed by the error term in eq. (1.10).

Another potential concern is that the production process abstracts from the quality of the labor force. We cannot directly control the worker skills. Nevertheless, we attempt to address the issue by introducing a robustness check using the wages in the estimation of the production function, assuming that differences in worker characteristics are perfectly reflected in their wages.[17]

Moreover, the violation of the assumption that the marginal cost of labor equals the average wage might introduce a bias. If firms have monopsony power, then the wage is below the marginal cost, which results in the overestimation of the gaps. In spite of this, there is no solid reason to believe that the markdowns are different for blue-collar and white-collar intensive firms.

1.3.3 Relating the Gaps to the Harmonization of Labor Contracts

Finally, we relate the gaps to the labor market characteristics. Particularly, we assess the effect of the harmonization of labor contracts. A straightforward way to do so would be to calculate the gaps for blue- and white-collar workers separately and compare their evolution

[17] It is important to capture some human capital characteristics such as experience or schooling and firm related characteristics such as training and tenure when studying productivity and wage relations. As pointed out by Van Biesebroeck (2011), some of these characteristics might affect the equality of productivity and wage premiums.

over time.[18] However, estimating the gaps for each type of worker requires the marginal cost of labor (approximated using the average wage) for each type. Although the data at hand do not differentiate the wage bill for different types of labor, we still can shed a light on the effects of a new policy regime by constructing a standard panel regression framework that explores the empirical relationship between key structural variables and the observed changes in the wedge:

$$RG^l_{it} = \beta_b share_i + \beta_p policy_t + \alpha \; share_i \times policy_t + \eta_i + \mu_t + \epsilon_{it}, \tag{1.10}$$

where RG^l_{it} is the real absolute gap for labor input of firm i at time t, $share_i$ is a share of blue-collar workers in 2012 for firm i, $policy_t$ is a dummy indicating the period after the harmonization of the contracts, [2014-2017], η_i and μ_t are *firm* and *year* specific fixed effects, respectively, and ϵ_{it} is iid error term.[19]

α is the coefficient of interest, which indicates the impact of the policy change depending on the pre-policy blue-collar intensity. Positive α means that the gap has increased for firms with a higher share of blue-collar workers after the policy implementation compared to the base group, i.e. post-policy allocative efficiency of blue-collar intensive firms has decreased relative to white-collar intensive firms. A negative coefficient implies an increase in allocative efficiency. Given the changes introduced to the labor law, we expect an increase in adjustment costs for blue-collar workers compared to white-collar workers. If it is indeed the case, we anticipate the coefficient α to be positive, $\alpha > 0$.

We choose to use the share of blue-collar workers in 2012 for a number of reasons. The closest alternative is to utilize the initial share (share at entry). We find using the entry share to be not representative of changes that occur in the firm over time (for example, growing or shrinking). Moreover, using the initial share actually means using the share that first appears in the dataset, which is not necessarily the actual share at entry. We choose 2012 because it is close to the date of the actual reform. We cannot take the data from 2013 because the adjustments to the law were announced in 2013, which potentially might have affected the input choice of firms before the actual implementation of the policy.

An advantage of our approach, compared to the straightforward way of calculating the gap for the two types of workers, is that production units in the Cobb-Douglas production function

[18] Ideally, you would expect the blue-collar workers' gap to increase after the policy change and the gap of white-collar workers to decrease. The opposing effects of the policy on the two types of workers make it hard to *a priori* predict in which direction the aggregate misallocation moves.

[19] Please note that $policy_t$ dummy will be absorbed by year-fixed effects and $share_i$ will be absorbed by firm-fixed effects.

are assumed to be imperfect substitutes. So, estimating the production function using both types of labor as separate units in the production process requires ignoring the firms that operate using only one type of employee. Given that a number of firms operate using only one type of labor, it is better to estimate the Cobb-Douglas production function using non-differentiated labor as an input (along with the other inputs), calculate the gap for labor, and then try to disentangle the effects of the two types of workers.

1.4 Data

Our primary data source is the annual accounts of Belgian firms from the National Bank of Belgium (NBB). We obtained an unbalanced panel for the period 1996-2017 and selected key variables for calculating the production function estimates and the gap, such as value-added (in thousand euros), tangible fixed assets (a proxy for capital) (in thousand euros), the average number of employees (in full-time equivalents (hereinafter, FTE)), material costs (in thousand euros), and remuneration (in thousand euros) per firm, including NACE Rev.2 codes for each firm.[20] All firms with limited liabilities are obliged to report the annual accounts. While a small firm can file a short form, large firms are obliged to file a complete form of the annual accounts.[21] Since the short form is restricted to value-added reports and only around 7% of firms submit complete accounts, in order to capture the representative sample of firms in Belgium, we will rely on the value-added production function estimation. Moreover, we will complement this data with the "social balance sheet" dataset, which contains more detailed information on the structure of the workforce: the average number of white-collar workers and blue-collar workers (FTE), collected from the BELFIRST (FInancial Reports and STatistics on BElgian and Luxembourg Companies) database (see eg. De Loecker (2011); Konings and Vanormelingen (2015) among others, that use the same data).

A book year starts on the 1st of January and ends on the 31st of December. Ideally, the data should correspond to 12 months of operation. When it is not the case, we introduced a set of corrections to properly annualize the account information.[22]

We used NACE two-digit gross value-added, gross output, and intermediate consumption

[20] We exclude construction industry (Section F) and upholstery (13929) and woodworking (16) sectors because they got smaller notice periods for their blue-collar workers, electricity, gas, steam and air conditioning supply (Section D) because of the limited number of records and all non-private sectors ($\geq$ 84) of the economy.

[21] A firm is considered as a large firm if it exceeds two out of three following thresholds: (i) employment of 50 FTE; (ii) turnover of 9 mln euro, and (iii) total assets of 4.5 mln euro. A firm is a small firm if it has not exceeded more than one of the above thresholds.

[22] Details are in Section 1.F.2.

price indices retrieved from the Eurostat to get real values for value-added, revenue, and material costs, respectively. If it was not available, we used NACE one-digit (section level) indices. CPI collected from the NBB is used to deflate wages. Economy-wide gross output formation deflator retrieved from UNECE Statistical Database is used to deflate tangible fixed assets.

The labor gap calculation requires data on the marginal input price for labor, which is the marginal wage. In the data, we observe the total wage bill for employees. By construction of the national account, the total wage bill includes remuneration, social security, and pensions. We use the average wage, calculated by dividing the total wage bill by the number of workers (FTE) for each year and firm, as an approximation for the marginal wage.

In estimating the production function we employ the technique proposed by Ackerberg et al. (2015) with materials as a proxy variable. We use materials over investment, because of the well-known zero-investment problem and lumpiness of the data. Records on materials include costs of supplies and goods and services and other goods. Material costs are poorly reported for the firms submitting a short form of the annual accounts.[23] To keep the sample as representative as possible for the whole Belgian private sector firms, we assume that within an industry, firms not reporting material costs have the same production technology as those firms that do report material costs.

The analysis is based, on average, 104,434 firms per year for the 1996-2017 year period. The pooled dataset comprises 236,660 unique firms. The sample on average covers at least 63% of non-public sector employment in Belgium ($\approx$ 1.5 mln FTE out of $\approx$ 2.4 mln FTE) in any given year. Column (1) of Table 1.1 presents mean values of key variables for the full sample. An average Belgian firm active in the private sector employs on average 14 employees, generates around 1,221 thousand euro in value-added, and pays around 50 thousand euro average wage per year. A firm employs more white-collar workers on average, however, there exists considerable variation in the labor composition across sectors. Column (2) of the table presents statistics for firms that report material costs. We can note that an average firm that reports material costs is twice as large, i.e. it employs 30 employees on average and generates around 2,702 thousand euro in value-added.

[23] Table 1.F.3.2 lists the percentage of observations not reporting materials costs data out of total observations by industry and the percent of value-added of those firms.

Table 1.1: Summary Statistics

	(1) **Full**	(2) **Restricted**	(3) **Blue-collar**	(4) **White-collar**
turnover (1000 euros)	12786.26	12882.45	4846.14	14810.96
value-added (1000 euros)	1220.73	2702.08	660.21	1209.16
employment (FTE)	14.45	30.0	11.79	11.03
tangible fixed assets (1000 euros)	1064.95	2278.69	536.79	982.84
material costs (1000 euros)	10670.92	10670.92	3642.41	12760.26
wage bill (1000 euros)	719.38	1587.87	451.68	649.25
blue-collar workers (FTE)	6.86	13.76	11.19	0.43
white-collar workers (FTE)	7.76	16.44	1.39	10.41
share of blue-collar workers	0.43	0.42	0.96	0.02
in-flow number of employees (FTE)	27.33	54.11803	18.28	13.13
out-flow number of employees (FTE)	26.72	53.13	17.58	12.60
hours effective (1000)	23.60354	48.45	18.64	18.57

The table presents summary statistics of the key variables used in the analysis. Column (1) covers the full sample of firms. Column (2) covers a sub-sample of firms that report material costs. Columns (3) and (4) focus on sub-samples of blue-collar intensive (share of blue-collar workers of at least 75 %) and white-collar intensive (share of blue-collar workers at most 25%) firms, respectively.

1.5 Results

1.5.1 Baseline Results

The first step towards measuring the labor gap is to estimate the production function coefficients. We estimate the production function at the NACE two-digit industry level for 5 different periods. Consequently, the input elasticities have 180 unique values for the Cobb-Douglas production function specification (36×5). On average, the capital coefficient is equal to 0.17, the labor coefficient on average is 0.85, and the average returns to scale is 1.02.[24]

After estimating the elasticities, we have calculated the wedge between the value of the marginal product of labor and its marginal cost using eqs. (1.8) and (1.9). Table 1.2 presents the average absolute labor gap by industry. For the Belgian economy across the 1996-2017 year period, the average absolute gap is equal to 31.3 thousand euro. The gaps are more than half of the average wage. The dispersion, captured by the coefficient of variation (CV), is quite high both within and across different industries. Across the economy, 75% of observations have positive gaps. The sign of the gap helps to identify the direction of misallocation. A positive (negative) labor gap implies that some product and/or labor market imperfections do not allow firms to expand (contract).

Figure 1.1 examines the year-to-year evolution of the labor gap. The figure plots the coef-

[24]More information on the procedure and detailed coefficients can be found in Section 1.E.

Table 1.2: Absolute Gap, by industry

NACE	Description	Mean	CV	Pos %	Obs
1–3	Agriculture, forestry, and fishing	32.10	1.30	67.66	35789
5–9	Mining and Quarrying	29.95	1.36	55.07	2139
10–12	Manufacturing Food products; Beverages; Tobacco products	22.06	1.4	66.58	61417
13–15	Manufacturing Textiles; Wearing apparel; Leather and related products	17.15	1.6	41.19	21320
17	Manufacturing Paper and paper products	26.11	1.29	57.9	5019
18	Manufacturing Printing and reproduction of recorded media	20.1	1.27	58.1	28907
19–21	Manufacturing Coke and refined petroleum products; Chemicals and chemical products; Basic pharmaceutical products and preparations	35.03	1.26	73.15	11469
22	Manufacturing Rubber and plastic products	22.78	1.36	57.92	11769
23	Manufacturing Other non-metallic mineral products	26.18	1.32	77.17	19449
24	Manufacturing Basic metals	36.86	1.3	59.11	3282
25	Manufacturing Fabricated metal products, except machinery and equipment	22.02	1.43	68.65	63905
26	Manufacturing Computer, electronic and optical products	23.82	1.25	46.65	5378
27	Manufacturing Electrical equipment	22.85	1.38	71.25	6522
28	Manufacturing Machinery and equipment	22.47	1.41	69.31	18053
29	Manufacturing Motor vehicles, trailers and semi-trailers	23.49	1.44	61.51	3183
30	Manufacturing Other transport equipment	25.87	1.25	53.38	1480
31–32	Manufacturing Furniture and other manufacturing	21.96	1.48	78.85	29851
33	Manufacturing Repair and installation of machinery and equipment	26.61	1.34	76.7	8068
36–39	Water supply, sewerage, waste management and remediation activities	44.48	1.16	77.45	12512
45	Wholesale and retail trade; repair of motor vehicles and motorcycles	27.46	1.26	83.56	134828
46	Wholesale trade, except motor vehicles and motorcycles	40.83	1.19	81.35	348637
47	Retail trade, except motor vehicles and motorcycles	22.98	1.34	74.1	404063
49	Land transport and via pipelines	17.36	1.52	66.78	97872
50–53	Water and air transport; Warehousing and support activities for transportation; Postal and courier activities	38.03	1.35	66.75	37332
55–56	Accommodation; Food and beverage services activities	14.8	1.51	63.32	233549
58	Publishing activities	34.95	1.23	73.04	8939
59–60	Motion picture, video and television, ...; Programming and broadcasting activities	45.39	1.17	76.1	10809
61	Telecommunications	49.06	1.15	57.37	3939
62–63	Computer programming, consultancy and related activities; Information service activities	31.89	1.23	78.38	62076
64–66	Financial and Insurance activities	55.2	0.96	89.37	127310
68	Real estate activities	55.93	1.11	75.61	77331
69–75	Professional, scientific, and technical activities	41.91	1.15	82.23	275005
77	Rental and leasing activities	50.44	1.16	80.84	19625
78	Employment activities	21.26	1.59	42.25	8991
79	Travel agency, tour operator reservation service and related activities	28.21	1.1	61.8	13061
80–82	Security and investigation activities; Services to buildings and landscape activities; Office administrative, office support and other business support activities	24.58	1.52	66.02	84672
	Total	31.28	1.34	74.61	2297551

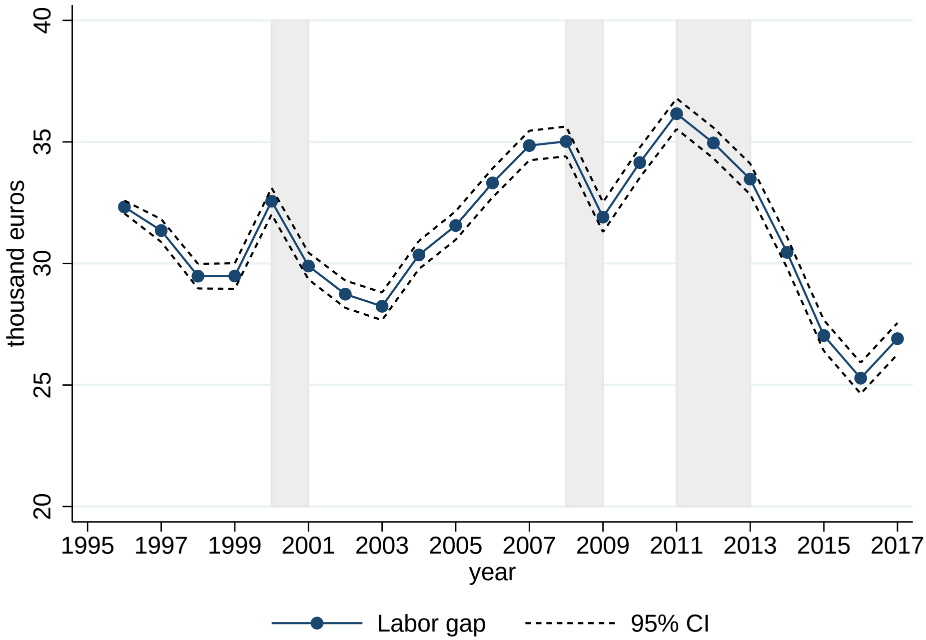
Average absolute labor gap was calculated by $\overline{RG^l_s} = \frac{\sum_{i \in s} RG^l_{it}}{N_s}$, reported in thousand euros. Coefficient of variation is $CV_s = \frac{sd_s}{\overline{RG^l_s}}$. Percent of positive labor gap is defined as $Pos = \frac{N_s^+}{N_s} \times 100$.

ficients of year dummies of the firm-fixed effect regression of the absolute value of the gap on yearly dummies. The gap fluctuates around 30 thousand euro. We observe an increase in the overall trend for the labor gap until around 2011. The drops in the evolution of the gap correspond to the recession periods. Recessions are usually characterized as having a cleansing effect on the economy. During the "bad times", the least productive firms are driven out of the market, and the available resources are reallocated to more productive production units (Aw et al., 2001; Foster et al., 2001; Van den bosch and Vanormelingen, 2017). The gap declines during recessions implying an improvement in allocative efficiency. This finding is in line with the literature on the cyclical behavior of the allocative efficiency that found that allocative efficiency increases during the downturns (Oberfield, 2013; Osotimehin, 2019). However, since this is out of the scope of this study, we are silent about the reasons behind this countercyclical behavior. Additionally, we see a sharp decline in the gap after 2013, which cannot be explained by recessions, and it coincides with the introduction of the harmonization of the labor contracts. Nevertheless, it is important to note that the measure of the gap involves any type of distortions. Hence, we do not take a stand on the potential source of the fall in the wedge at this stage.

Next, we study the effect of the harmonization of labor contracts on return-cost wedges. The policy was argued to increase adjustment costs for blue-collar workers compared to white-collar employees. The empirical approach to address the question is a simple difference-in-difference with continuous treatment intensity. Identification of the diff-in-diff analysis relies on the parallel trends assumption, i.e. for the analysis to be valid the labor gaps for blue- and white-collar intensive firms should be parallel prior to the reform. We verify the common trend assumption holds by plotting the evolution of the average labor gaps for sub-group of blue-collar and white-collar intensive firms (Figure 1.2).

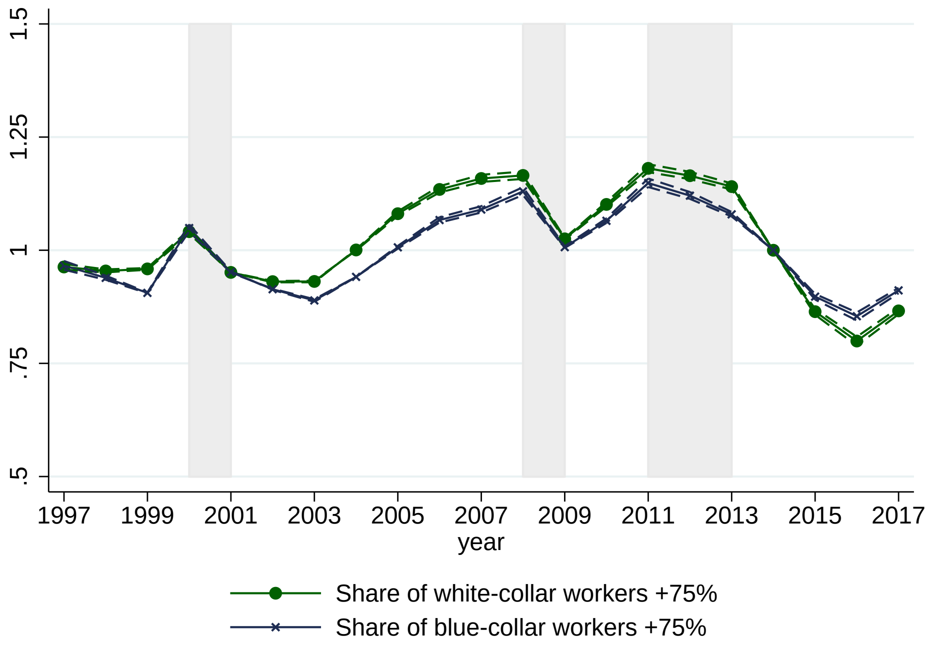
Table 1.3 presents the results of the model that captures the difference between the two types of labor force (eq. (1.10)). Columns (1) - (2) show the results for the full sample of firms, i.e. including firms that do not report material expenses, under the assumption that they use the same production technology as firms that do report material costs. The specification in column (2) includes the average growth rate of value-added at the NACE 3-digit industry level to control for industry-level demand shocks. Columns (3) - (4) report results for the specifications where we use value-added purged from measurement error to compute the marginal revenue product of labor (eq. (1.7′)). Consequently, we use the restricted sample of firms that report material costs. The results suggest that after the policy change, on average the labor gap increased for firms employing a high share of blue-collar workers relative to firms with a low share of blue-collar

Figure 1.1: Absolute Gap: 95% Confidence Interval for Change in Gap



Gap estimates are in thousand euros. Standard errors are clustered at the firm level. The vertical gray bars mark recession periods dated by OECD.

Figure 1.2: Common trends assumption



The figure plots the average labor gap for blue-collar and white-collar intensive firms, where the labor gap of 2014 is normalized to 1 for both groups for better visualization and comparability. The vertical gray bars mark recession periods dated by OECD.

workers. For example, in column (2) the results predict that after the policy, a firm with 90% blue-collar workers witnessed an increase in the gap of 3,120 euro relative to a firm with only 10% share of blue-collar workers.[25]

Due to the data constraints, we pool the two types of the labor force in calculating the labor gap. Consequently, our results could be influenced by changes in the relative shares of blue- and white-collar workers after the policy implementation as we deduce that on average the gap for a blue-collar worker is lower compared to the gap for a white-collar worker.[26] Hence, if after the policy change the share of blue-collar workers would decrease by more for blue-collar intensive firms, this could explain part of our findings. However, we estimate the model similar to eq. (1.10), with the share of blue-collar workers as the dependent variable, and find that the share of blue-collar workers increases more in blue-collar intensive firms. Therefore, our findings represent a lower bound of the policy effect (see Section 1.B for details).

Table 1.4 repeats the analysis for the manufacturing, distributive trade, and services sectors, respectively. Only for the distributive trade sector, the result seems not to hold. One possible explanation is that some narrowly defined sectors got a temporary exemption from the policy until December 2017. We address the issue in section 1.5.4. Overall, the reported values indicate the harmonization of labor contracts increased the allocative inefficiency of the labor input for firms with more blue-collar workers relative to white-collar workers. It is important to note that, this does not imply that the efficiency of the blue-collar workers has declined. It means that all else being equal, in the absence of the increase in adjustment cost for blue-collar workers efficiency gain would have been higher.

We execute a number of robustness checks[27], reported in Table 1.5. First, to test whether compositional differences between new entrants in the post-policy and exiters in the pre-policy period impact the results, we focus on the balanced panel, namely on firms that are present in all sample years and results are highly similar to the baseline results. Second, output elasticities in the Cobb-Douglas production function are constant across firms in the same sector and time period, and the value of the marginal product is driven solely by the variation in output over labor ratio. To address the concern, we repeat the same analysis using the translog production function specification, which guarantees firm-year variability of elasticities. The baseline conclusion still holds.

[25] $0.8 * 3.900 = 3.12$

[26] We perform a firm-fixed effect regression on sub-samples of blue-collar intensive (share of blue-collar workers no less than 75%) and white-collar intensive (share of blue-collar workers no more than 25%) firms with the labor gap as a dependent variable. We find the average labor gap for white-collar intensive firms to be larger. That being the case, we assume that the gap for a blue-collar worker is lower compared to the gap for a white-collar worker.

[27] cf. Section 1.C for more details.

Table 1.3: Baseline Model

	Full		Restr.	
	(1)	(2)	(3)	(4)
share × policy	4.050***	3.900***	1.205***	1.112***
	(0.203)	(0.202)	(0.285)	(0.282)
Ind. Growth Rate		16.505***		9.974***
		(0.474)		(0.492)
Constant	33.757***	31.238***	30.435***	25.191***
	(0.177)	(0.161)	(0.180)	(0.136)
R^2	0.016	0.018	0.029	0.030
Obs.	1594551	1557888	591570	572177
Nr.Clust.	111222	111220	63947	63910

Clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include firm and year fixed effects. Columns (1)-(2) use the full sample. Columns (3)-(4) purge value-added from measurement error and therefore refers only to firms that report as well material costs.

Table 1.4: Sectoral analysis

	Manuf.		Trade		Serv.	
	(1)	(2)	(3)	(4)	(5)	(6)
share × policy	1.724**	1.954**	-0.921**	-1.254***	4.911***	4.764***
	(0.863)	(0.860)	(0.367)	(0.366)	(0.264)	(0.262)
Ind. Growth Rate		21.281***		22.180***		14.168***
		(1.006)		(1.186)		(0.670)
R^2	0.039	0.044	0.017	0.017	0.020	0.022
Obs.	222119	215260	630157	613860	706307	693619
Nr.Clust.	13147	13147	41603	41601	54071	54071

Clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include firm and year fixed effects. Columns (1)-(2) report results for the manufacturing (NACE 10-33), columns (3)-(4) for the distributive trade (NACE 45-47) and columns (5)-(6) for the services (NACE 49-82) sectors.

Next, we estimate the parameters of the production function under the assumption that these are fixed over time. As shown in columns (5)-(6) the results remain qualitatively and quantitatively the same. Finally, working with the labor input defined as the number of employees could be problematic for a couple of reasons. First, the number of full-time equivalents (FTE) used for the employment measure ignores whether or not an employee is active, abstracting from overtime, sick-leave, maternity/paternity leave, or labor hoarding. Second, because of the obvious concerns about quality differences of the workforce. To address the first concern, we use effective hours worked as an alternative measure for employment. The results are consistent with the baseline estimates (Columns (7)-(8)). Assuming that all quality differences are reflected in differences in average wages, in addressing the second potential problem, we use the wage bill as an instrument for the labor input in the ACF estimation procedure.[28] The results, columns (9)-(10), are robust to this modification.

Table 1.5: Robustness Checks

	Balanced		Translog		Fixed		Hours		Wage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
share × policy	3.185***	3.125***	1.879***	1.762***	4.075***	3.899***	2.012***	1.916***	3.272***	3.207***
	(0.404)	(0.399)	(0.442)	(0.439)	(0.202)	(0.201)	(0.173)	(0.172)	(0.144)	(0.144)
Ind. Growth Rate		14.659***		18.179***		16.770***		11.548***		8.432***
		(0.742)		(0.741)		(0.473)		(0.369)		(0.352)
R^2	0.017	0.020	0.015	0.017	0.017	0.018	0.005	0.006	0.007	0.007
Obs.	516670	493185	554671	535516	1594551	1557888	1575734	1538680	1594551	1557888
Nr.Clust.	23485	23485	63134	63081	111222	111220	110810	110808	111222	111220

Clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include firm and year fixed effects. Columns (1)-(2) report results for the balanced panel. Columns (3)-(4) use estimates from a translog production function. Columns (5)-(6) use production function parameters that are fixed over time. Columns (7)-(8) use hours of work as an alternative measure of employment. Columns (9) - (10) use estimates from Cobb-Douglas production function with wage bill as an additional instrument in the ACF estimation procedure.

1.5.2 Positive and Negative Gaps

The absolute value of the labor gap measures the distance from the socially optimal labor allocation. Nevertheless, the sign of the gap helps identify the direction of firm-level misallocation, i.e. the direction of the necessary adjustment. Therefore, some information might be potentially lost when using the absolute value of the gap, and adjustment costs may have different implications for the distribution of positive and negative gaps. To address the concern and have a more complete picture of the distributions, Table 1.6 reports summary statistics for sub-samples of only positive and only negative labor gaps. For consistency and interpretation, throughout the analysis, we still use the absolute values of the negative gaps. The average positive gap is more than

[28] Similar to Amiti and Konings (2007); De Loecker and Warzynski (2012), where they modify the control function to account for differences in the export status.

three times higher than the negative counterpart. The overall distribution of the negative gap seems to be more right-skewed relative to the positive one. Given the average wage per year of 50 thousand euro, an average negative gap of 11 thousand euro means that the marginal return from labor is smaller than the cost of about 2.6 months of salary, while an average positive gap of 38 thousand euro implies that the value produced by a marginal employee is higher than the cost by 9 months of salary.

Table 1.6: Summary: Positive and Negative Gap

	RG^l_{it} (1)	$+RG^l_{it}$ (2)	$-RG^l_{it}$ (3)
Number of obs.	2,297,551	1,714,169	583,382
Share (%)	100	74.6	25.4
Mean	31.276	38.283	10.689
SD	42.025	45.906	13.983
p10	2.129	3.139	1.074
p50 (median)	15.035	20.750	6.520
p90	82.061	100.890	24.159

Column (1) reports summary statistics of the labor gap for the whole sample. Column (2) reports summary statistics of sub-sample of labor gaps with only positive values. Column (3) reports summary statistics of sub-sample of only negative labor gaps. For consistent interpretation, we take the absolute value of the negative gap.

The dynamics of the positive and negative values of the gaps are opposite (Figure 1.A.1). Both of them show an increasing trend over time. The evolution of the negative gap is more stable, while the positive gaps show sharp declines during the recession periods and after the year 2013. This largely drives the dynamics of the average absolute gap given a large number of positive gaps in the sample. Indeed, from the graph, we can conclude that the different (unobserved) market regulations can have opposite implications for the dynamics of positive and negative gaps. Consequently, we test whether the harmonization of labor contracts had a symmetric effect. Table 1.7 shows the results from estimating eq. (1.10) for the sub-samples of positive and negative gaps. We find that the gaps have increased for blue-collar worker intensive firms compared to white-collar intensive firms irrespective of the sign. Although the relative increase is smaller for negative gaps, it is statistically significant.

Table 1.7: Positive and Negative

	Positive Gap		Negative Gap	
	(1)	(2)	(3)	(4)
share × policy	4.017***	3.665***	0.544***	0.484***
	(0.258)	(0.257)	(0.151)	(0.152)
Ind. Growth Rate		23.076***		-4.738***
		(0.645)		(0.320)
R^2	0.019	0.021	0.010	0.008
Obs.	1239618	1213213	354933	344675
Nr.Clust.	108268	108245	73562	73125

Clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include firm and year fixed effects. Columns (1)-(2) report results for the positive gap. Columns (3)-(4) report results for the negative gap. For consistent interpretation, we use the absolute value of the negative gap in the regression.

1.5.3 Revenue Production Function

The main implication for the approach by Petrin and Sivadasan (2013) is that a change in the market environment will generally affect all input gaps. On the other hand, a change in adjustment cost for one input will only affect the gap for that particular input that experienced a change. In other words, if the changes in the gap would be due to changes in markups or output taxes, for example, then we would find similar results for other variable input gaps as for the labor gap.

To this end, we also estimate production function where output is measured as deflated revenue and inputs are materials, capital and labor.[29] The disadvantage is that our sample size decreases, as only larger firms are obliged to report revenue and material costs. The advantage however, is that we have a freely variable input (materials) gap next to the labor gap.[30] If we believe the labor gap to decline due to the introduction of the policy, then the gap for intermediate input should follow a different evolution. On the other hand, if the gap for materials shows the same pattern as the labor gap, then the fluctuation in the labor gap cannot be attributed solely to the policy change. Moreover, we would observe a positive and significant increase in the material gap from the estimation of eq. (1.10). For completeness, we add estimations for the capital gap.

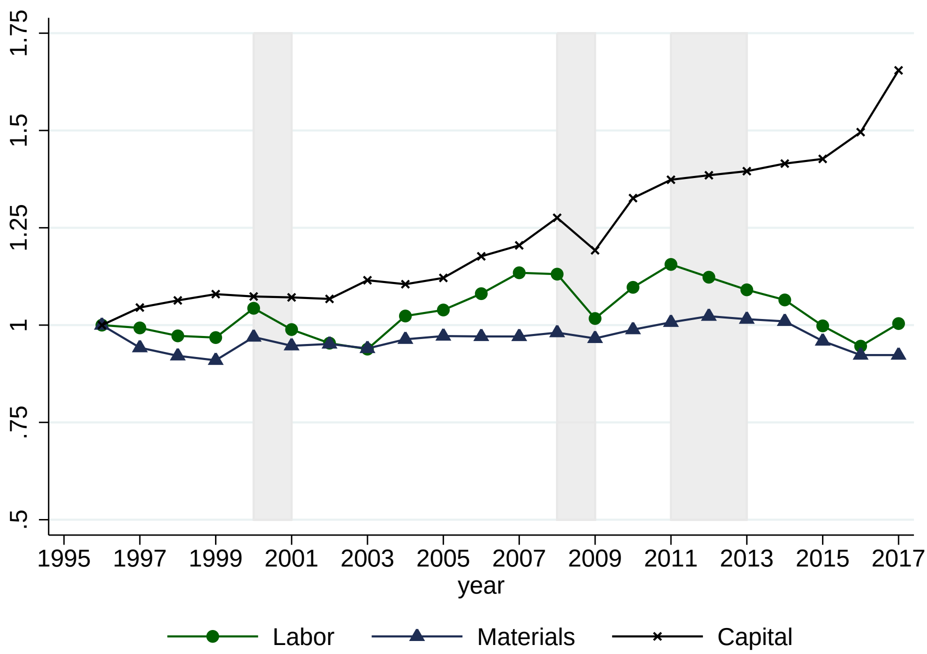
The evolution of all input gaps, i.e. materials, labor, and capital, are plotted in Figure 1.3.

[29] Similar to eq. (1.6), $y_{it} = \alpha^k k_{it} + \alpha^l l_{it} + \alpha^m m_{it} + \varepsilon_{it}$, where α^X represent the elasticities from revenue production function estimation, to indicate that they are different from estimation of the value-added production function.

[30] Similar to eq. (1.9), $\tilde{G}^l_{it} = |V\tilde{M}P^l_{it} - W^l_{it}|$ is the labor gap, while $\tilde{G}^m_{it} = |V\tilde{M}P^m_{it} - P^m_{st}|$ and $\tilde{G}^k_{it} = |V\tilde{M}P^k_{it} - P^k_{st}|$ are the material and capital gaps, respectively, where P^m_{st} and P^k_{st} are NACE Rev.2 two-digit industry specific intermediate input and gross capital formation prices.

In contrast to the labor gap, the material gap displays a stable trend, while the capital gap is increasing over time. This implies that the change in gaps for labor is not the result of distortions that disturb allocation of all inputs, but rather due to a change in the adjustment cost for labor input. Next, we estimate eq. (1.10) for the material, capital, and labor gaps and find that the labor gap increased for firms with a high share of blue-collar workers relative to firms with a low share, after the policy change. Contrary to the results on the labor gaps, the coefficient on the interaction term is statistically not different from zero for materials gaps, implying that there is no change in the gaps for materials after 2014. The coefficient on the interaction term is negative for the capital gap, which is not consistent with the expectations on the effect of the policy. The evidence, hence, suggests that the change in the labor gaps is attributable to the harmonization of labor contracts. Table 1.8 presents the results.

Figure 1.3: Labor, Materials, and Capital Gaps



Gaps are reported as an index with 1996 as the base year. The figure plots the coefficients from the firm-fixed-effects regression of the absolute value of the gaps on yearly indicator variables. Standard errors are clustered at the firm level. The vertical gray bars mark recession periods dated by OECD.

Table 1.8: Revenue Production Function

	Labor Gap		Material Gap		Capital Gap	
	(1)	(2)	(3)	(4)	(5)	(6)
share × policy	5.067***	4.770***	0.004	0.004	-0.495***	-0.478***
	(1.008)	(1.003)	(0.004)	(0.004)	(0.029)	(0.029)
Ind. Growth Rate		53.127***		0.054***		-0.182*
		(3.563)		(0.016)		(0.105)
R^2	0.003	0.004	0.001	0.001	0.005	0.005
Obs.	588028	568515	588028	568515	588028	568515
Nr.Clust.	64322	64273	64322	64273	64322	64273

Clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include firm and year fixed effects. Columns (1)-(2) report results for the labor gap. Columns (3)-(4) report results for the material gap. Columns (5)-(6) report results for the capital gap.

1.5.4 Temporary Exemption

Although the policy had national coverage, some industries of the economy were temporarily exempted from increased notice period for the blue-collar workers until December 2017. Given that the exemption is within the study period, in this section we perform the analysis ignoring those sectors. In identifying the exempted sectors we manually match the description of the sectors with their corresponding NACE codes. However, such descriptions as large retail stores (JC n.311) cannot be matched two one particular sector. Therefore, we (i) leave it in the analysis, (ii) ignore the whole trade sector. The results are shown in Table 1.9. Columns (1)-(2) show the results with the trade sector, while columns (3)-(4) without. The baseline results hold. Columns (5)-(6) show the results for the temporarily exempted sectors. For these firms, we do not observe any difference in the gaps between blue- and white-collar intensive firms after the policy implementation.

1.5.5 Construction Industry

In this section, we perform an experiment in which the evolution of the gap for construction industry is compared to the rest of the Belgian economy. The construction industry was allowed to have shorter notice periods for their blue-collar workers permanently. Given this, we believe it to serve a good counterfactual in identifying the changes in the gap and relating it solely to harmonization of the labor contracts in Belgium.[31]

[31] Please see the evolution of the gap for construction and the rest of the industries in Figure 1.A.2 in the Appendix. Prior to the policy the two gaps had similar evolution.

Table 1.9: Temporary exemption

	with trade		without trade		exempted	
	(1)	(2)	(3)	(4)	(5)	(6)
share × policy	1.217***	1.128***	2.528***	2.432***	3.659	3.206
	(0.285)	(0.283)	(0.375)	(0.371)	(3.877)	(3.857)
Ind. Growth Rate		9.991***		10.657***		8.684***
		(0.497)		(0.574)		(2.939)
R^2	0.029	0.030	0.027	0.029	0.040	0.042
Obs.	584359	565237	354236	343286	7211	6940
Nr.Clust.	63266	63229	38943	38915	681	681

Clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include firm and year fixed effects. Columns (1)-(2) report results ignoring narrowly defined industries that got a temporary exemption from the policy leaving the trade sector in the sample. Columns (3)-(4) report results ignoring narrowly defined industries that got a temporary exemption from the policy and ignoring the trade sector. Columns (5)-(6) report results for the temporarily exempted sectors.

Table 1.10 shows the results of the model in eq. (1.10). Contrary to the results that we got for the rest of the economy and to the anticipated consequences of the policy, we find the coefficient of interest to be insignificant. The policy change seemed to have no effect on the gaps in the construction industry, which is consistent with the coverage of the policy. This hints to the fact that changes that we observed in the previous sections can be associated with the policy change.

Table 1.10: Construction Sector

	Full		Restr.	
	(1)	(2)	(3)	(4)
share × policy	-0.962	-0.847	-1.041	-0.936
	(0.615)	(0.612)	(0.830)	(0.825)
Ind. Growth Rate		13.693***		3.073**
		(1.595)		(1.515)
R^2	0.023	0.024	0.019	0.017
Obs.	319446	312324	101028	97489
Nr.Clust.	22914	22914	12174	12170

Clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include firm and year fixed effects. Columns (1)-(2) report results for the full sample. Columns (3)-(4) report results for the restricted sample.

1.5.6 Voluntary Worker Turnover

In all countries, some sectors of the economy are characterized by higher job flows (Foster et al., 2006). Managers in industries with high voluntary worker turnover rates should have more freedom in adjusting their labor input without firing them. Therefore, if we believe the change in the labor gaps to be driven by the change in labor adjustment costs, we predict the change to be larger for industries with a lower voluntary worker turnover rate. Thereby we split the sample into two groups: industries with worker turnover above the median and below. Moreover, this sample split should not have any systematically different effect on freely adjustable input gaps.

To this end, we will use data on the inflow and outflow of workers reported in the annual accounts. The data at hand do not track the reasons behind the separations. The outflow of workers includes all workers that quit due to retirement, firing, unemployment with company supplement, and other reasons, including the number of people who continue to work at the company independently. Therefore, we will proxy the voluntary worker turnover by excess worker turnover (or churning flow rate). This is worker turnover that is not needed to compensate for a given job turnover, i.e. worker turnover less job turnover. Job turnover rate is the minimum requirement of turnover needed, because growing firms need more workers, while shrinking firms require fewer workers. Anything that exceeds the job turnover rate is "excessive" (Ilmakunnas and Maliranta, 2005). The basic idea is that, assuming that from the perspective of firms, given high firing costs, both measured by monetary costs and some potential disruption in the production process, they are reluctant to adjust the labor force without any serious reasons. Hence, excess worker turnover at least partly reflects voluntary employee turnover.

Worker flows are calculated following Burgess et al. (2000) on NACE Rev.2 four-digit industry level:

$$WF_{st} = WIF_{st} + WOF_{st},$$

where WF_{st} is worker flow rate (worker turnover rate), WIF_{st} is worker inflow rate (hiring rate) and WOF_{st} is worker outflow rate (separation rate) in industry s at time t. Hiring and separation rates are:

$$\begin{aligned} WIF_{st} &= \frac{\sum_i \Delta H_{it}}{\sum_i (E_{it} + E_{it-1})/2}, \\ WOF_{st} &= \frac{\sum_i |\Delta F_{it}|}{\sum_i (E_{it} + E_{it-1})/2}, \end{aligned}$$

where E_{it} is employment of firm i at time t, E_{it-1} is employment of firm i at time $t-1$, H_{it}

is inflow of workers (number of workers who have been registered in the general staff register during the financial year) and F_{it} is outflow of workers (number of workers who ended their contract during the financial year).

Job flows are calculated using Davis and Haltiwanger (1999) on NACE Rev.2 four-digit industry level:

$$JR_{st} = JC_{st} + JD_{st},$$

where JR_{st} is job reallocation rate (job turnover rate), JC_{st} is job creation rate and JD_{st} is job destruction rate in industry s at time t. Job creation and job destruction rates are:

$$\begin{aligned} JC_{st} &= \frac{\sum_i \Delta E_{it}^{+}}{\sum_i (E_{it} + E_{it-1})/2}, \\ JD_{st} &= \frac{\sum_i |\Delta E_{it}^{-}|}{\sum_i (E_{it} + E_{it-1})/2}, \end{aligned}$$

where ΔE_{it}^{+} is positive change of employment, $|\Delta E_{it}^{-}|$ is absolute value of negative change of employment.

Finally, we calculate excess worker turnover rate as the difference between worker and job turnover rates:

$$CF_{st} = WF_{st} - JR_{st}. \tag{1.11}$$

Once we calculate the excess worker turnover rate, we split the sample into two subsamples. One with industries whose excess worker turnover rate is above the median excess worker turnover rate, and the other with below the median.

As it was anticipated, we find that increase in gaps for blue-collar worker intensive firms is larger for industries below the median voluntary turnover (in columns (1)-(2)), whilst the results for materials do not show any systematic differences (Table 1.11).

1.5.7 Markups

In light of the existing literature on rising super-star firms, Abraham and Bormans (2020) show that manufacturing and wholesale and retail industries in Belgium have become increasingly concentrated. With imperfect competition, the estimated gap involves the additional markup term. As illustrated in Figure 1.A.3, for firms with negative gaps, the analysis in absolute values is ambiguous in the presence of markups. For instance, with the negative gap that becomes more negative with the increase in adjustment costs (movement from A to B), the absolute value of the

Table 1.11: Based on Labor Turnover Rate

	Labor gap				Material gap			
	Above		Below		Above		Below	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
share × policy	0.580	0.019	6.940***	6.856***	-0.042***	-0.042***	0.024***	0.024***
	(1.102)	(1.084)	(1.816)	(1.799)	(0.007)	(0.007)	(0.007)	(0.007)
Ind. Growth Rate		34.635***		57.555***		0.055*		0.062***
		(5.180)		(5.354)		(0.032)		(0.020)
R^2	0.003	0.003	0.007	0.008	0.003	0.002	0.001	0.001
Obs.	168544	162477	232267	223697	168544	162477	232267	223697
Nr.Clust.	18336	18336	20142	20142	18336	18336	20142	20142

Clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include firm and year fixed effects. Columns (1)-(2) and (5)-(6) report results for industries with turnover above the median for the labor and material gaps, respectively. Columns (3)-(4) and (7)-(8) report for industries with turnover below the median for the labor and material gaps, respectively.

gap increases, while from the perfect competition point of view the economic efficiency improves because the price-wage gap decreases. Contrary, with movement from B to C, in which, similarly, the negative gap becomes more negative, economic efficiency declines. Hence, to avoid this ambiguity, we restrict the analysis to firms with positive gaps only. These are the only observations for which for sure an increase (decrease) in gaps results in a decrease (increase) in economic efficiency. We re-run the model of eq. (1.10) for the sub-sample of firms with positive gaps and present the results in Table 1.12. We still observe an increase in the labor gap for blue-collar intensive firms compared to white-collar intensive firms. The difference is more pronounced compared to the baseline results. The results for the materials gap are larger, but still statistically not significant. Overall, the evidence is in favor of the fact that harmonization of labor contracts introduced significant costs to blue-collar intensive firms.

Table 1.12: Revenue Production Function: Only Positive Gaps

	Labor Gap		Material Gap	
	(1)	(2)	(3)	(4)
share × policy	11.780***	11.079***	0.005	0.004
	(1.703)	(1.690)	(0.009)	(0.009)
Ind. Growth Rate		84.071***		0.210***
		(5.458)		(0.033)
R^2	0.008	0.009	0.007	0.007
Obs.	354525	344010	260704	252757
Nr.Clust.	50513	50279	41070	40893

Clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include firm and year fixed effects. Columns (1)-(2) report results for the labor gap. Columns (3)-(4) report results for the material gap.

1.6 Conclusion

To summarize, this paper used the value of marginal product and input price gap methodology proposed by Petrin and Sivadasan (2013) to examine overall allocative inefficiency in Belgium for the 1996-2017 period. Contrary to most of the literature in the field, the paper focused on labor input and highlighted the importance of labor market regulations in driving the dynamics of aggregate productivity. We also focused on the recent labor reform introduced to harmonize labor contracts for blue- and white-collar workers, which increased the firing costs of blue-collar workers, primarily through the increase in notice periods. We found sizable gaps for labor input even prior to the increase in costs of dismissing employees. The average gap for the sampling period is estimated to be 31 thousand euro per year, which is slightly higher than half of the average yearly wage in Belgium. Moreover, we found statistically significant changes in the within-firm absolute gap between the marginal product of labor and the wage after the increase in job security. In line with the policy change and its implication, we have documented that firms with a high share of blue-collar workers witnessed an increase in their labor gaps relative to firms with a high share of white-collar workers. The findings suggest that the Belgian labor reform did affect the allocative efficiency of the labor input. This finding is potentially important because it confirms that an exogenous increase in adjustment costs reduces efficiency. Naturally, it is hard to differentiate the effect of this policy from other shocks in the economy. Therefore, we perform several placebo tests that allow us to attribute the changes we observe in the baseline estimation to the harmonization of the labor contracts. In the spirit of difference-in-difference analysis, we confirmed our results by comparing labor input gaps with freely adjustable input (material) gaps. The idea is that "control" input gaps should not be affected by changes to adjustment costs for labor. Indeed, we found a large and statistically significant difference in the labor gaps for blue-collar intensive firms after the policy implementation, while we did not observe any economically and statistically significant difference for material gaps. These results verify the importance of policy adjustments in influencing efficiency.

Moreover, in the spirit of the placebo test, we performed the same analysis on the construction industry. Even though the harmonization of labor contracts covered the whole Belgian economy, due to the shortage of employees and in order to maintain the social protection of the workers, the construction industry was permanently exempted from the policy change. Therefore, it served as a good "control" group. We performed the same analysis on firms in the construction industry and found no statistically significant difference in the labor gaps post-reform period. The evidence, thus, confirms that the increase in the difference of labor gap of blue-collar intensive firms is attributable to the harmonization of labor contracts, i.e. the increase in firing costs for blue-collar workers.

Worker turnover is part of the process of the reallocation of labor input happens and contributing to aggregate growth and productivity. Firms with a high turnover rate should have more freedom in adjusting their employment without bearing the high costs of firing. So, we studied the industries based on voluntary worker turnover rate. We found that the gaps for blue-collar intensive firms in industries with low voluntary worker turnover rates are higher than for industries with high voluntary turnover rates. The baseline results held, implying that at least some of the changes are attributable to the policy change.

Though the results support the hypothesis that raising adjustment costs for labor raises the inefficiency, they should be interpreted with caution until some further evidence accumulates. Moreover, there are some potential limitations of the estimation procedure that we implement that arise from the unavailability of firm-level prices in estimating the production function, which biases the input elasticities. Moreover, in the presence of monopsony power, the assumption that the marginal cost is equal to the average wage is violated, which will result in the overestimation of the labor gaps. Finally, the difference-in-difference estimates could also be potentially biased due to the presence of adjusted fixed costs after the policy change. Nevertheless, the study creates additional evidence on the importance of labor market institutions and policies that affect labor adjustment.

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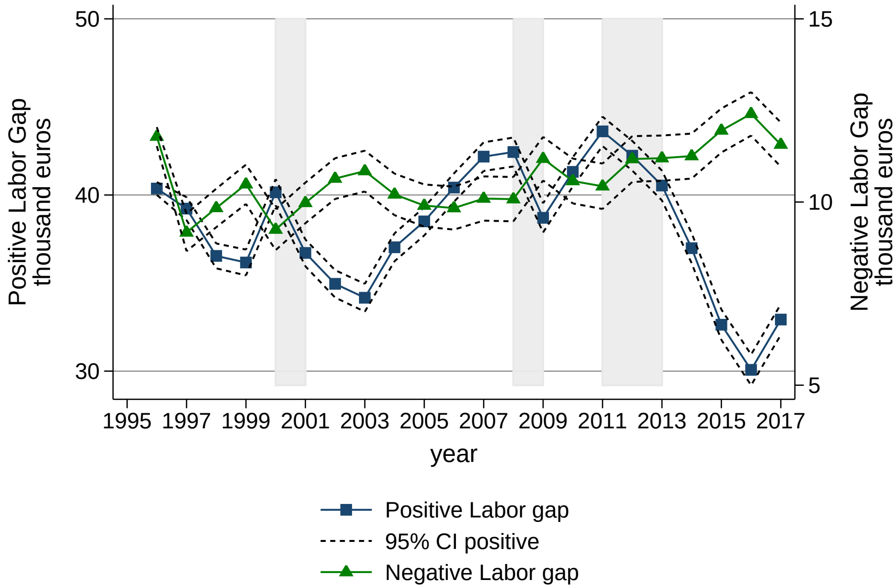
1.A Additional Figures and Tables

Figure 1.A.1: Positive and Negative Gap



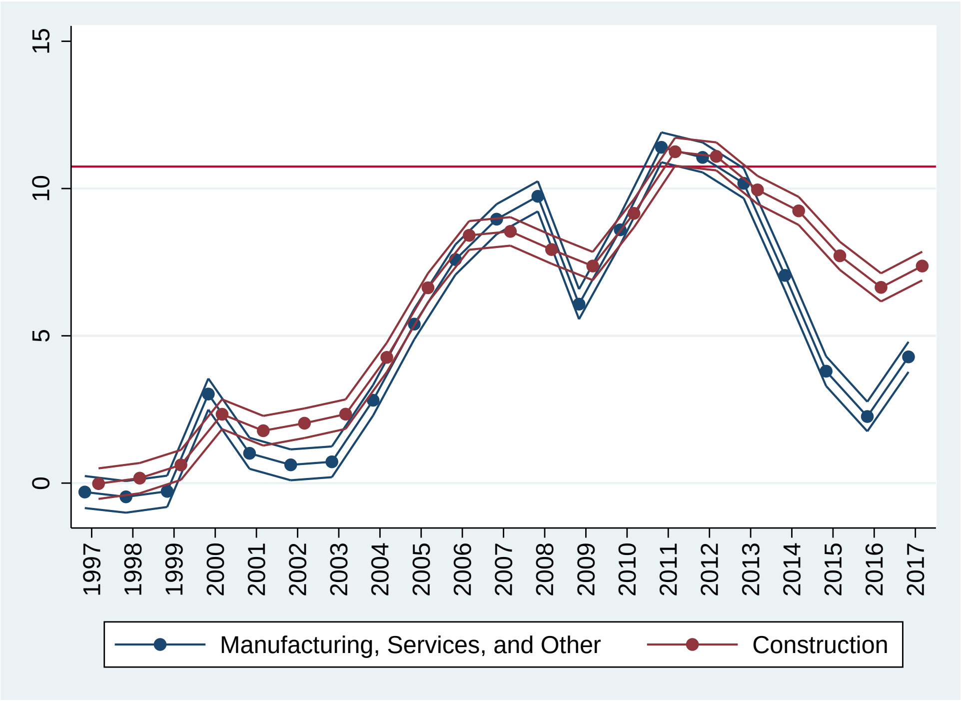
The figure plots the coefficients from the firm-fixed-effects regression of the absolute value of the gaps on yearly indicator variables for samples of only positive and only negative values of the gaps. For consistency and visualization, we use absolute value of the negative gaps. Standard errors are clustered at the firm level. The vertical gray bars mark recession periods dated by OECD.

Table 1.A.1: Revenue Production Function: Robustness

	Restr.				Fixed			
	Labor		Material		Labor		Material	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
share × policy	4.997***	4.615***	0.001	0.002	6.233***	5.837***	0.007	0.007
	(0.768)	(0.760)	(0.002)	(0.002)	(0.828)	(0.820)	(0.004)	(0.004)
Ind. Growth Rate		42.992***		-0.034***		36.109***		0.054***
		(2.695)		(0.008)		(2.913)		(0.016)
R^2	0.005	0.006	0.002	0.002	0.003	0.003	0.001	0.001
Obs.	579717	560576	579717	560576	582012	562871	582012	562871
Nr.Clust.	63254	63216	63254	63216	63334	63294	63334	63294

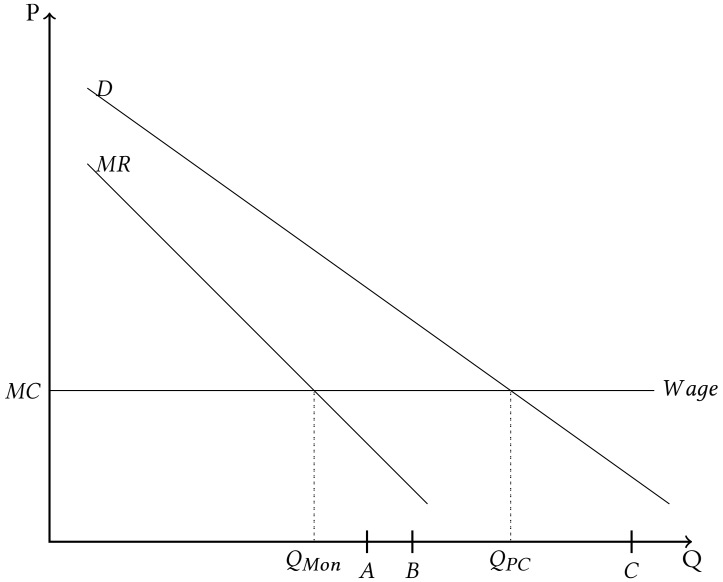
Clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include firm and year fixed effects. Columns (1)-(2) report results for the labor and columns (3)-(4) for the material gaps of restricted sample. Columns (5)-(6) report results for the labor and columns (7)-(8) for the material gaps calculated using production function parameters that are fixed over time.

Figure 1.A.2: Common trend: Construction vs. other industries



The figure plots the coefficients from the firm-fixed-effects regression of the absolute value of the gaps on yearly indicator variables for sample of firms in the construction and the rest of the industries. Standard errors are clustered at the firm level.

Figure 1.A.3: Gaps with Imperfect Competition



Source: Petrin and Sivadasan (2006).

1.B Bias from Pooling the Two Types of Labor Force

In a situation where we have information on both blue- and-white collar workers and their respective wage bills, contrary to eq. (1.5), we would have estimated the following production function:

$$Q_{it} = A_{it} H_{it}^{\beta^H} B_{it}^{\beta^B} K_{it}^{\beta^K}, \tag{1.B.1}$$

where H_{it} and B_{it} are the number of white- and blue-collar workers, respectively. Once the value of marginal product for blue- and white-collar workers are calculated, the value of the absolute gap between the value of marginal product and marginal input price for blue- and white-collar workers are given by:

$$G_{it}^H = |VMP_{it}^H - W_{it}^H|,$$
$$G_{it}^B = |VMP_{it}^B - W_{it}^B|, \tag{1.B.2}$$

where W_{it}^X is the average wage per worker by type. To observe the total gap by firm, we would calculate the following:

$$\hat{G_{it}} = G_{it}^H \times \frac{H_{it}}{L_{it}} + G_{it}^B \times \frac{B_{it}}{L_{it}}. \tag{1.B.3}$$

After opening up the terms and rearranging them, we get:

$$\hat{G_{it}} = (\beta^H + \beta^B) \times \frac{Q_{it}}{L_{it}} \times P_{it} - W_{it}^H \times \frac{H_{it}}{L_{it}} - W_{it}^B \times \frac{B_{it}}{L_{it}}. \tag{1.B.4}$$

So, the average gap depends on the relative white- and blue-collar worker output elasticities, their respective wages, and employment shares.

Contrary, what we estimate is the pooled effect, from equation eq. (1.9):

$$G_{it}^l = \beta^l \times \frac{Q_{it}}{L_{it}} \times P_{it} - W_{it}^l, \tag{1.B.4*}$$

where $W_{it}^l = \frac{W_{it}^H \times H_{it} + W_{it}^B \times B_{it}}{L_{it}}$. Comparing eqs. (1.B.4) and (1.B.4*), we expect the possible bias to originate from (i) the estimates of output elasticities; and, (ii) the shares of blue- and white-collar workers in the production function and their wages.

The aggregation of the two types in the production function distorts the estimates of output elasticities. More detailed classification of labor results in more accurate estimates (Dougherty, 1972). Nevertheless, as long as the difference between β^l and $(\beta^H + \beta^B)$ stays the same after the policy implementation, it is not going to affect the estimate that we attribute to the policy change. To this end, we perform a test on the difference between the two before and after the policy and find that, indeed, the difference between the two estimates are not statistically different from each other. Therefore, this does not affect our estimates.

Another potential source of bias is the share of blue-collar (white-collar) workers. The policy might alter the hiring behavior of the firms, hence, lead to a change in the share of blue-collar (white-collar) workers in the production process. Therefore, depending on the shift between blue- and white-collar workers and the difference in values of their gaps, the pooling of the two types of workers can lead to over or underestimation of the impact of the policy on the average gap. To identify the direction of the bias, first, we speculate about the average gap for each type of labor force. To this end, we perform firm-fixed effect regression on sub-samples of blue-collar intensive (share of blue-collar workers no less than 75%) and white-collar intensive (share of blue-collar workers no more than 25%) firms:

$$RG^{l}_{it} = \alpha_0 + \alpha_1 growthrate + \eta_i + \mu_t + \epsilon_{it},$$

where the constant, α_0, captures the value of the average gap for the sub-sample. Table 1.B.1 presents the results. We see that the average gap for white-collar intensive firms is larger. That being the case, we assume that the gap for the blue-collar worker is lower compared to the gap for white-collar workers. Hence, keeping the gap for both types of workers constant, increasing the share of blue-collar workers, will decrease the average gap.

Table 1.B.1: Average gap

	(1) Blue-collar	(2) White-collar
Ind. Growth Rate	15.635***	16.193***
	(0.618)	(0.669)
Constant	25.672***	37.288***
	(0.144)	(0.276)
R^2	0.010	0.021
Obs.	1189854	760322
Nr.Clust.	161930	57216

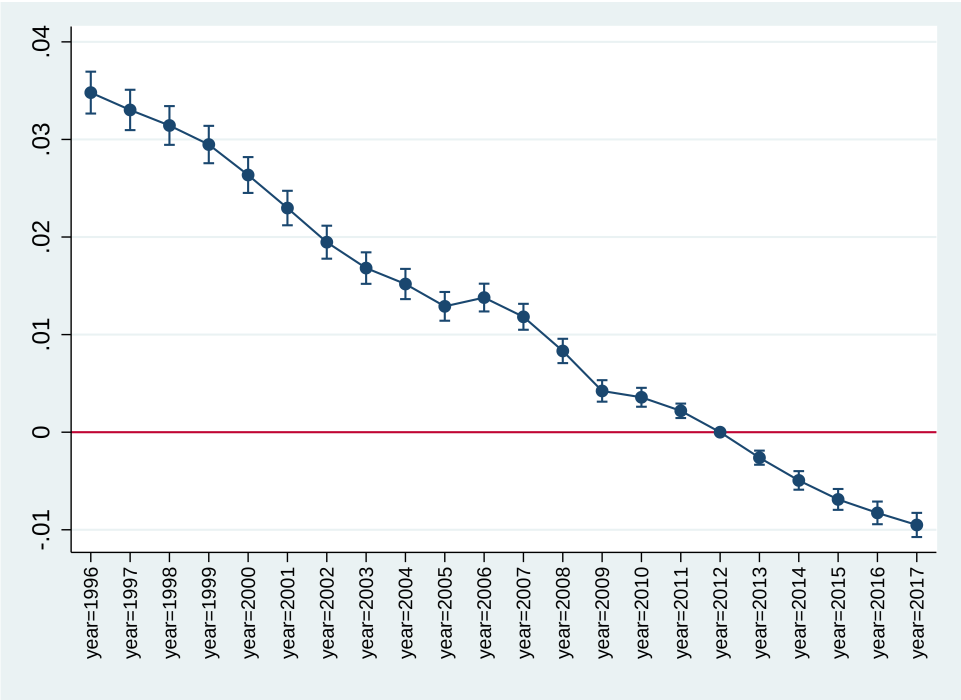
Standard errors in parentheses

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

Furthermore, we study the change in the share of blue-collar workers after the policy implementation. First, we look at the evolution of the share of blue-collar workers. Throughout the sampling period, from Figure 1.B.1, we observe a clear declining trend in the average share of blue-collar workers. Besides, we estimate the following model, which is the same as eq. (1.10) except that the dependent variable here is the share of blue-collar workers of firm i at time t:

$$blue_{it} = \alpha_b share_i + \alpha_p policy_t + \gamma \ share_i \times policy_t + \eta_i + \mu_t + \epsilon_{it}. \tag{1.B.5}$$

Figure 1.B.1: Evolution of the share of blue-collar labor



The figure plots the coefficients (and standard errors) from the firm-fixed-effects regression of the share of blue-collar workers on yearly indicator variables. The coefficients represent the relative change in the average share of blue-collar workers compared to the share in 2012. Standard errors are clustered at the firm level.

Table 1.B.2 presents the results. Positive and significant γ coefficient (in combination with the declining trend) means that, on average, the share of blue-collar workers after the policy decreased less for firms with a high share of blue-collar workers relative to firms with a low share of blue-collar workers (*ceteris paribus*). Given that the gap after the policy increased for firms with

a high share of blue-collar workers relative to firms with a low share of blue-collar workers, the results that we obtain are the lower bound of the policy effect.

To sum up, although pooling of the two types of labor force may generate some bias, our results are not affected considerably.

Table 1.B.2: Share of blue-collar workers

	(1)	(2)
share × policy	0.012***	0.010***
	(0.001)	(0.001)
Ind. Growth Rate		-0.006***
		(0.002)
Constant	0.454***	0.452***
	(0.001)	(0.001)
R^2	0.007	0.007
Obs.	1634933	1597457
Nr.Clust.	112655	112655

Standard errors in parentheses

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

1.C Robustness Checks

1.C.1 Transmitted Component

A common concern in the productivity literature is the interpretation of the error term. The ongoing argument is about whether the estimated error is fully a productivity term, or whether it includes a measurement error. In the baseline estimation, we utilized the full error, but this subsection focuses on the estimation results from the predictable component of the error term.

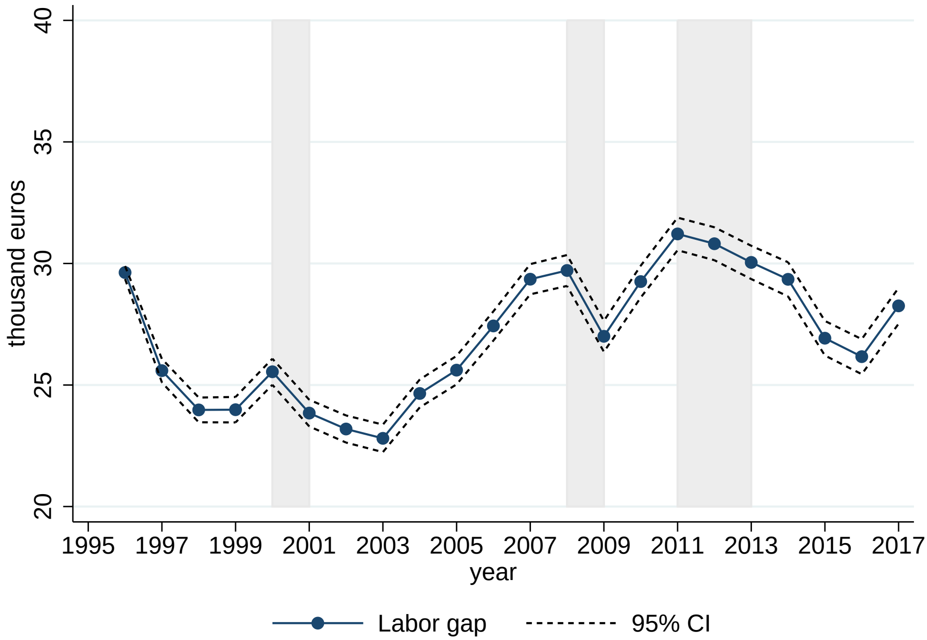
In order to eliminate the unpredicted part of the productivity term, we run the first stage regression of value-added on variable inputs and a polynomial in capital and proxy variable (materials). Then, we linearly predict the level of the value-added ($\hat{y_{it}}$), which yields the value-added corrected for the unpredictable part of the error term. Finally, to calculate productivity we subtract the coefficient estimates multiplied by their corresponding input levels from this newly calculated predicted value-added. Due to the poor records on the materials and the nature of calculating the transmitted component, we can use only a sub-sample of firms that report their material costs.

Table 1.C.1.1: Restricted sample: Absolute Gap, by industry

NACE	Description	Mean	CV	Pos %	Obs
1-3	Agriculture, forestry, and fishing	23.39	0.98	64.13	10851
5-9	Mining and Quarrying	21.6	0.97	55.83	1166
10-12	Manufacturing Food products; Beverages; Tobacco products	18.95	1.07	62.27	27864
13-15	Manufacturing Textiles; Wearing apparel; Leather and related products	13.53	1.16	38.47	9793
17	Manufacturing Paper and paper products	24.37	1.02	53.99	2884
18	Manufacturing Printing and reproduction of recorded media	16.48	0.95	50.84	11690
19-21	Manufacturing Coke and refined petroleum products; Chemicals and chemical products; Basic pharmaceutical products and preparations	31.06	0.96	72.92	7968
22	Manufacturing Rubber and plastic products	17.42	1.01	52.76	6503
23	Manufacturing Other non-metallic mineral products	19.83	0.99	75.31	9627
24	Manufacturing Basic metals	31.3	1.09	59.99	2127
25	Manufacturing Fabricated metal products, except machinery and equipment	16.24	1.02	63.32	24918
26	Manufacturing Computer, electronic and optical products	22.87	0.92	40.2	3037
27	Manufacturing Electrical equipment	17.75	0.99	66.69	3335
28	Manufacturing Machinery and equipment	18.11	1.04	63.64	8767
29	Manufacturing Motor vehicles, trailers and semi-trailers	18.41	1.13	58.28	2054
30	Manufacturing Other transport equipment	24	1.01	44.8	779
31-32	Manufacturing Furniture and other manufacturing	18.08	1.08	73.65	11091
33	Manufacturing Repair and installation of machinery and equipment	20.55	0.99	68.57	3083
36-39	Water supply, sewerage, waste management and remediation activities	40.02	0.83	79.46	7020
45	Wholesale and retail trade; repair of motor vehicles and motorcycles	22.19	0.9	79.62	54846
46	Wholesale trade, except motor vehicles and motorcycles	37.72	0.85	77.22	158852
47	Retail trade, except motor vehicles and motorcycles	16.7	0.97	69.52	131507
49	Land transport and via pipelines	14.96	1.07	60.25	40260
50-53	Water and air transport; Warehousing and support activities for transportation; Postal and courier activities	35.64	0.9	69.19	21035
55-56	Accommodation; Food and beverage services activities	12.92	1.05	61.29	77918
58	Publishing activities	26.31	0.86	71.17	4333
59-60	Motion picture, video and television, ...; Programming and broadcasting activities	35.47	0.88	76.56	5004
61	Telecommunications	48.26	0.85	54.26	2385
62-63	Computer programming, consultancy and related activities; Information service activities	27.67	0.86	66.84	25812
64-66	Financial and Insurance activities	45.89	0.7	84.28	46354
68	Real estate activities	51.13	0.81	78.22	29140
69-75	Professional, scientific, and technical activities	31.4	0.85	74.14	90980
77	Rental and leasing activities	49.96	0.83	81.37	8147
78	Employment activities	18.79	1.13	42.05	4264
79	Travel agency, tour operator reservation service and related activities	26.33	0.83	66.41	5237
80-82	Security and investigation activities; Services to buildings and landscape activities; Office administrative, office support and other business support activities	20.8	1	63.79	31058
	Total	26.63	1.02	70.32	891689

Average absolute labor gap was calculated by $\overline{RG_s^l} = \frac{\sum_{i \in s} RG_{it}^l}{N_s}$, reported in thousand euros. Coefficient of variation is $CV_s = \frac{sd_s}{\overline{RG_s^l}}$. Percent of positive labor gap is defined as $Pos = \frac{N_s^+}{N_s} \times 100$.

Figure 1.C.1.1: Transmitted component: 95% Confidence Interval for Change in Gap



Gap estimates are in thousand euros. Standard errors are clustered at the firm level. The vertical gray bars mark recession periods dated by OECD.

1.C.2 Balanced Panel

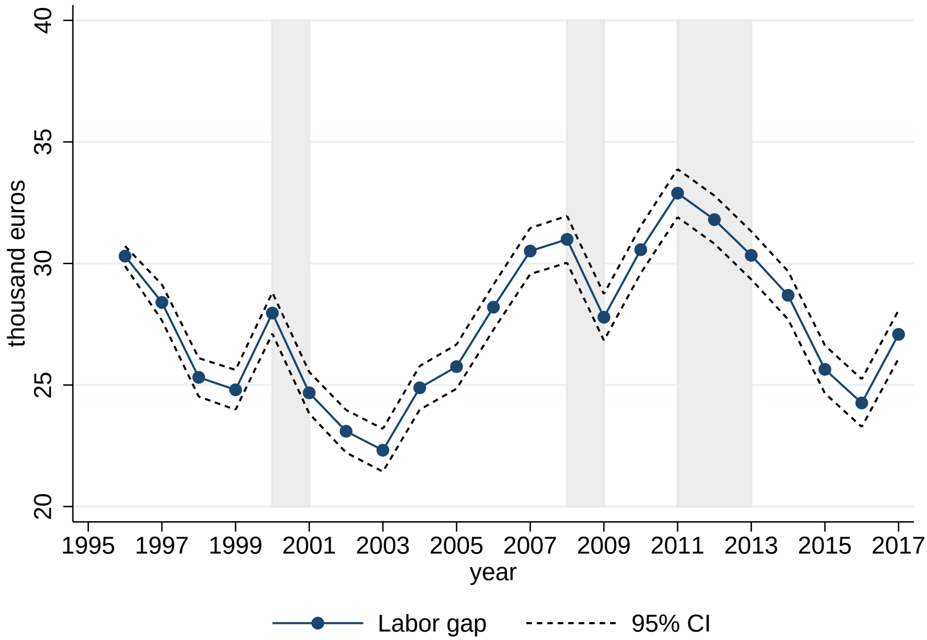
To investigate if compositional differences between new entrants in the post-policy and exiters in the pre-policy period impact the results, we perform the same analysis on the sample of firms that operate along the whole sampling period, namely firms that operate 22 years. We have 23,553 such firms.

Table 1.C.2.1: Balanced panel: Absolute Gap, by industry

NACE	Description	Mean	CV	Pos %	Obs
1-3	Agriculture, forestry, and fishing	26.57	1.37	65.04	7502
5-9	Mining and Quarrying	27.71	1.38	57.51	1012
10-12	Manufacturing Food products; Beverages; Tobacco products	23.53	1.39	69.74	20548
13-15	Manufacturing Textiles; Wearing apparel; Leather and related products	14.37	1.58	47.37	7260
17	Manufacturing Paper and paper products	24.59	1.17	66.56	2222
18	Manufacturing Printing and reproduction of recorded media	17.4	1.21	64.8	7722
19-21	Manufacturing Coke and refined petroleum products; Chemicals and chemical products; Basic pharmaceutical products and preparations	31.97	1.25	77.56	5566
22	Manufacturing Rubber and plastic products	19.71	1.24	61.13	5346
23	Manufacturing Other non-metallic mineral products	23.04	1.26	80.93	7920
24	Manufacturing Basic metals	34.76	1.3	61.27	1562
25	Manufacturing Fabricated metal products, except machinery and equipment	18.14	1.42	71.03	22418
26	Manufacturing Computer, electronic and optical products	21.1	1.21	44.57	1914
27	Manufacturing Electrical equipment	19.8	1.36	72.9	2970
28	Manufacturing Machinery and equipment	18	1.41	69.74	7832
29	Manufacturing Motor vehicles, trailers and semi-trailers	18.38	1.2	59.63	1298
30	Manufacturing Other transport equipment	21.4	1.03	59.76	594
31-32	Manufacturing Furniture and other manufacturing	19.1	1.54	81.48	10208
33	Manufacturing Repair and installation of machinery and equipment	18.63	1.35	76.86	2178
36-39	Water supply, sewerage, waste management and remediation activities	45.25	1.13	82.95	4136
45	Wholesale and retail trade; repair of motor vehicles and motorcycles	24.1	1.25	87.18	41756
46	Wholesale trade, except motor vehicles and motorcycles	37.44	1.2	87.51	104390
47	Retail trade, except motor vehicles and motorcycles	21	1.35	78.26	86614
49	Land transport and via pipelines	13.13	1.56	68.99	28930
50-53	Water and air transport; Warehousing and support activities for transportation; Postal and courier activities	39.25	1.33	67.99	9196
55-56	Accommodation; Food and beverage services activities	13.32	1.49	67.82	27830
58	Publishing activities	35.02	1.2	76.94	1804
59-60	Motion picture, video and television, ...; Programming and broadcasting activities	35.62	1.07	79.46	1232
61	Telecommunications	55.1	1.09	60.29	418
62-63	Computer programming, consultancy and related activities; Information service activities	25.07	1.25	81.85	7458
64-66	Financial and Insurance activities	50.38	0.98	92.13	19272
68	Real estate activities	65.01	0.98	81.69	11088
69-75	Professional, scientific, and technical activities	30.85	1.27	82.84	35486
77	Rental and leasing activities	58.38	1.09	86.97	4114
78	Employment activities	20.81	1.66	41.71	1254
79	Travel agency, tour operator reservation service and related activities	29.33	1.04	61.42	3388
80-82	Security and investigation activities; Services to buildings and landscape activities; Office administrative, office support and other business support activities	24.43	1.51	69.94	13728
	Total	27.56	1.37	78.15	518166

Average absolute labor gap was calculated by $\overline{RG_s^l} = \frac{\sum_{i\in s} RG_{it}^l}{N_s}$, reported in thousand euros. Coefficient of variation is $CV_s = \frac{sd_s}{\overline{RG_s^l}}$. Percent of positive labor gap is defined as $Pos = \frac{N_s^+}{N_s} \times 100$.

Figure 1.C.2.1: Balanced Panel: 95% Confidence Interval for Change in Gap



Gap estimates are in thousand euros. Standard errors are clustered at the firm level. The vertical gray bars mark recession periods dated by OECD.

1.C.3 Translog Production Function Specification

In this section, we use the translog production function specification, which is a generalization of the Cobb-Douglas production function. It includes interaction terms between inputs to make sure that inputs are not separable. The translog analogue of (eq. (1.6)) is given by:

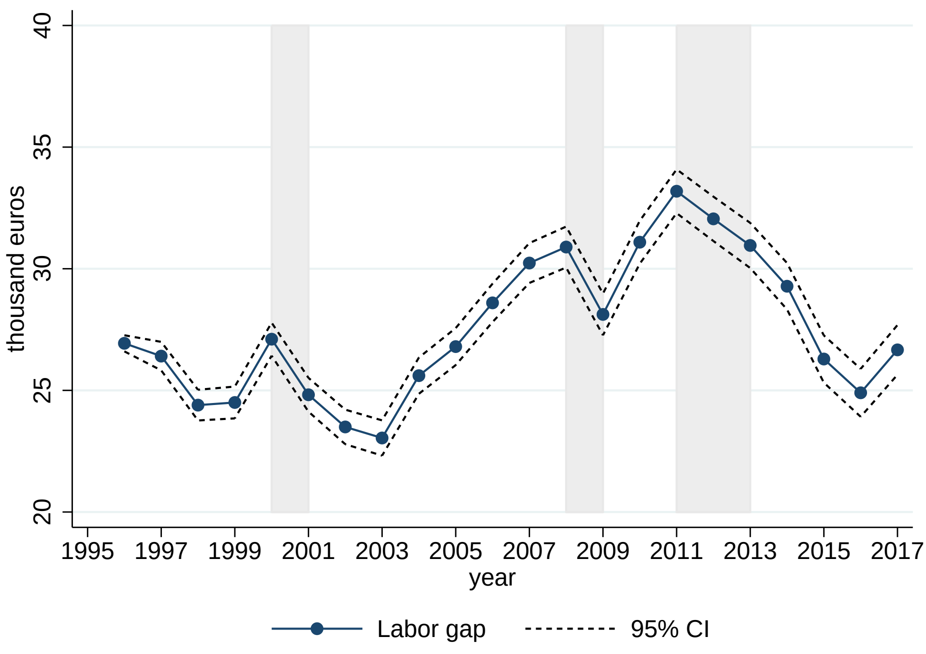
$$y_{it} = \beta_t^l l_{it} + \beta_t^k k_{it} + \beta_t^{ll} l_{it}^2 + \beta_t^{kk} k_t^2 + \beta_t^{lk} l_{it} k_{it} + \omega_{it} + \epsilon_{it}. \tag{1.C.3.1}$$

The functional form of this production function allows the elasticities to vary by firms:

$$\begin{aligned} \hat{\theta}_{it}^l &= \hat{\beta}_t^l + 2\hat{\beta}_t^{ll} l_{it} + \hat{\beta}_t^{lk} k_{it} \qquad (1.C.3.2) \\ \hat{\theta}_{it}^k &= \hat{\beta}_t^k + 2\hat{\beta}_t^{kk} k_{it} + \hat{\beta}_t^{lk} l_{it}. \end{aligned}$$

Once firm-specific output elasticities are estimated, the same procedure follows.

Figure 1.C.3.1: Translog: 95% Confidence Interval for Change in Gap



Gap estimates are in thousand euros. Standard errors are clustered at the firm level. The vertical gray bars mark recession periods dated by OECD.

Table 1.C.3.1: Translog: Absolute Gap, by industry

NACE	Description	Mean	CV	Pos %	Obs
1-3	Agriculture, forestry, and fishing	25.28	1.22	62.82	10775
5-9	Mining and Quarrying	30.46	1.11	55.29	1143
10-12	Manufacturing Food products; Beverages; Tobacco products	20.02	1.41	59.52	27427
13-15	Manufacturing Textiles; Wearing apparel; Leather and related products	14.51	1.51	38.76	9589
17	Manufacturing Paper and paper products	22.81	1.21	50.67	2593
18	Manufacturing Printing and reproduction of recorded media	16.64	1.25	50.34	11567
19-21	Manufacturing Coke and refined petroleum products; Chemicals and chemical products; Basic pharmaceutical products and preparations	30.89	1.23	71.09	7658
22	Manufacturing Rubber and plastic products	18.94	1.22	50.81	6233
23	Manufacturing Other non-metallic mineral products	22.4	1.28	76.14	9523
24	Manufacturing Basic metals	35.73	1.25	52.54	2090
25	Manufacturing Fabricated metal products, except machinery and equipment	16.56	1.45	63.35	24568
26	Manufacturing Computer, electronic and optical products	24.6	1.14	41.14	2987
27	Manufacturing Electrical equipment	20.92	1.28	69.34	3200
28	Manufacturing Machinery and equipment	20.08	1.38	67.59	8590
29	Manufacturing Motor vehicles, trailers and semi-trailers	21.11	1.46	48.77	1989
30	Manufacturing Other transport equipment	24.35	1.11	41.13	671
31-32	Manufacturing Furniture and other manufacturing	19.99	1.45	81.08	10937
33	Manufacturing Repair and installation of machinery and equipment	20.65	1.36	75.94	2843
36-39	Water supply, sewerage, waste management and remediation activities	39.81	1.09	77.51	6791
45	Wholesale and retail trade; repair of motor vehicles and motorcycles	23.29	1.18	85.54	53135
46	Wholesale trade, except motor vehicles and motorcycles	39.94	1.14	83.03	140693
47	Retail trade, except motor vehicles and motorcycles	17.4	1.29	73.4	130780
49	Land transport and via pipelines	12.94	1.56	64.36	39700
50-53	Water and air transport; Warehousing and support activities for transportation; Postal and courier activities	36.23	1.26	70.22	17834
55-56	Accommodation; Food and beverage services activities	12.47	1.31	69.27	77676
58	Publishing activities	33.71	1.18	71.41	3764
59-60	Motion picture, video and television, ...; Programming and broadcasting activities	40.72	1.13	77.27	4176
61	Telecommunications	49.93	1.04	58.08	2204
62-63	Computer programming, consultancy and related activities; Information service activities	30.86	1.18	77.23	22839
64-66	Financial and Insurance activities	51.93	0.94	86.93	39637
68	Real estate activities	40.49	1.13	79.55	26704
69-75	Professional, scientific, and technical activities	34.13	1.19	78.77	85711
77	Rental and leasing activities	42.37	1.13	81.07	7693
78	Employment activities	18.65	1.57	34.62	4264
79	Travel agency, tour operator reservation service and related activities	31.96	1.05	74.14	4930
80-82	Security and investigation activities; Services to buildings and landscape activities; Office administrative, office support and other business support activities	22.87	1.47	70.09	29009
	Total	27.17	1.34	74.09	841923

Average absolute labor gap was calculated by $\overline{RG_s^l} = \frac{\sum_{i\in s} RG_{it}^l}{N_s}$, reported in thousand euros. Coefficient of variation is $CV_s = \frac{sd_s}{\overline{RG_s^l}}$. Percent of positive labor gap is defined as $Pos = \frac{N_s^+}{N_s} \times 100$.

1.C.4 Fixed Elasticities

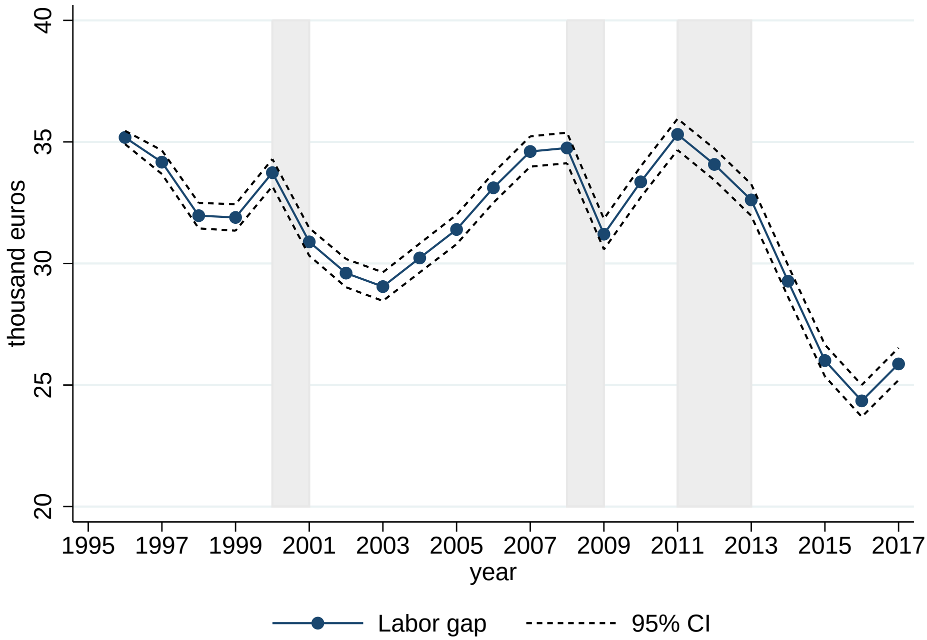
To investigate whether the results are driven by varying elasticities, we perform the same analysis assuming that firms operate under the same production within the NACE 2-digit industry.

Table 1.C.4.1: Fixed elasticities: Absolute Gap, by industry

NACE	Description	Mean	CV	Pos %	Obs
1-3	Agriculture, forestry, and fishing	32.02	1.30	68.11	35789
5-9	Mining and Quarrying	33.61	1.3	61.34	2139
10-12	Manufacturing Food products; Beverages; Tobacco products	20.9	1.45	66.88	61417
13-15	Manufacturing Textiles; Wearing apparel; Leather and related products	16.85	1.63	41.85	21320
17	Manufacturing Paper and paper products	22.36	1.34	49.77	5019
18	Manufacturing Printing and reproduction of recorded media	19.84	1.29	58.26	28907
19-21	Manufacturing Coke and refined petroleum products; Chemicals and chemical products; Basic pharmaceutical products and preparations	37.94	1.2	78.65	11469
22	Manufacturing Rubber and plastic products	22.39	1.38	59.07	11769
23	Manufacturing Other non-metallic mineral products	25.33	1.34	75.09	19449
24	Manufacturing Basic metals	35.61	1.32	60.05	3282
25	Manufacturing Fabricated metal products, except machinery and equipment	22.09	1.43	69.51	63905
26	Manufacturing Computer, electronic and optical products	23.53	1.25	45.5	5378
27	Manufacturing Electrical equipment	20.65	1.45	64.18	6522
28	Manufacturing Machinery and equipment	22.65	1.41	70.84	18053
29	Manufacturing Motor vehicles, trailers and semi-trailers	22.48	1.5	61.23	3183
30	Manufacturing Other transport equipment	21.79	1.28	38.99	1480
31-32	Manufacturing Furniture and other manufacturing	21.81	1.48	78.83	29851
33	Manufacturing Repair and installation of machinery and equipment	25.93	1.35	74.78	8068
36-39	Water supply, sewerage, waste management and remediation activities	44.54	1.16	77.24	12512
45	Wholesale and retail trade; repair of motor vehicles and motorcycles	28.71	1.23	84.54	134828
46	Wholesale trade, except motor vehicles and motorcycles	40.88	1.19	81.84	348637
47	Retail trade, except motor vehicles and motorcycles	23.06	1.34	74.14	404063
49	Land transport and via pipelines	17.19	1.53	66.84	97872
50-53	Water and air transport; Warehousing and support activities for transportation; Postal and courier activities	38.4	1.34	67.74	37332
55-56	Accommodation; Food and beverage services activities	15.56	1.48	65.59	233549
58	Publishing activities	34.82	1.23	73.78	8939
59-60	Motion picture, video and television, ...; Programming and broadcasting activities	45.44	1.17	76.52	10809
61	Telecommunications	44.78	1.2	54.89	3939
62-63	Computer programming, consultancy and related activities; Information service activities	31.54	1.24	78.84	62076
64-66	Financial and Insurance activities	55.92	0.95	89.72	127310
68	Real estate activities	55.61	1.11	75.25	77331
69-75	Professional, scientific, and technical activities	41.61	1.16	82.03	275005
77	Rental and leasing activities	50.49	1.16	80.78	19625
78	Employment activities	21.5	1.6	43.28	8991
79	Travel agency, tour operator reservation service and related activities	31.85	1.09	67.36	13061
80-82	Security and investigation activities; Services to buildings and landscape activities; Office administrative, office support and other business support activities	24.8	1.52	66.7	84672
	Total	31.40	1.34	75.08	2297551

Average absolute labor gap was calculated by $\overline{RG_s^l} = \frac{\sum_{i\in s} RG_{it}^l}{N_s}$, reported in thousand euros. Coefficient of variation is $CV_s = \frac{sd_s}{\overline{RG_s^l}}$. Percent of positive labor gap is defined as $Pos = \frac{N_s^+}{N_s} \times 100$.

Figure 1.C.4.1: Fixed elasticities: 95% Confidence Interval for Change in Gap

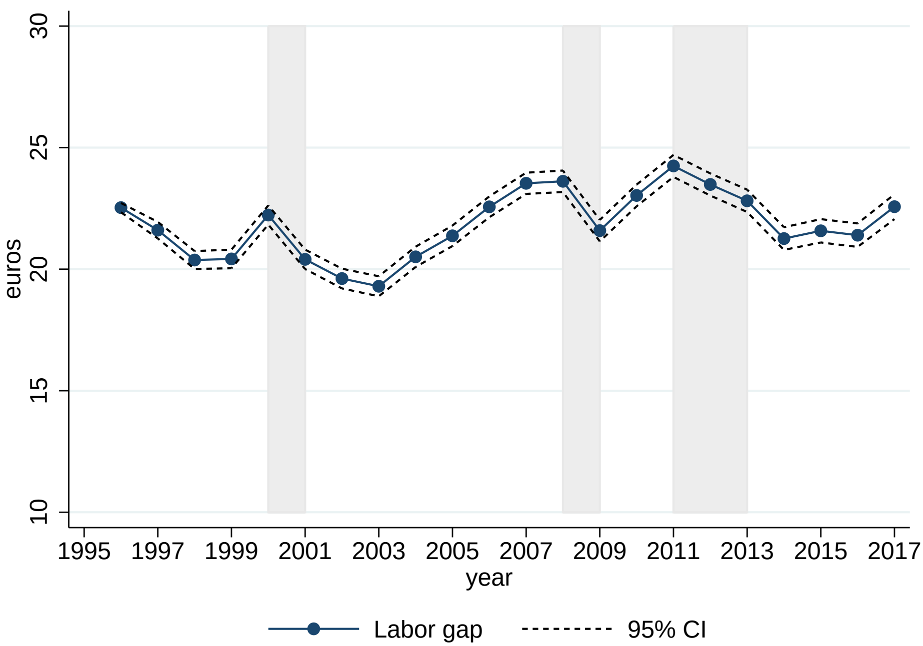


Gap estimates are in thousand euros. Standard errors are clustered at the firm level. The vertical gray bars mark recession periods dated by OECD.

1.C.5 Alternative Employment Measure

One can argue that the number of full-time equivalents (FTE) used for the employment measure does not truly reflect the amount of labor input involved in the production. Firstly, it neglects if the employee is actually active. The FTE measures abstracts from overtime, sick-leave, maternity/paternity leave, or labor hoarding, while the number of hours actually worked is based on active employees and represents the actual number of salaried hours making this a proper proxy measure for the number of workers involved in the production process. Moreover, the number of full-time equivalents may not necessarily reflect the changes that employers may have introduced in response to the new policy, such as changing total hours worked. This section uses effective hours worked as an alternative measure for employment. The value of the gap is in euros per hour worked.

Figure 1.C.5.1: Hours worked: 95% Confidence Interval for Change in Gap



Gap estimates are in euros per hour. Standard errors are clustered at the firm level. The vertical gray bars mark recession periods dated by OECD.

Table 1.C.5.1: Hours worked: Absolute Gap, by industry

NACE	Description	Mean	CV	Pos %	Obs
1-3	Agriculture, forestry, and fishing	22.43	1.42	65.67	35279
5-9	Mining and Quarrying	21.21	1.37	52.79	2112
10-12	Manufacturing Food products; Beverages; Tobacco products	15.62	1.5	67.63	60645
13-15	Manufacturing Textiles; Wearing apparel; Leather and related products	13.01	1.64	45.66	21184
17	Manufacturing Paper and paper products	15.86	1.45	54.44	4982
18	Manufacturing Printing and reproduction of recorded media	13.91	1.4	58.76	28783
19-21	Manufacturing Coke and refined petroleum products; Chemicals and chemical products; Basic pharmaceutical products and preparations	23.35	1.35	73.47	11355
22	Manufacturing Rubber and plastic products	15.59	1.43	58.19	11617
23	Manufacturing Other non-metallic mineral products	19.14	1.34	80.16	19179
24	Manufacturing Basic metals	23.67	1.32	54.58	3234
25	Manufacturing Fabricated metal products, except machinery and equipment	15.89	1.53	69.79	62908
26	Manufacturing Computer, electronic and optical products	15.82	1.32	47.76	5302
27	Manufacturing Electrical equipment	15.65	1.47	69.76	6415
28	Manufacturing Machinery and equipment	15.63	1.5	71.74	17849
29	Manufacturing Motor vehicles, trailers and semi-trailers	16.34	1.54	61.69	3140
30	Manufacturing Other transport equipment	17.66	1.37	56.77	1462
31-32	Manufacturing Furniture and other manufacturing	15.23	1.58	78.07	29598
33	Manufacturing Repair and installation of machinery and equipment	18.59	1.49	73.55	7765
36-39	Water supply, sewerage, waste management and remediation activities	33.23	1.15	82.04	12364
45	Wholesale and retail trade; repair of motor vehicles and motorcycles	18.94	1.36	83.6	133510
46	Wholesale trade, except motor vehicles and motorcycles	27.08	1.29	80.61	347361
47	Retail trade, except motor vehicles and motorcycles	16.15	1.47	73.92	403753
49	Land transport and via pipelines	11.81	1.72	67.79	96110
50-53	Water and air transport; Warehousing and support activities for transportation; Postal and courier activities	26.17	1.43	67.78	36823
55-56	Accommodation; Food and beverage services activities	12.38	1.6	69.02	230223
58	Publishing activities	22.59	1.33	70.55	8954
59-60	Motion picture, video and television, ...; Programming and broadcasting activities	31.89	1.24	77.63	10642
61	Telecommunications	30.61	1.26	54.27	3855
62-63	Computer programming, consultancy and related activities; Information service activities	22.47	1.35	78.13	60801
64-66	Financial and Insurance activities	37.33	1.04	89.23	126497
68	Real estate activities	39.13	1.18	74.27	78177
69-75	Professional, scientific, and technical activities	29.26	1.25	81.03	274183
77	Rental and leasing activities	36.66	1.21	81.31	19620
78	Employment activities	14.83	1.77	43.06	8790
79	Travel agency, tour operator reservation service and related activities	19.58	1.17	65.62	13140
80-82	Security and investigation activities; Services to buildings and landscape activities; Office administrative, office support and other business support activities	18.16	1.59	65.91	82907
	Total	21.85	1.43	75.05	2280519

Average absolute labor gap was calculated by $\overline{RG_s^l} = \frac{\sum_{i\in s} RG_{it}^l}{N_s}$, reported in euros per hour. Coefficient of variation is $CV_s = \frac{sd_s}{\overline{RG_s^l}}$. Percent of positive labor gap is defined as $Pos = \frac{N_s^+}{N_s} \times 100$.

1.C.6 Quality control

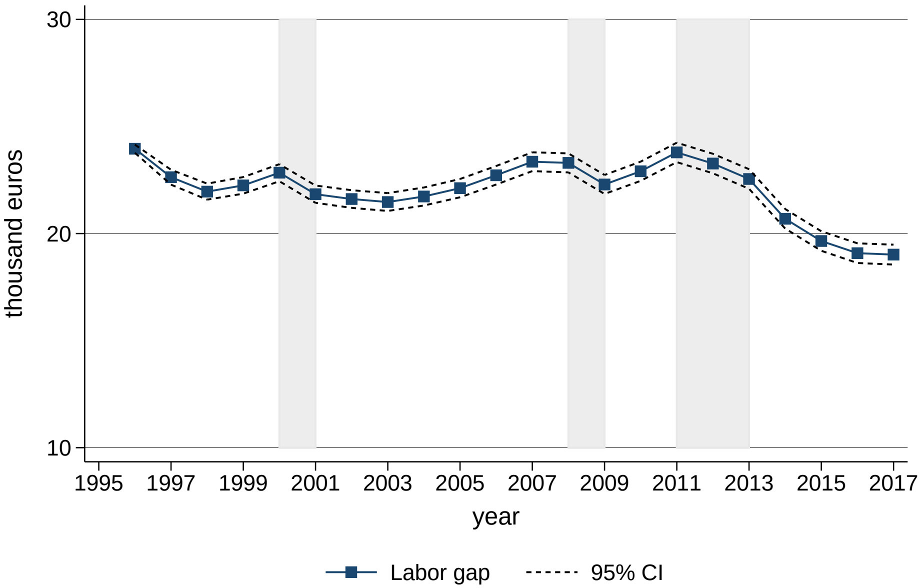
Another concern in using the number of full-time equivalents (FTE) is that it does not capture the quality differences of the labor force. To address the concern, first, we assume that all quality differences among the workers is translated into differences in wages. Then, we use the wage bill as a proxy for labor input in the ACF estimation procedure. Basically, we extend the control function to account for the labor quality differences, i.e. instead of $\omega_{it} = f_t^{-1}(l_{it}, k_{it}, m_{it})$ we use $\omega_{it} = f_t^{-1}(l_{it}, k_{it}, m_{it}, w_{it})$, where w_{it} is the average wage bill.

Table 1.C.6.1: Quality control: Absolute Gap, by industry

NACE	Description	Mean	CV	Pos %	Obs
1-3	Agriculture, forestry, and fishing	23.08	1.23	52.06	35789
5-9	Mining and Quarrying	22.94	1.13	28.85	2139
10-12	Manufacturing Food products; Beverages; Tobacco products	15.29	1.28	38.27	61417
13-15	Manufacturing Textiles; Wearing apparel; Leather and related products	15.92	1.18	21.73	21320
17	Manufacturing Paper and paper products	19.98	1.16	37.82	5019
18	Manufacturing Printing and reproduction of recorded media	16.96	1.05	35.1	28907
19-21	Manufacturing Coke and refined petroleum products; Chemicals and chemical products; Basic pharmaceutical products and preparations	23.87	1.22	42.29	11469
22	Manufacturing Rubber and plastic products	18.57	1.06	25.7	11769
23	Manufacturing Other non-metallic mineral products	16.75	1.24	36.04	19449
24	Manufacturing Basic metals	30.41	0.99	36.32	3282
25	Manufacturing Fabricated metal products, except machinery and equipment	16.36	1.27	38.61	63905
26	Manufacturing Computer, electronic and optical products	21.89	1.04	31.37	5378
27	Manufacturing Electrical equipment	16.58	1.28	39.36	6522
28	Manufacturing Machinery and equipment	17.87	1.34	48.57	18053
29	Manufacturing Motor vehicles, trailers and semi-trailers	19.04	1.3	40.03	3183
30	Manufacturing Other transport equipment	21.13	1.01	24.46	1480
31-32	Manufacturing Furniture and other manufacturing	14.86	1.48	45.09	29851
33	Manufacturing Repair and installation of machinery and equipment	19.29	1.31	53.36	8068
36-39	Water supply, sewerage, waste management and remediation activities	28.54	1.2	54.81	12512
45	Wholesale and retail trade; repair of motor vehicles and motorcycles	17.39	1.34	53.79	134828
46	Wholesale trade, except motor vehicles and motorcycles	27.74	1.23	59.77	348637
47	Retail trade, except motor vehicles and motorcycles	16.8	1.32	54.8	404063
49	Land transport and via pipelines	13.85	1.31	36.85	97872
50-53	Water and air transport; Warehousing and support activities for transportation; Postal and courier activities	30.26	1.22	52.53	37332
55-56	Accommodation; Food and beverage services activities	11.83	1.23	34.26	233549
58	Publishing activities	24.09	1.17	43.9	8939
59-60	Motion picture, video and television, ...; Programming and broadcasting activities	32.71	1.15	60.16	10809
61	Telecommunications	36.78	1.04	38.69	3939
62-63	Computer programming, consultancy and related activities; Information service activities	22.75	1.23	51.6	62076
64-66	Financial and Insurance activities	35.17	1.07	73.16	127310
68	Real estate activities	39.96	1.09	63.99	77331
69-75	Professional, scientific, and technical activities	28.08	1.18	59.51	275005
77	Rental and leasing activities	35.54	1.16	66.72	19625
78	Employment activities	20.6	1.17	26.65	8991
79	Travel agency, tour operator reservation service and related activities	21.64	1.06	52.24	13061
80-82	Security and investigation activities; Services to buildings and landscape activities; Office administrative, office support and other business support activities	19.35	1.39	47.88	84672
	Total	22.01	1.32	51.82	2297551

Average absolute labor gap was calculated by $\overline{RG_s^l} = \frac{\sum_{i \in s} RG_{it}^l}{N_s}$, reported in euros per hour. Coefficient of variation is $CV_s = \frac{sd_s}{\overline{RG_s^l}}$. Percent of positive labor gap is defined as $Pos = \frac{N_s^+}{N_s} \times 100$.

Figure 1.C.6.1: Quality control: 95% Confidence Interval for Change in Gap



Gap estimates are in thousand euros. Standard errors are clustered at the firm level. The vertical gray bars mark recession periods dated by OECD.

1.D Petrin-Levinsohn Methodology

1.D.1 Measuring Lost Output from Allocative Inefficiency

Assume N single-product firm economy. Each firm's production function is given as

$$Q^i = Q^i(X_i, M_i, \omega_i),$$

where $X_i = (X_{i1}, ..., X_{iK})$ is a vector of K primary inputs (labor and capital), $M_i = (M_{i1}, ..., M_{iJ})$ is a vector of intermediate inputs (output of firm j) (materials) used in a production of i's firm/product and ω_i is a technical efficiency term. Costs are important components because they can lead to kinks or jumps in APG. Therefore,

$$Q_i = Q^i(X_i, M_i, \omega_i) - F_i,$$

where F_i is the sum of all fixed and sunk costs normalized to the equivalent of the foregone output. The total output of firm i that goes to final demand is then

$$Y_i = Q_i - \sum_j M_{ji},$$

where $\sum_j M_{ji}$ is the sum of all i's output that are used as an intermediate input in firm i and other firms j. Given the differential of final demand, $dY_i = dQ_i - \sum_j M_{ji}$, and assuming that prices, given as P_i, are uniquely determined by Q, a change in aggregate output is

$$\sum_{i=1}^{N} P_i dY_i.$$

APG is then

$$APG(t) \equiv \sum_{i=1}^{N(t)} P_i(t)dY_i(t) - \sum_{i=1}^{N(t)} \sum_k W_{ik}(t)dX_{ik}(t), \tag{1.D.1.1}$$

where changes in the use of primary inputs are reflected in the second part of the right-hand side of the identity. Here, W_{ik} denotes the price of input k and X_{ik} is the amount of input k used. Usually, in firm-level datasets we do not observe firms' final output that goes to final demand, rather we see their value-added and/or revenues. The lack of output data does not enable us to calculate APG using eq. (1.D.1.1). Nevertheless, the national accounting identity requires

$$\sum_i P_i Y_i = \sum_i VA_i,$$

where VA_i denotes the value-added. This allows to transform the initial eq. (1.D.1.1) and calculate APG[32]:

$$APG(t) = \sum_i dVA_i - \sum_i \sum_k W_{ik} dX_{ik}. \qquad (1.D.1.2)$$

Assuming Q_i is differentiable, APG can be decomposed into a technical efficiency and reallocation terms:

$$\begin{aligned} APG &= \left[\sum_i P_i d\omega_i\right] + \left[-\sum_i P_i dF_i\right] + \\ &\left[\sum_i \sum_k \left(P_i \frac{\partial Q_i}{\partial X_{ik}} - W_{ik}\right) dX_{ik} + \sum_i \sum_j \left(P_i \frac{\partial Q_i}{\partial M_{ij}} - P_j\right) dM_{ij}\right], \\ &= [TE] + [F] + [RE] \end{aligned} \qquad (1.D.1.3)$$

where $d\omega_i$ is a change in technical efficiency and $\sum_i P_i d\omega_i$ is a gain from changes in technical efficiency, $\frac{\partial Q_i}{\partial X_{ik}}$ is a partial derivative of production function with respect to the kth primary input, $\frac{\partial Q_i}{\partial M_{ij}}$ is a partial derivative of production function with respect to the jth intermediate input and $-\sum_i P_i dF_i$ is the value of lost output from any fixed and sunk costs. W_{ik} and P_j are input cost terms for primary and intermediate inputs, respectively. The technical efficiency term, $[TE]$,[33] is a contribution of firms producing more output holding inputs constant, while the reallocation term, $[RE]$, is a contribution of changes in input reallocation across firms to changes in final demand. The fixed cost term, $[F]$, is a combination of fixed and sunk costs.

The RE is formed using the value of marginal product (VMP) for every input (X_k) at firm i, generically given as

$$VMP_{ik} \equiv P_i \frac{\partial Q_i}{\partial X_{ik}}, \qquad (1.D.1.4)$$

and include a VMP term and input cost terms of primary and intermediate inputs for every firm.

[32] Given that $VA_i = P_i Q_i - \sum_j P_j M_{ij}$ and $dVA_i \equiv P_i dQ_i - \sum_j P_j dM_{ij}$.

[33] where $\frac{\partial Q_i}{\partial \omega}$ is normalized to 1.

1.D.2 Gaps and Allocative Efficiency

Using labor as an example, holding total labor input constant and assuming common input costs (wages), reallocating one unit of labor from firm j to firm i (where $MP_i > MP_j$) would lead to $dL_i = 1$ and $dL_j = -1$, and will result in an increase in the value of output by

$$P_i \frac{\partial Q_i}{\partial L_i} - P_j \frac{\partial Q_j}{\partial L_j}.$$

Thus, aggregate output increases without any changes to technical efficiency or aggregate input use if an input reallocates from a firm with a low marginal product to a firm with a higher one.

Petrin and Sivadasan (2013) define the average productivity gain from adjusting labor by one unit in the optimal direction as

$$\frac{1}{N}\sum_{i=1}^{N}\left(P_i \frac{\partial Q_i}{\partial L_i} - W_i\right) D_i = \frac{1}{N}\sum_{i=1}^{N}\left|P_i \frac{\partial Q_i}{\partial L_i} - W_i\right|, \tag{1.D.2.1}$$

where D_i is an indicator variable representing a unit reallocation of labor in an efficient direction for firm i:

$$D_i = \begin{cases} 1 & \text{if} \quad P_i \frac{\partial Q_i}{\partial L_i} > W_i \\ -1 & \text{if} \quad P_i \frac{\partial Q_i}{\partial L_i} < W_i \end{cases}.$$

Thus, eq. (1.D.2.1) gives a simple lower bound approximation to possible efficiency gains from reallocating labor resources for "one-step" in the direction of more efficiency.[34]

Let E_0 and E_1 be the two potential states, where E_0 is a state with some firing costs and E_1 denotes a state of the economy with no costs. We use the reallocation of inputs, outputs and prices from E_0 to E_1 over the interval $t \in [0,1]$. The reallocation terms are used to measure a change in aggregate productivity growth arising from changes in the allocative efficiency term:

$$\Delta AE \equiv \int_0^1 \sum_i \sum_k \left(P_{it} \frac{\partial Q_{it}}{\partial X_{ikt}} - W_{ikt}\right) dX_{kt} + \int_0^1 \sum_i \sum_j \left(P_{it} \frac{\partial Q_{it}}{\partial M_{ijt}} - P_{jt}\right) dM_{jt}. \tag{1.D.2.2}$$

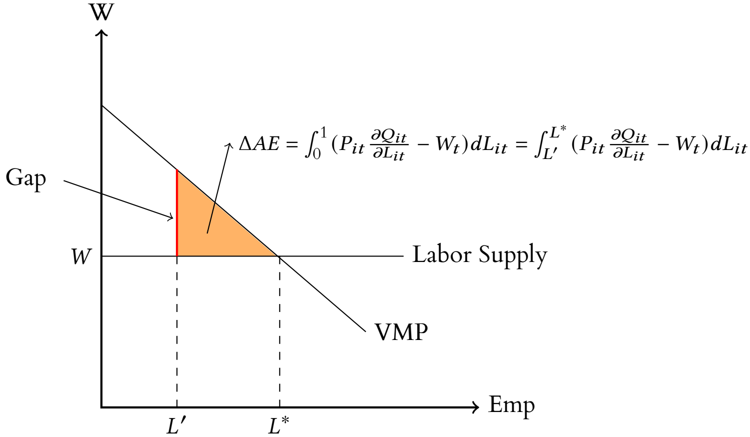
This implies that, *ceteris paribus*, the average absolute labor gap across firms is the average productivity gain from reallocating labor by one unit to an efficient direction at every firm.[35]

For example, consider a situation illustrated in Figure 1.D.2.1 with a labor-input firm facing a perfectly elastic supply curve. Imagine a firm in an environment of E_0, where it faces a positive gap between the value of the marginal product and the wage. This gap could be due to any

[34] Assuming that reallocation is not constrained.

[35] Can be applied to any input.

Figure 1.D.2.1: Allocative Efficiency Gain from Eliminating the Gap



Source: Petrin and Sivadasan (2013).

frictions in the market, such as firing costs, markups, taxes, and others. Elimination of the gap reallocates the firm to the employment level L^* - the socially optimal level. The potential gain from allocative efficiency then would be the area below the VMP and above the labor supply (= competitive wage) curves.

1.E Production Function Estimation

This section aims to provide an overview on different methods of the production function estimation.[36] As it was discussed in Section 1.3, our measure of aggregate productivity growth calculation is obtained using the value-added records. Therefore, we will discuss the estimation procedure on the value-added production function.

Common to the productivity literature, we will use the Cobb-Douglas production function:

$$Y_{ist} = A_{ist} L_{ist}^{\beta_s^l} K_{ist}^{\beta_s^k}, \tag{1.E.1}$$

where Y_{ist} is value-added, A_{ist} is productivity/efficiency, L_{ist} is labor input and K_{ist} is capital input, for firm i in industry s at time t. Elasticities for labor and capital are indexed with s highlighting the industry specific estimations. Take the natural log transformation of the equation above:

$$y_{ist} = \beta_s^l l_{ist} + \beta_s^k k_{ist} + \varepsilon_{ist}, \tag{1.E.2}$$

where small letters represent log variables of their upper counterparts.[37]

Let's split ε_{it} (full error) into two components:

$$\varepsilon_{it} = \omega_{it} + \eta_{it}, \tag{1.E.3}$$

where ω_{it} is an unobservable that is predictable by a firm when it decides on its inputs, and η_{it} is an unobservable that the firm has no information about while deciding on the inputs (also, can be considered as a measurement error in the output). Hence, η_{it} is iid exogenous shock and ω_{it}, known as productivity shock (transmitted component), is causing the endogeneity problem (simultaneity bias). The above definition allows us to calculate the natural logarithm of productivity as

$$\omega_{it} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} - \eta_{it} \tag{1.E.4}$$

once we know the input coefficients.

Another problem that needs to be addressed in estimating productivity is the, so called, selection bias. It results from a relation between productivity shock and entry and exit to the market. A firm with a larger capital stock is less likely to exit the market, even if it has low productivity

[36] Please see Van Beveren (2012) and Van Biesebroeck (2007) for a more comprehensive overview.

[37] For notational simplicity we will ignore s subscript for all variables.

shock than a firm with low capital stock, because it is expected to produce more in the future, and hence, generate more profits. The negative correlation between capital stock and probability of exit conditional on productivity shock will bias the capital coefficient downwards.

The model introduced by Olley and Pakes (1996) (hereinafter, OP) and Levinsohn and Petrin (2003) (hereinafter, LP) address these issues. In the OP model labor is a perfectly variable input chosen at time t, after observing ω_{it}, hence has no dynamic implications. So, the model excludes adjustment (firing-hiring) costs to labor inputs. Conversely, capital is a fixed input and is accumulated according to a dynamic investment process. The assumption here is that it takes a whole time period to order, deliver and install the capital. So, firms decide on their capital input at period $t-1$. Moreover, the authors assume firms' information set, I_{it}, to include past and current productivity shocks and satisfy $E[\varepsilon_{it}|I_{it}] = 0$ condition. Productivity shock follows first-order Markov process:

$$p(\omega_{it+1}|I_{it}) = p(\omega_{it+1}|\omega_{it}).$$

Given $E(\omega_{it+1}|I_{it}) = g(\omega_{it})$ we can re-write

$$\omega_{it+1} = g(\omega_{it}) + \xi_{it+1},$$

where $g(\omega_{it})$ is a predictable component and by construction $E(\xi_{it+1}|I_{it}) = 0$.

OP propose that under certain assumptions investment decisions can be used to deduce the productivity.LP, on the other hand, argue that it is better to use intermediate inputs, such as materials, fuels, or electricity, as a control variable for unobserved productivity rather than investment, because these are usually zero or poorly reported. Optimal investment choice will result in a dynamic investment demand function:

$$i_{it} = f_t(k_{it}, \omega_{it}),$$

where f_t is a solution to dynamic programming. However, we solve it semiparametrically. So, we will treat f^{-1} non-parametrically, for instance, a third-order polynomial with a full set of interactions. Under the condition of strict monotonicity[38] and given that productivity is the only scalar unobservable in the investment equation, the investment function is invertible:

$$\omega_{it} = f_t^{-1}(k_{it}, i_{it}).$$

[38] f_t is strictly monotonic in ω_{it}

As the first stage of the OP estimation procedure estimate the following equation including the industry and time-specific fixed effects:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + f_t^{-1}(k_{it}, i_{it}) + \eta_{it} \tag{1.E.5}$$

and collect industry-specific labor elasticities.

Since capital is decided one period before $E(\xi_{it} k_{it}) = 0$, $\hat{\omega}_{it} = g(P; \hat{\phi}(k_{it}, i_{it}) - \beta_k k_{it})$ and $\hat{\omega}_{it} = \hat{\omega}_{it-1} + \hat{\omega}^2_{it-1} + \hat{\omega}^3_{it-1} + \xi_{it}$, as the second stage of the OP estimation procedure run non-linear least squares estimation on the following equation and obtain industry specific capital elasticities:

$$y_{it} - \hat{\beta}_l l_{it} = g_{t-1}(P; \hat{\phi}(k_{it}, i_{it}) - \beta_k k_{it}) + g_{t-1}(P; \hat{\phi}(k_{it}, i_{it}) - \beta_k k_{it})^2 + g_{t-1}(P; \hat{\phi}(k_{it}, i_{it}) - \beta_k k_{it})^3 + \xi_{it} + \eta_{it},$$

where $\hat{\phi} = \hat{y_{it}} - \hat{\beta}_l l_{it}$ is calculated from the first stage and P is the probability of survival.[39]

Ackerberg et al. (2015) (hereinafter, ACF) questions the flexible input assumption of the OP/LP methods. They propose to keep the assumptions used by OP/LP in identifying the capital coefficients. On contrary, allowing exogenous, serially correlated, unobserved firm-specific shocks to the price of labor. Moreover, the ACF model allows firm-specific unobserved adjustment costs dynamic effects (hiring or firing costs) for labor.

Recall that productivity evolves according to the first order Markov process:

$$\omega_{it} = E(\omega_{it} | I_{it-1}) + \xi_{it} = E(\omega_{it} | \omega_{it-1}) + \xi_{it},$$

which implies that a firm's expectation of future productivity depends solely on the current productivity level. Hence, all elements of I_{it-1} are orthogonal to ξ_{it}. Capital is chosen in period $t-1$, so it is in I_{it-1}. Labor on the other hand is not in I_{it-1} since according to ACF labor is decided sometime between $t-1$ and t. Hence, l_{it-1} can be used as an instrument for l_{it}. Collectively,

[39] Correcting for selection bias (intermediate step):

$$Pr(\chi_{t+1} = 1 | \underline{\omega}_{t+1}(k_{t+1})) = Pr(\omega_{t+1} \geq \underline{\omega}_{t+1}(k_{t+1}) | \underline{\omega}_{t+1}(k_{t+1}), \omega_t)$$

Consider the expectation of $y_{t+1} - \beta_l l_{t+1}$ conditional on information at t and survival:

$$E(y_{t+1} - \beta_l l_{t+1} | k_{t+1}, \chi + t + 1 = 1) = \beta_0 + \beta_k k_{t+1} + E(\omega_{t+1} | \omega_t, \chi_{t+1} = 1) = \beta_k k_{t+1} + g(\underline{\omega}_{t+1}, \omega_t)$$

$$\text{where} \quad g(\underline{\omega}_{t+1}, \omega_t) = \beta_0 + \int_{\underline{\omega}_{t+1}} \omega_{t+1} \frac{F(d\omega_{t+1} | \omega_t)}{\int_{\underline{\omega}_{t+1}} F(d\omega_{t+1} | \omega_t)}$$

Calculate the probabilities of survival using probit estimation (including the industry specific fixed effects and time trend).

these generate the following moment conditions:

$$E[\xi_{it}\beta_k \cdot k_{it}] = 0 \qquad (1.E.6)$$
$$E[\xi_{it}\beta_l \cdot l_{it-1}] = 0.$$

To consistently estimate the input elasticities, use the sample analogs of these moment conditions. Practically this can be done using a two-stage estimation procedure. Estimate eq. (1.E.5) to obtain η_{it} and initial values of β_l and β_k, which allows to construct initial values for ω_{it} from eq. (1.E.4). Non-parametric regression of ω_{it} on ω_{it-1} gives estimates for $\xi_{it}(\beta_k, \beta_l)$. These estimates are used to drive the sample moment conditions closer to zero and obtain input coefficients. Since the estimation equation does not have an analytic expression, the model relies on bootstrapping to obtain standard errors.

Wooldridge (2009) showed how to obtain estimates in one step using the GMM estimator, which is relatively more efficient because does not require bootstrapping.

We proceed with the ACF methodology, because it deals with the issues originally addressed by OP and LP, in addition to extending their model to allow for adjustment costs to labor input. Table 1.E.1 shows the coefficients of the Cobb-Douglas production function estimated with the ACF methodology. We observe that on average coefficient on labor input is increasing over the sampling period, while it decreases for capital coefficient. Figure 1.E.1 illustrate this evolution.

It is worth noting that a problem that we face in estimating productivity is the unavailability of data on input and output prices at the firm level. This limitation results in an inability to distinguish between productivity and profitability. The issue is common in the productivity literature and requires additional assumptions on the market structure. We assume that firms are single homogeneous product firms and operate in competitive input and output markets.[40] If not, our productivity measure resembles residual profitability rather than a true productivity estimate. This implies that gain in productivity from reallocation is, by construction, a gain in revenue productivity.

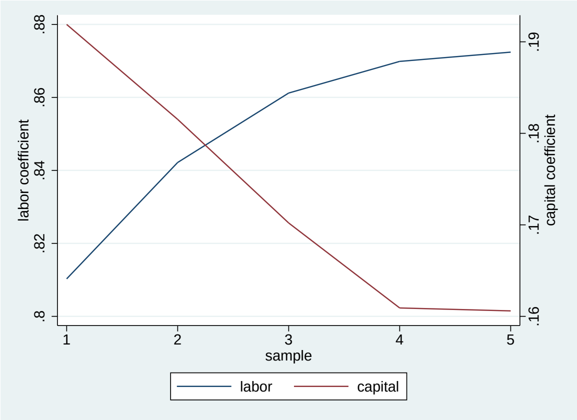
To convince the reader that the results are independent of the production function estimation technique used, correlation matrices for labor and capital estimates for ACF, OLS, LP, and Wooldridge methodologies are presented in tables 1.E.2 and 1.E.3, respectively.[41] From the table we observe different methodologies to result in similar estimates for labor coefficient. The

[40] For those interested in the issue and possible solutions, we suggest looking at De Loecker and Goldberg (2014).
[41] The same industry classification and period sample split applied.

Table 1.E.1: Cobb-Douglas production function coefficient estimates

NACE /	**Labor**					**Capital**				
sample	*1*	*2*	*3*	*4*	*5*	*1*	*2*	*3*	*4*	*5*
1–3	0.616	0.730	0.712	0.706	0.718	0.176	0.182	0.193	0.201	0.199
5–9	0.689	0.832	0.748	0.699	0.716	0.181	0.187	0.246	0.288	0.285
10–12	0.758	0.836	0.884	0.896	0.912	0.224	0.213	0.196	0.198	0.195
13–15	0.703	0.714	0.770	0.780	0.790	0.262	0.244	0.196	0.176	0.168
17	0.919	0.967	0.984	1.002	1.004	0.142	0.108	0.104	0.083	0.086
18	0.778	0.835	0.838	0.841	0.856	0.220	0.215	0.203	0.200	0.194
19–21	0.823	0.865	0.872	0.908	0.912	0.249	0.216	0.193	0.181	0.177
22	0.847	0.855	0.896	0.907	0.908	0.154	0.181	0.135	0.112	0.118
23	0.870	0.851	0.862	0.849	0.856	0.159	0.184	0.172	0.164	0.163
24	0.751	0.804	0.794	0.860	0.841	0.222	0.225	0.247	0.180	0.233
25	0.857	0.870	0.856	0.865	0.885	0.153	0.157	0.164	0.164	0.154
26	0.908	0.907	0.913	0.919	0.909	0.164	0.161	0.137	0.117	0.134
27	0.910	0.941	0.950	0.938	0.938	0.108	0.103	0.103	0.104	0.097
28	0.880	0.869	0.905	0.917	0.908	0.122	0.160	0.134	0.113	0.114
29	0.796	0.861	0.918	0.904	0.908	0.209	0.190	0.127	0.140	0.131
30	0.893	0.936	0.961	1.012	0.938	0.158	0.105	0.102	0.099	0.178
31–32	0.850	0.884	0.876	0.880	0.888	0.197	0.163	0.168	0.164	0.159
33	0.891	0.908	0.904	0.880	0.892	0.182	0.132	0.141	0.137	0.142
36–39	0.673	0.704	0.712	0.715	0.722	0.329	0.253	0.243	0.230	0.219
45	0.850	0.869	0.891	0.899	0.917	0.180	0.186	0.176	0.177	0.169
46	0.861	0.913	0.944	0.966	0.974	0.134	0.110	0.099	0.086	0.078
47	0.752	0.772	0.796	0.808	0.811	0.198	0.202	0.203	0.201	0.196
49	0.745	0.786	0.813	0.819	0.833	0.262	0.228	0.215	0.209	0.199
50–53	0.747	0.756	0.806	0.798	0.806	0.175	0.184	0.156	0.160	0.156
55–56	0.716	0.749	0.770	0.786	0.788	0.209	0.211	0.207	0.200	0.201
58	0.939	0.988	1.028	1.034	1.033	0.107	0.110	0.058	0.037	0.046
59–60	0.742	0.888	0.872	0.901	0.909	0.150	0.097	0.119	0.111	0.113
61	0.877	0.759	0.835	0.957	0.952	0.171	0.277	0.286	0.211	0.214
62–63	0.935	0.963	0.999	1.012	1.016	0.156	0.123	0.099	0.089	0.082
64–66	0.846	0.899	0.943	0.936	0.932	0.146	0.127	0.127	0.118	0.112
68	0.695	0.705	0.732	0.726	0.740	0.278	0.257	0.246	0.251	0.249
69–75	0.925	0.946	0.949	0.953	0.958	0.162	0.143	0.132	0.125	0.115
77	0.703	0.690	0.719	0.724	0.759	0.440	0.381	0.373	0.352	0.314
78	0.802	0.859	0.857	0.857	0.868	0.142	0.132	0.106	0.104	0.097
79	0.781	0.762	0.853	0.804	0.741	0.204	0.220	0.156	0.155	0.150
80–82	0.837	0.845	0.841	0.859	0.867	0.184	0.167	0.166	0.152	0.145
Total	0.810	0.842	0.861	0.870	0.872	0.192	0.182	0.170	0.161	0.161

Figure 1.E.1: Average input elasticities



correlation coefficients are quite high (ranging from 0.616 to 0.902). Capital estimates show less similarity (from 0.372 to 0.866), which could be due to the sensitivity of each methodology to measurement errors, usually observed in the capital.[42] Nevertheless, given that we estimate the gap for labor input, which requires labor elasticity, and the correlation between different estimation techniques being high and significant, we believe our gap calculations to perform similar results independent of the production function estimation choice.

Table 1.E.2: Correlations Matrix: Labor Estimates

	OLS	LP	Wooldridge	ACF
OLS	1			
LP	0.684***	1		
Wooldridge	0.675***	0.902***	1	
ACF	0.847***	0.611***	0.628***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.E.3: Correlations Matrix: Capital Estimates

	OLS	LP	Wooldridge	ACF
OLS	1			
LP	0.416***	1		
Wooldridge	0.372***	0.672***	1	
ACF	0.866***	0.433***	0.446***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[42] Interested reader can refer to Collard-Wexler and De Loecker (2016) for insights of the issue and proposed solution.

1.F Data Description

1.F.1 Industry Classification

We use statistical classification of economic activities in the European Community on NACE Revision 2 two-digit level as a basis. The NACE code of a firm for the sampling period is fixed to the one for which it was classified the longest. Due to small number of observations for some of the industries, we combine some NACE two-digit codes according to industry breakdown of the National Bank of Belgium (A64) and some with related (closest) industries. We exclude all non-private sectors of the economy (from Section O), construction industry (Section F), upholstery (NACE Rev.2 5-digit 13929) and woodworking (NACE Rev.2 2-digit 16) sectors. Due to small number of observations, we also exclude electricity, gas, steam and air conditioning supply industry (Section D) from the analysis. Table 1.F.1.1 presents industry descriptions.

Table 1.F.1.1: Industry Classification

Division	Description
1-3	Agriculture, forestry, and fishing
5-9	Mining and quarrying
10-12	Manufacture of food products; beverages; tobacco products
13-15	Manufacture of textiles; wearing apparel; leather and related products
16	Manufacture of wood, products of wood and cork, except furniture, manufacture of articles of straw and plaiting materials
17	Manufacture of paper and paper products
18	Manufacture of printing and reproduction of recorded media
19-21	Manufacture of coke and refined petroleum products; chemicals and chemical products; basic pharmaceutical products and preparations
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacturing machinery and equipment
29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
31-32	Manufacture of furniture and other manufacturing
33	Manufacture of repair and installation of machinery and equipment
36-39	Water supply, sewerage, waste management and remediation activities
45	Wholesale and retail trade; repair of motor vehicles and motorcycles
46	Wholesale trade, except motor vehicles and motorcycles
47	Retail trade, except motor vehicles and motorcycles
49	Land transport and via pipelines
50-53	Water and air transport; Warehousing and support activities for transportation; Postal and courier activities
55-56	Accommodation; Food and beverage services activities
58	Publishing activities
59-60	Motion picture, video and television programme production, sound recording and music publishing activities; Programming and broadcasting activities
61	Telecommunications
62-63	Computer programming, consultancy and related activities; Information service activities
64-66	Financial and insurance activities
68	Real estate activities
69-75	Professional, scientific, and technical activities
77	Rental and leasing activities
78	Employment activities
79	Travel agency, tour operator reservation service and related activities
80-82	Security and investigation activities; Services to buildings and landscape activities; Office administrative, office support and other business support activities

1.F.2 Book Year

Conventionally, a book year starts on the 1st of January and ends on the 31st December. When it is not the case, we have to make some adjustments by proportionally reallocating the information from a broken book year to the appropriate calendar years. Before doing so, we ignore all observations that do not report the date of closing financial year or the number of months the accounts refers to and when the accounts refers to more than 24 months, which complicates the reallocation of information.

We allocate the part of the original observation to the corresponding calendar year based on the number of months. First, we generate rows that will represents months of the year. Then, we divide the original data to the number of months the data refers to, hence, artificially generating "monthly" data. Finally, we combine appropriate months to match the calendar year. We can only do this if that year has information for 12 months. Otherwise, we extrapolate the information. Note that this shifts some data to 1994-1995 (if the book year in 1996 spans more than one book year). We keep only data from 1996 till 2017 after adjusting for the broken book year issue.

1.F.3 Imputed Data

We impute missing values for key variables in the following cases: (i) a missing in-between $t-1$ and $t+1$ value is replaced with their average; (ii) a missing the first year value is replaced with the following year value; and, (iii) a missing last year value is replaced with its lag.

1.F.4 Sample

Originally, we start with around 666,000 (unique VAT numbers) firms in our dataset. However, not all observations can be used. First, we ignore outliers and deal with broken book year issue. Second, we impute some parts of the missing data and ignore all observations that have missing values for value-added, capital, employment and wage bill. Moreover, given that production function estimation involves log-transformation of the variables, we ignore all negative and zero values of these variables. Finally, we ignore all public sectors and construction industry, upholstery and woodworking sectors from our analysis. We do, also, ignore Belgian Railway Company, Belgium's the largest employer, because driven by the EU regulation, it changes its legal entity throughout the sampling period. So the pooled dataset comprises 236,660 firms for 1996-2017 year period (2,297,551 observations). For the restricted sample we use 126,235 firms (891,689 observations). Table 1.F.3.1 presents summary statistics by industry.

Figure 1.F.3.1 plots the average wage calculated from the raw data and the official reported average wages from the OECD statistical database for comparison. We observe an increasing

Table 1.F.3.1: Summary statistics by industry

Industry	turnover	value-added	employment	tangibles	materials	wage bill	blue	white	share	in-flow	out-flow	hours
1–3	2474.09	357.72	5.44	727.74	2075.17	172.47	4.37	0.84	0.87	50.04	49.68	9.15
5–9	10825.90	2909.48	28.12	2473.12	6941.36	1378.32	21.86	6.30	0.79	5.65	5.35	42.74
10–12	26613.60	2304.07	26.43	1843.91	22643.35	1268.96	18.09	8.31	0.65	10.27	9.75	41.82
13–15	13853.77	1759.28	32.37	911.74	10824.03	1171.33	25.58	6.63	0.76	6.81	7.61	46.75
17	34211.14	4989.87	57.11	4272.07	28119.29	2937.80	41.89	14.49	0.72	11.48	11.62	87.79
18	4497.58	865.15	12.54	723.43	3101.47	590.69	8.12	4.51	0.55	4.55	4.47	19.90
19–21	147143.73	23649.23	130.91	17244.09	126235.56	10646.42	52.30	75.00	0.45	21.32	19.69	208.25
22	21771.00	3532.20	43.24	1974.05	16887.69	2229.71	29.46	13.22	0.73	9.18	8.92	68.00
23	14226.08	2486.18	31.32	2099.52	10787.85	1604.14	23.41	7.59	0.80	8.33	8.04	48.49
24	162825.41	20265.26	215.30	15481.11	138333.52	13859.72	149.56	56.84	0.76	25.18	30.01	328.63
25	7104.54	1176.72	18.56	645.31	5068.69	838.02	14.21	4.38	0.81	5.97	5.54	29.11
26	32222.91	7041.52	74.05	1777.02	24210.28	4758.34	28.99	43.73	0.39	14.82	15.03	120.34
27	22426.05	4406.68	56.15	1361.79	16202.85	2995.93	34.24	21.05	0.66	11.37	11.63	88.01
28	21491.49	3434.79	40.86	1178.78	15490.04	2199.42	26.73	13.70	0.68	9.32	8.95	63.56
29	140231.94	16133.97	228.56	7423.45	118510.21	12056.91	183.23	38.38	0.76	32.72	34.65	350.37
30	44428.74	9634.91	112.04	5155.78	29708.92	6502.72	55.94	53.96	0.64	15.75	14.38	167.81
31–32	6731.09	784.37	13.96	454.68	5350.70	530.29	10.59	3.46	0.75	4.05	4.01	21.59
33	13152.26	1486.91	23.14	979.76	10137.46	1135.00	17.56	5.97	0.72	7.27	6.20	37.39
36–39	17719.52	4000.96	31.66	15747.79	12631.29	1757.43	18.81	12.44	0.71	8.49	7.18	52.75
45	19781.55	663.08	8.49	481.18	19066.47	413.04	4.70	3.78	0.70	3.46	3.15	14.17
46	21019.59	1197.78	10.61	496.89	19297.39	609.59	3.29	7.38	0.33	5.78	5.38	17.77
47	6271.71	474.26	8.89	337.26	5486.26	310.92	1.44	7.58	0.23	8.76	8.37	13.95
49	4047.87	812.92	13.74	673.28	2968.76	565.39	11.87	2.01	0.88	11.16	10.56	23.95
50–53	18911.88	3625.65	46.90	5598.46	13869.02	2300.44	10.81	36.00	0.37	15.02	14.09	78.65
55–56	935.67	255.49	5.70	317.60	566.65	184.01	4.78	1.04	0.91	26.89	26.49	9.08
58	11556.35	2090.33	22.47	445.69	8392.94	1377.25	2.01	20.70	0.07	8.45	7.84	37.38
59–60	7448.43	1588.59	16.24	928.83	5443.02	941.80	1.77	14.61	0.13	41.15	39.89	29.33
61	97527.54	28461.64	141.03	27803.46	53867.58	10923.02	21.37	121.28	0.07	25.21	25.27	266.09
62–63	5291.15	1208.12	13.19	326.28	3168.43	933.41	0.19	13.50	0.03	5.82	4.62	23.08
64–66	6374.61	962.10	6.17	957.15	4523.12	440.32	0.37	5.76	0.05	3.20	2.68	10.43
68	3040.43	597.68	4.14	4687.81	2079.60	181.85	1.52	2.73	0.27	3.02	2.68	6.73
69–75	3892.02	687.20	7.02	329.38	2978.55	434.61	0.54	6.58	0.08	9.35	8.64	11.88
77	10039.78	2398.67	8.41	5873.82	5566.64	429.38	3.40	5.23	0.45	6.70	6.18	14.03
78	23247.58	10155.21	279.91	248.04	2969.22	9599.10	162.18	131.42	0.22	3491.64	3468.73	459.00
79	12885.52	561.82	9.20	190.47	12067.79	398.79	0.63	8.55	0.05	7.74	7.23	15.87
80–82	3347.47	879.36	19.16	411.35	1823.21	702.42	15.53	4.35	0.62	22.58	20.94	29.79
Total	12786.26	1220.73	14.45	1064.95	10670.92	719.38	6.86	7.76	0.43	27.33	26.72	23.60

Turnover, value-added, tangible fixed assets, material costs and wage bill are measured in thousands euros; employment, blue- and white-collar workers, in-flow and out-flow of workers are measured in full-time equivalents, effective hours worked is measured in thousands.

trend in the average wage across the sampling period. The calculated average wage closely tracks the reported one, indicating that the data are representative at aggregate level.

Figure 1.F.3.1: Average Annual Wages

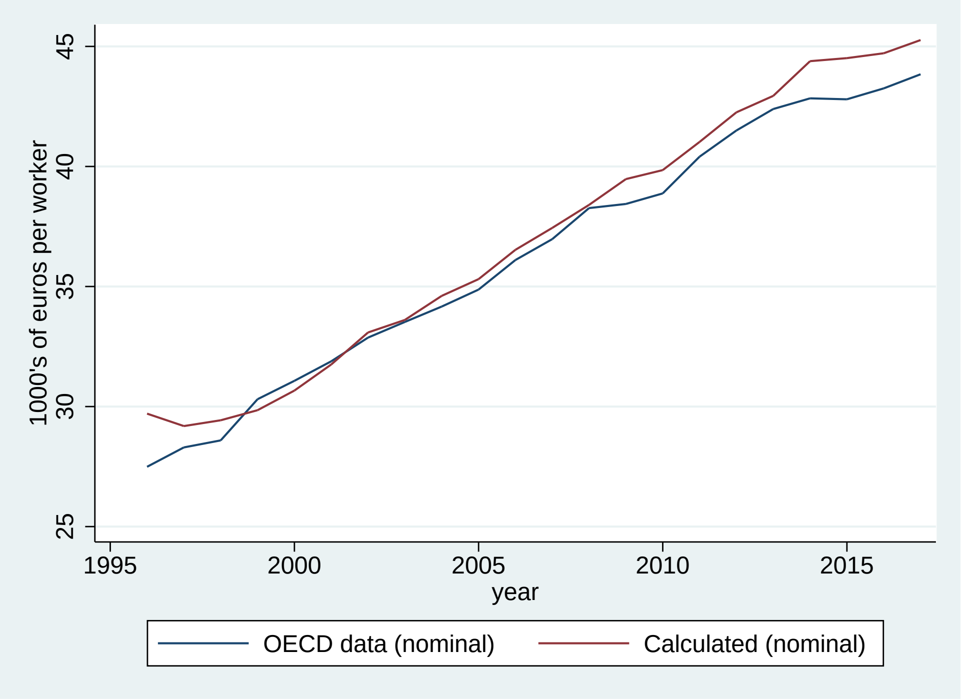


Table 1.F.3.2: Material Costs

Industry	% Obs.	% VA
1-3	69.68	57.22
5-9	45.49	8.97
10-12	54.63	8.07
13-15	55.77	12.51
17	42.54	4.75
18	59.56	24.04
19-21	30.53	0.73
22	44.74	7.78
23	50.50	9.20
24	35.19	0.93
25	61.01	24.96
26	43.53	3.17
27	48.87	5.85
28	51.44	8.23
29	35.47	1.07
30	47.36	2.04
31-32	62.85	28.41
33	61.79	15.73
36-39	43.89	5.54
45	59.32	23.21
46	54.44	13.87
47	67.45	27.64
49	58.86	35.12
50-53	43.65	4.78
55-56	66.64	44.39
58	51.53	6.80
59-60	53.71	12.57
61	39.45	0.50
62-63	58.42	15.63
64-66	63.59	15.80
68	62.32	25.45
69-75	66.92	26.56
77	58.49	8.97
78	52.57	3.45
79	59.90	20.52
80-82	63.32	22.72

The above table shows: Column (1) - percentage of observations not reporting material costs; Column (2) - percentage of value-added of those firms not reporting material costs

Chapter 2

Employment Dynamics with Convex Hiring Rules[1]

2.1 Introduction

Recent literature has focused on the mechanisms through which shocks propagate to the economy and over time (Vavra, 2014; Bloom et al., 2018; Ilut et al., 2018; Baley and Blanco, 2019). Understanding the underlying mechanisms is important because changes in the volatility of aggregate macroeconomic indicators have been argued as a central source of business cycles. At the microeconomic level, adjustments to the shocks are shaped by institutional characteristics. In the labor market, union barganing and employment protection laws ensure wage and employment stability. Stricter employment protection reflects greater downward adjustment costs for labor and a more rigid labor market. Stable wages and employment are good for workers, however labor market rigidity constraints the reallocation of labor, hence reducing productivity and firm performance.[2]

Labor market rigidities are believed to be a particularly appealing explanation behind the differences in macroeconomic indicators between the European countries and the US.[3] The US labor force is characterized by a high degree of mobility facing a far less rigid institutional en-

[1]This chapter is joint work with Prof.dr.Stijn Vanormelingen.
We gratefully acknowledge comments from participants at VIVES Seminar series.

[2]Baily et al. (1992); Olley and Pakes (1996); Foster et al. (2001); Petrin and Levinsohn (2012); Collard-Wexler and De Loecker (2015) show the contribution of the reallocation component to the aggregate productivity growth. Lagos (2006); Da-Rocha et al. (2019) show how labor market policies affect the productivity of firms through their response to the aggregate fluctuations.

[3]See, for example, Siebert (1997); Botero et al. (2004) on how rigidities in the labor market affect labor force participation and unemployment rates in a wide array of countries. Please also see van Ark et al. (2008); Bassanini et al. (2009) on the effect of labor market regulations on the productivity differences across Europe and the US.

vironment, distinguishing it from other advanced economies, such as continental Europe. According to the Employment Protection Legislation (EPL) index developed by the OECD,[4] which measures the degree of stringency of rules regarding the dismissal of employees and severance pay levels, the US has a score of 0.09, while the average index for the EU-15 is 2.27, where a higher value represents stronger protection.[5] Stronger labor market protection constrains firms to react to market fluctuations, i.e. when the negative shock hits, firms cannot easily adjust by firing employees due to high firing costs. High adjustment costs slow the firm's reactions to changes and reduce investment and employment variability (Haltiwanger et al., 2014), i.e. it prevents firms from absorbing the effect of the shocks.

Cyclicality in aggregate outcomes is the result of significant non-linearities in the propagation of shocks. A long tradition in macroeconomics studying the business cycles considers linear models, which by construction exclude non-linear dynamics. Hence, workhouse macroeconomic models cannot fully generate patterns found in the data (Auerbach et al., 2020). Moreover, looking at the variation in exogenous shocks was key in explaining the cyclical patterns of the aggregate macroeconomic indicators. Nevertheless, the distribution of the productivity shock is not the only source to explain the volatility in the aggregate employment growth. To this end, Ilut et al. (2018) show that the shape of the hiring rule can endogenously transform the distribution of employment growth, and induce counter- or pro-cyclical volatility of the aggregate employment growth.

This paper takes a step further and argues that the shape of the hiring rule is determined by labor market rigidities. Ilut et al. (2018) show that a concave hiring rule can generate countercyclical dispersion and negative skewness in the distribution of the employment growth in the US. However, the authors do not take a stand on what determines this concave shape. One possible explanation given was that firing costs are lower than hiring costs. As a result, when a negative shock hits, the cheaper form of adjustment is to fire people. While we closely follow Ilut et al. (2018) for our analysis, we add to their argument by providing some insights into one of the possible determinants of the shape of the hiring rule. Precisely, we argue that the shape is determined by the degree of labor market protection legislation.

In this regard, it could be of considerable interest to focus on Europe, which on average has a far more rigid labor market compared to the US. Several studies on Europe have documented that firing costs are higher than hiring costs (Goux et al., 2001; Abowd and Kramarz, 2003; Kra-

[4] OECD Indicators of Employment Protection.

[5] The range of strictness of EPL index is from 0 to 6, where a higher score represents stricter employment protection. Please visit "Calculating summary Indicators of EPL Strictness: Methodology" for details on how the index is calculated.

marz and Michaud, 2010; Dhyne et al., 2015). We hypothesize that stricter employment protection legislation results in (more) convex hiring rule generating pro-cyclical employment growth volatility. To test the hypothesis, we first focus on Belgium as a baseline reference country. The advantage of focusing on Belgium is that the data at hand covers all firms with limited liabilities and we observe firms for a longer period of time, 1996-2018. Later, we extend the analysis to other European countries with different adjustment costs.

First, using non-parametric regression we find that the hiring rule in Belgium is convex. Then, we show that contrary to the stylized fact of the counter-cyclicality of most of the economic activities, the volatility of employment growth of Belgium is pro-cyclical in cross-section and time-series, as predicted by the convex hiring rule mechanism. Second, we study the distribution of productivity innovation. We report that the distribution of TFP shocks is less volatile. Hence, we argue that the asymmetry in hiring and firing cannot be attributed to the asymmetric TFP shocks alone. Finally, using data for four other countries in Europe, we confirm that a more rigid labor market results in a more convex hiring rule.

Another evidence that strengthens the hypothesis is that we observe a linear hiring rule when employment is measured as the actual hours worked. When a shock hits, a cheaper (almost costless) form of labor adjustment is to alter the number of hours worked, at least in the short-run. Moreover, Belgium has a system of temporary unemployment, in which during recession periods workers receive unemployment benefits, and they return to their previous work positions once the economy gets better. Given the low (or non-existent) adjustment cost for hours worked and features of the labor market in Belgium, a firm is expected to respond in a similar way for negative and positive shocks. The fact that we find a linear hiring rule for changes in hours of work strengthens the evidence that stricter employment protection, partly reflected in higher adjustment costs, results in a more convex hiring rule.

This paper is closely related to the research that studies the optimal level of labor input given the adjustment costs. The key finding of this literature is that optimal decision rules are asymmetric, i.e. employment adjusts differently for negative and positive shocks.[6] Asymmetric adjustment costs along uncertainty (Hamermesh, 1989; Bentolila and Bertola, 1990), level of competition (Caballero, 1991), and type of labor contracts (Goux et al., 2001) were used to explain the level of asymmetry in response to shocks. Our paper provides additional evidence on the source of the asymmetric response. We argue that the shape of the hiring rule, at least partially determined by the labor market institutions, can generate the asymmetry of shocks. Similarly to the findings

[6] This applies to decisions on any input.

in the literature, when firing costs are higher than hiring costs, labor responds more to "good shocks" than to "bad" ones, i.e., the managers are more hesitant to incur firing costs to dismiss workers when a negative shock hits than incurring hiring costs to hire new employees when economic activity increases.

Our study also contributes to the research that focuses on the role of microeconomic adjustment behavior in the dynamics of the aggregate economy. A key stylized fact established in this strand of literature is a counter-cyclical movement of cross-sectional volatility and negative skewness of macroeconomic indicators, such as employment growth and productivity. See Kehrig (2015); Bloom et al. (2018); Ferraro (2018) for recent studies on the US, and Higson et al. (2004) for the UK. Contrary to the stylized fact, we report pro-cyclical volatility of the employment growth in Belgium. This finding is more in line with the recent research reporting pro-cyclical volatility of investment dynamics in the US (Bachmann et al., 2013a; Bachmann and Bayer, 2014).

Moreover, this paper provides additional evidence on the importance of responsiveness in shaping the distribution of economic activities (Berger and Vavra, 2019; Decker et al., 2020). It contributes to the debate on the relative importance of exogenous shocks and endogenous responsiveness to these shocks. It highlights the fact that policies may shape how micro-level shocks propagate to aggregate fluctuations and are magnified.

Information on the firm behavior during the business cycles helps formulate effective policies. Additionally, identifying the determinants of the cyclical patterns of the aggregate outcomes helps to account for its elements in macroeconomic modeling and predictions. This is of central interest to economists and policy-makers, in general, interested in the growth and performance of firms.

The rest of the paper is organized as follows. Section 2.2 outlines the methodology. Section 2.3 describes the data used to test the hypothesis. The baseline results are described in section 2.4. Section 2.5 focuses on the sectoral analysis. Section 2.6 provides further evidence on the relationship between the market rigidity and the shape of the hiring rule. Section 2.7 presents some concluding remarks.

2.2 Methodology

We build our analysis on the mechanism described by Ilut et al. (2018). We direct the interested reader to the original paper for more details and proof. Below, we briefly outline the idea of the mechanism.

Imagine an economy with a continuum of firms that make certain hiring decisions. Each firm has information on its future profitability, denoted as s. We call it a "signal" throughout the paper. Assume that the signal of firm i at time t, s_{it}, consists of common and idiosyncratic components:

$$s_{it} = a_{jt} + \epsilon_{it}, \tag{2.2.1}$$

where ϵ_{it} is i.i.d. error term with mean zero, and a_{jt} is a common industry j shock.

Assume that firms respond to signals by adjusting their employment following the hiring rule:

$$n_{it} = f(s_{it}), \tag{2.2.2}$$

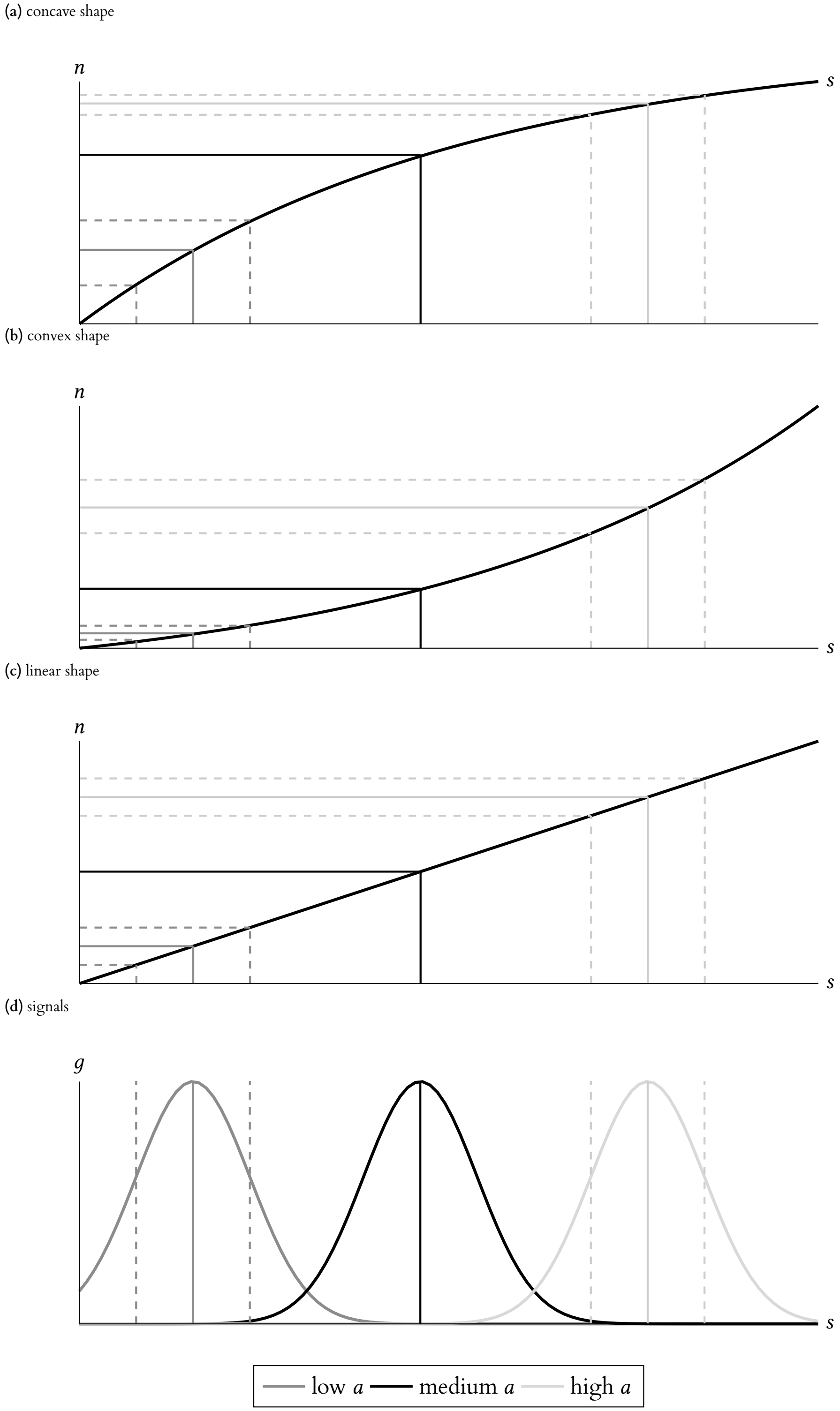
where n_{it} is the employment growth rate of firm i at time t and function f is a smooth, strictly increasing function, which defines the optimal employment given the realization of the signal s.

The function f can have a linear or concave (convex) shape, to allow for symmetric or asymmetric adjustments, respectively. Asymmetric adjustment implies firms respond less (more) to positive shocks and more (less) to negative signals for the concave (convex) shape of the hiring rule. The model is in line with the traditional productivity literature that assumes that firm-level productivity follows a first-order Markov process, i.e. firms predict their future productivity based on their observation of their current productivity, with or without any extra information on noise in signals.

Let $G_n(n|a)$ and $G_s(s|a)$ represent, respectively, conditional cumulative distributions of employment growth and signals given common shocks to firms, a. Define high values of a as "good times", i.e. times when a firm receives on average good news about its profitability, and the better news is reflected only in a higher mean of the signal.

Figure 2.2.1 illustrates the intuition behind the mechanism for three possible shapes of the hiring rule. The top three - Figures 2.2.1a to 2.2.1c - illustrate the three shapes of the response function f, where the realization of a signal s is on the x-axis and growth of employment is on the y-axis. The bottom figure, Figure 2.2.1d, depicts three densities, $g_s(s|a)$, associated with three different realizations of signal s. The middle density (solid black) is a reference point. A movement to the left of the density marks the arrival of bad times, while movement to the right implies an arrival of better times. The figure clearly illustrates how asymmetric adjustment translated into pro-cyclical or counter-cyclical micro and macro volatility depending on the shape of the hiring rule. Consider macro volatility first. The solid horizontal lines correspond to the mean

Figure 2.2.1: Employment growth and signals



employment growth of three signal realizations. For concave (convex) function, the difference between the reference mean employment growth (solid black line) and the average employment growth from the low realization of a (solid dark grey line) is larger (smaller) than the difference of the reference point and employment growth of high realization of the signal (solid light grey line). This implies that with the concave (convex) hiring rule, bad news generates more (less) aggregate responses compared to the aggregate response from good news. For completeness, Figure 2.2.1c illustrates the symmetric response to positive and negative shocks arising from the linear hiring rule.

For the micro volatility, consider the interquartile ranges of signal distributions illustrated by the dashed lines. For illustrational purposes, we use the interquartile range as one measure of cross-sectional volatility. Nevertheless, the logic equally applies to other measures. From the graph, the concave (convex) response function accentuates (attenuates) dispersion in signals in bad times and attenuates (accentuates) it in good times.

Ilut et al. (2018) document a concave shape for function f for the US economy. They argue that this concave shape alone can generate counter-cyclical dispersion and negative skewness of the employment growth distribution observed in the US. One of the possible explanations of the concave hiring rule is that hiring costs are substantially larger than firing costs in the US. Contrary, given the labor and product market regulations in Belgium that are far more rigid compared to the US, and hiring costs being lower than firing costs (Dhyne et al., 2015), we expect a convex-shaped hiring rule. Hence, generating pro-cyclical volatility of employment growth.

The mechanism also suggests that asymmetric adjustments induce skewness. In particular, it implies that the employment growth distribution is more skewed than the distribution of the shock that it underlies. The mechanism suggests that the concave (convex) hiring rule generates negative (positive) skewness for the distribution of employment growth. However, it does not predict certain cyclical movements. We keep the attention on the dispersion of the employment growth rate and leave the discussion on skewness to Section 2.B.

2.3 Data

The data used in this paper is the annual accounts of all Belgian firms with limited liabilities collected from the National Bank of Belgium. While small firms can opt to file a short form, large firms are obliged to submit a complete form.[7]

Ideally, an accounting year spans from January, 1 to December, 31, and each data point should correspond to 12 months of operation. We introduce a set of corrections when necessary to properly annualize the data.

We have an unbalanced panel for the 1996-2018 years. We have selected key variables, which allow us to calculate the employment growth and estimate the production function. Precisely, we obtained data on the average number of employees (in full-time equivalents (hereinafter, FTE)), value-added (in thousand euros), tangible fixed assets (a proxy for capital) (in thousand euros), material costs (in thousand euros), and remuneration (in thousand euros) per firm, including NACE Rev.2 five-digit codes for each firm.

We exclude all non-private sectors (NACE Rev.2 two-digit ≥ 84) of the economy from the analysis and ignore all firms that have gap years in their reporting of employment.[8]

Figure 2.A.1 shows how these changes affected aggregate employment across the sample period. We can see that the aggregate employment after the necessary cleaning and from the original data follow the same evolution.

For the baseline case, we use a log difference of employment[9] as an approximate of the growth rate:

$$n_{it} \equiv \Delta log(L_{it}),$$

where n_{it} is the growth rate of employment and L_{it} is the average number of workers, of firm i at time t.

The research is conducted on 99,631 firms per year (on average). It covers the 1996-2018 year period. The pooled sample consists of 257,490 unique VAT numbers of firms. The data used covers at least 71% of Belgian non-public sector employment. The summary statistics of the key variables are presented in Table 2.3.1. From the table, an average firm has on average 16 employees, generates around 1,360 thousand euro in value-added, and pays around 50 thousand euro on average as wages.

[7] A firm is classified as large in case it satisfies at least two of the following thresholds: (i) employment of 50 FTE and more; (ii) turnover of at least 9 mln euro, and (iii) total assets of at least 4.5 mln euro. A firm is considered small if it does not satisfy more than one of the thresholds described.

[8] This constitutes around 13% of all firms within the study period. We also ignore the Belgian Railway company, because it changes its legal entity throughout the period. Since it is the largest Belgian company, its entry and exit impact the employment growth rate distribution.

[9] Given the formula for the employment growth rate, we automatically lose firms that appear only once in the sample.

Table 2.3.1: Summary statistics

	Obs.	Mean	SD	Min	Max
value-added (1000 euros)	2291516	1359.912	19132	0.001	4551431
employment (FTE)	2291516	16.318	191	0.5	47729
tangible fixed assets (1000 euros)	2226505	1190.471	22575	0.002	3680862
wage bill (1000 euros)	2290435	814.489	9574	0.007	1640402
blue-collar workers (FTE)	2211226	8.326	84	0	13735
white-collar workers (FTE)	2211226	8.133	139	0	39855
hours worked (1000) (1997-2014)	1750299	25.865	310.07	0.0025	85363

2.4 Baseline Results

In this section, the ultimate goal is to estimate the shape of the hiring rule. To this end, using both non-parametric and parametric model specification techniques, we study the average response of the employment growth on productivity innovation. Once we observed the shape of the hiring rule, we look for the variation in the aggregate employment growth. We start by reporting the cyclical patterns of dispersion of the employment growth distribution. We focus on the standard deviation and interquartile range, in both cross-section and time-series, as measures of dispersion. Finally, to rule out the possibility of the asymmetric response of employment growth being driven by the asymmetries in the underlying shocks, we compare the properties of TFP innovation distribution to that of the employment growth.

2.4.1 Shape of the Hiring Rule

To study the response of employment growth on TFP innovation, we need to construct a measure for productivity innovation. First, from the Cobb-Douglas production function, we derive the Solow residual for every firm i in year t:

$$Y_{it} = K_{it}^{\beta_k} L_{it}^{\beta_l} e^{\epsilon_{it}}.$$

We log-transform the equation above to get

$$y_{it} = \beta^k k_{it} + \beta^l l_{it} + \epsilon_{it}, \tag{2.4.3}$$

where y_{it} is the natural logarithm of production (measured as value-added), k_{it} and l_{it} are the log of capital and labor input measured by tangible fixed assets and the average number of workers in full-time equivalents, respectively, and ε_{it} is the Solow residual. The production elasticities of labor and capital inputs are the median shares of the input's expenditure in sales, as in Asker et al. (2014).[10] The β^x-s are specific to NACE Rev.2 three-digit industry level.[11] This allows for rich heterogeneity in elasticities and at the same time leaves enough observations per industry for reference.

Ultimately, we are interested in TFP shocks. Assume that the Solow residual contains trend of the growth, gt, common industry, α_j, and firm-specific, α_i, fixed effects, and a stationary component, Z_{it}:

$$\epsilon_{it} = gt + \alpha_j + \alpha_i + Z_{it}. \tag{2.4.4}$$

The distribution of Z_{it} assumed to be stationary over time and have a zero mean. After subtracting the common component, we detrend the residual, and impose an AR(1) assumption on Z_{it}. We obtain

$$\epsilon_{it} - \alpha_j - gt = \alpha_i + \rho Z_{it-1} + z_{it}, \tag{2.4.5}$$

where z_{it} is the TFP innovation we are after.

Once we predict the TFP innovation, z_{it}, from the above equation with panel fixed-effect regression, we examine the average response of employment growth to TFP innovations by non-parametrically estimating

$$n_{it} = g(z_{it}). \tag{2.4.6}$$

We partition the data into sub-samples by firm size[12], and estimate the above equation for each sub-sample.[13] Figure 2.4.2 displays the result of the non-parametric estimation. The estimated regression line, the local polynomial smooth line, resembles the function $g(\cdot)$. It depicts the estimated employment growth given the TFP innovation. The solid line displays the mean employment change. The main takeaway is that employment growth response is asymmetric, i.e. it responds differently to positive and negative shocks. The shape of asymmetry is convex over the domain of TFP innovations, i.e. employment growth responds less to negative TFP

[10] Using a more sophisticated total factor productivity (hereinafter, TFP) estimation techniques (such as, Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015) requires some assumptions on the timing of the information and the choice of inputs, which might potentially conflict with the timing assumptions of the proposed mechanism, where choices are made based on current signals.

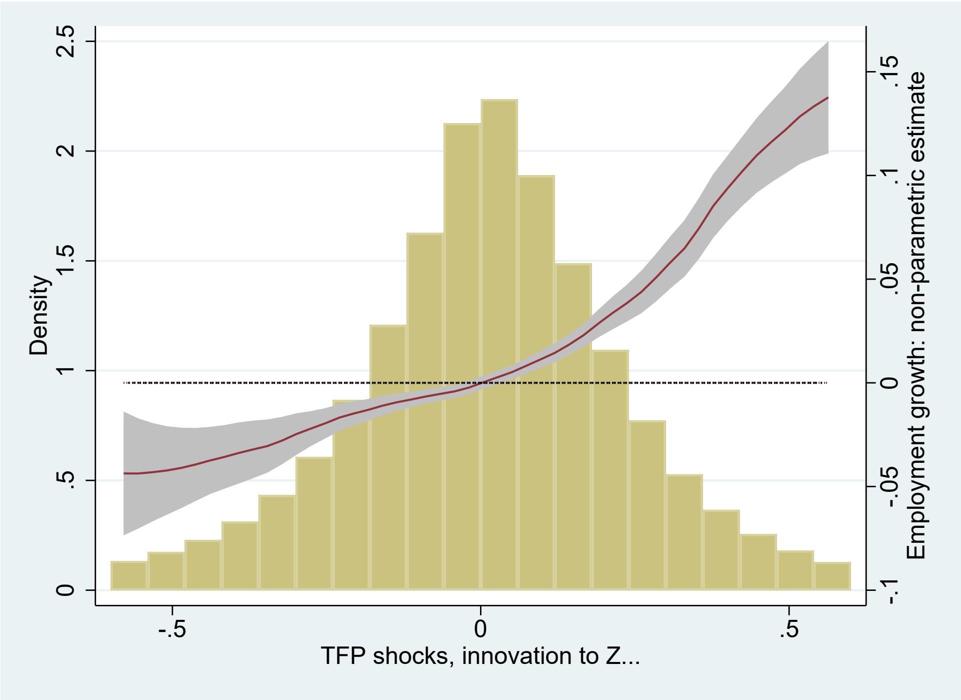
[11] We combined some small NACE Rev.2 three-digit industries.

[12] Micro = [0.5,10); small = [10,50); medium = [50,100); large = [100+).

[13] Please note that we use estimated values of TFP shocks from production function as a regressor in eq. (2.4.5), which creates an attenuation bias. The situation described is the setup of measurement error in generated regressors (predicted values or residuals of linear regression as regressors). The issue has received great attention in the literature (Murphy and Topel, 1985; Hausman, 2001). According to Hausman (2001), the attenuation bias usually results in a downward bias of the estimates. Therefore the issue is usually neglected in the literature.

shock realizations. On average, after one standard deviation TFP shock (+0.21) employment increases by 2.7 percent, and decreases by -1.3 percent for one standard deviation negative shock (-0.21). In Figure 2.4.2, the grey shaded area presents 95% confidence interval. The convex shape is observed even for the lower and upper bounds of the confidence interval. The key takeaway is that Belgium is characterized by a convex hiring rule and firms are more responsive in adjusting labor to positive shocks.[14]

Figure 2.4.2: Employment growth and TFP innovations



To test for robustness of the result above, we experiment with functional forms of the baseline model. So, we estimate the following general specification:

$$n_{it} = \beta_0 + \beta_1 gt + \beta_2 Z_{it-1} + \beta_3 l_{it} + \beta^{\xi} \xi_{it} + u_{it}, \tag{2.4.7}$$

where gt is the time trend, Z_{it-1} is the lag of TFP (from eq. (2.4.4)), l is the log of employment,

[14] In eq. (2.4.6), we assume a contemporaneous response to shocks, while there could be a lag response to shock. In this regard, we non-parametrically estimate $n_{it} = g(z_{it-1})$, and present the result in Figure 2.A.4 in Appendix.

u_{it} is the iid error term, and ξ is a function of the TFP innovation, for which we use:

$$\beta^{\xi}\xi_{it} = \begin{cases} \beta_4 z_{it} + \beta_5 (z_{it})^2 & \text{(1) quadratic} \\ \beta_4 z_{it} + \beta_5 (z_{it})^2 + \beta_6 (z_{it})^3 & \text{(2) non-monotonic} \\ \beta_4 z_{it} + \beta_7 z_{it} \times 1\{z_{it} > 0\} & \text{(3) piecewise linear} \end{cases}$$

to capture asymmetric adjustments.

For $\beta_4 > 0$ and $\beta_5 > 0$, the first specification indicates that employment growth is increasing and convex. The second specification allows for a more non-monotonic relationship between employment growth and TFP innovation shock. The last specification assumes a linear relationship at the same time allowing separate slopes for positive and negative shocks. We run a firm fixed-effect regression for each of the specifications. We include all the controls specified in the general model. The lagged TFP is added because we believe the shock to result in different employment adjustments depending on the TFP level. The log of employment is added to capture a firm size effect, while the time trend captures the long-term trend of employment growth.

Table 2.4.2 presents the results. Across all specifications, the estimates imply considerable evidence in favor of asymmetric responses. All the estimated coefficients are statistically significant. For example, for the first specification, an employment response to a one standard deviation positive TFP innovation is 1.42% ($0.064 \times 0.21 + 0.017 \times (0.21)^2 = 0.0142$), while to a negative TFP innovation the response, on average, is -1.27% ($0.064 \times (-0.21) + 0.017 \times (-0.21)^2 = -0.0127$). The last rows, "Positive response" and "Negative response", display the average employment adjustment for positive and negative TFP shocks, respectively. "Difference" reports the difference in absolute values of positive and negative responses. The baseline conclusions hold across all specifications: Belgium is characterized by convex hiring rule, i.e. firms respond more to positive shocks.

2.4.2 Employment Growth Distribution

With the concave (convex) hiring rule, the model predicts counter-cyclical (pro-cyclical) volatility of employment growth. In this subsection, we explore the cyclical patterns in the data.

Table 2.4.3 presents summary statistics of cross-sectional dispersion measures of employment growth. The first two columns present the baseline results - an unweighted average of moments. Both of them indicate the presence of heterogeneity in firms' employment adjustment. For example, from column (2), the employment growth of a firm at the top quartile is 5 percentage

Table 2.4.2: Firm-level employment asymmetry

	(1) Quadratic	(2) Cubic	(3) Piece-wise linear
z_{it}	0.064***	0.035***	0.050***
	(0.001)	(0.002)	(0.002)
z_{it}^2	0.017***	0.018***	
	(0.004)	(0.004)	
z_{it}^3		0.196***	
		(0.013)	
$z_{it} \times 1\{z_{it} > 0\}$			0.027***
			(0.004)
R^2	0.1375	0.1377	0.1375
Obs.	1853406	1853406	1853406
Nr.Clust.	214830	214830	214830
Negative response	-0.97%	-0.84%	-1.05%
Positive response	1.14%	1.00%	1.62%
Difference	0.17%***	0.16%***	0.46%***

Standard errors in parentheses

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

The table reports the results of the firm-fixed effect regression of eq. (2.4.7). Standard errors are clustered at the firm level. Positive and Negative response shows average employment response after positive and negative TFP shock, respectively. Difference reports the two-sample mean-comparison t-test.

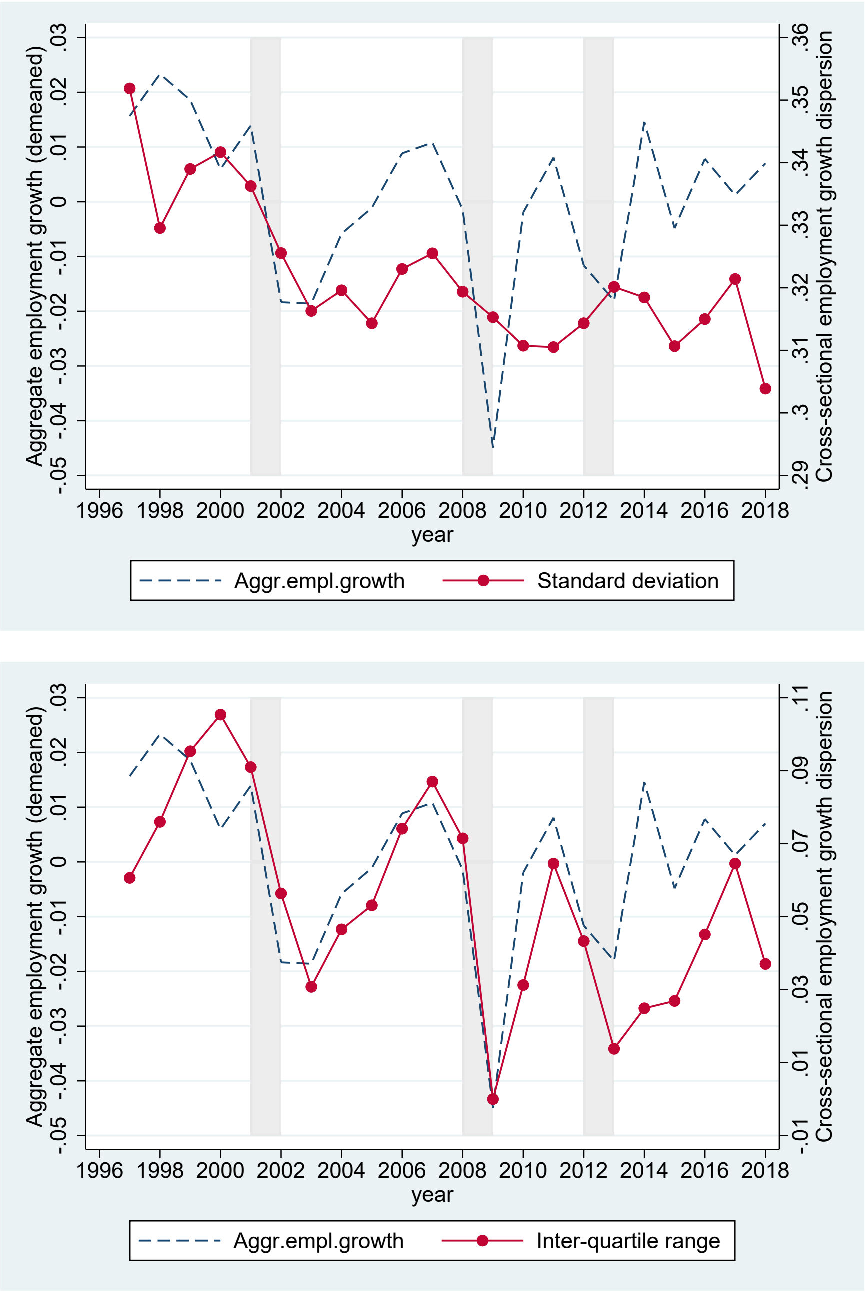
Table 2.4.3: Dispersion of employment growth

	Baseline		Robustness			
			weighted		DH	
	(1)	(2)	(3)	(4)	(5)	(6)
	$SD_t(n_{it})$	$IQR_t(n_{it})$	$SD_t(n_{it})$	$IQR_t(n_{it})$	$SD_t(n_{it}^{DH})$	$IQR_t(n_{it}^{DH})$
Long-run average	.322	.054	.24	.096	.295	.054
Booms	.325	.062	.248	.098	.297	.062
Recessions	.321	.051	.245	.1	.295	.051
Great Recession, 2008-2009	.317	.036	.226	.101	.292	.036
Corr(dE_t^{aggr}, $Moment_t$)	.408*	.669***	.37*	.14	.373*	.669***

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

These are the averages of the dispersion measures of the cross-sectional employment distribution plotted in Figure 2.4.3. dE_t^{aggr} is the aggregate employment growth rate. Recessions are defined as years with two consecutive negative quarterly GDP growth rates. Booms are defined as years with two consecutive quarterly GDP growth rates above the trend. To identify boom and recession years we use quarterly GDP growth data from OECD. Columns (1)-(2) are the baseline results. Columns (3)-(4) are the weighted averages. Columns (5)-(6) are based on Davis and Haltiwanger (1992) employment growth measure.

Figure 2.4.3: Evolution of the employment growth dispersion



On the right axis, the figures display the evolution of SD (top) and IQR (bottom) of employment growth. On the left axis, the figures display the evolution of demeaned aggregate employment growth (gray dashed line). The vertical gray bars cover recession periods identified using OECD quarterly GDP growth data.

points higher, on average, than at the bottom quartile. Figure 2.4.3 displays the evolution of the dispersion measures summarized in Table 2.4.3. The figure shows that the dispersion of employment growth declines during recessions and increases during the booms[15], i.e. pro-cyclical movement of the cross-sectional volatility. As Table 2.4.3 presents the correlation coefficients of employment growth and cross-sectional dispersion measures are positive and significant. Although it is not the main purpose of this research, we observe a declining trend of both measures of dispersion across the sampling period, which is consistent with Bijnens and Konings (2020) that report a decline in business dynamism for Belgium for a longer time span.

As described by Bijnens and Konings (2020), the Belgian economy has many small firms that change their employment by incremental amount[16] or show no employment changes at all. As a result, there is a large weight on zero values. To make sure that this characteristic has no impact on the conclusions made above, we perform the same analysis but with value-added as weights. The results are reported in Columns (3) and (4) of Table 2.4.3. Additionally, we experiment with alternative measure of employment growth proposed by Davis and Haltiwanger (1992)[17] (hereinafter, DH). The results are presented in Columns (5) and (6). The baseline conclusions are broadly robust to weighted moments and an alternative measure of employment growth.

The model predicts pro-cyclical volatility of growth of employment in cross-section and time-series, at the firm-level and the higher levels of aggregation. Time-series dispersion is computed at firms, NACE Rev.2 three-digit industries, NACE Rev.2 one-digit industries and the aggregate economy levels. The time-series standard deviation, Vol_t of employment growth is constructed within 5-year rolling windows:

$$Vol_{it} \equiv \sqrt{\frac{1}{4}\sum_{\tau=-2}^{2}(n_{it+\tau} - \bar{n_{it}})^2}, \tag{2.4.8}$$

where $\bar{n_{it}} \equiv \frac{1}{5}\sum_{\tau=-2}^{2} n_{it+\tau}$ is the average employment growth of firm i in the 5-year window around t. We restrict the calculations to a 5-year-rolling window because a longer window would filter out too many changes and the sample period is too short. Moreover, we consider only those firms that at least operate 5 consecutive years. We calculate the volatility on different levels of aggregation, to examine whether the micro-level patterns wash-out at higher levels. We also account for a trend, because we do not want any long-run trends to affect the business cycle

[15] Recession years: 2001, 2008-2009, 2012; Boom years: 1997, 1999-2000, 2002, 2004, 2006-2007, 2010, 2015, 2017-2018.

[16] Moreover, a firm that grows from 1 to 1.1 FTE, will have a growth rate of 9.53%, the same growth will be for the firm that grows from 100 to 110 FTE.

[17] $n_{it}^{DH} = \frac{2(L_{it}-L_{it-1})}{L_{it}+L_{it-1}}$

results.

Table 2.4.4: Employment growth moments in time-series

	Aggregation Level			
	Firm	**NACE 3-digit**	**NACE 1-digit**	**Aggregate**
Long-run average	.196	.052	.034	.016
Booms	.196	.05	.032	.015
Recessions	.196	.052	.038	.019
Great Recession, (2008-2009)	.193	.045	.039	.023
Corr(dE_t^{aggr}, $Moment_t$)	.07	.02	-.214	-.192

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

The table displays the longitudinal volatility at various levels of aggregation. For the first column, we calculate the measures for each firm and report the average. For the second and third columns, we calculate the measures at the corresponding industry levels and report the averages. For the aggregate measure, we calculate the measures at the aggregate level and report the average.

We present the calculations of time-series dynamics at four aggregation levels in Table 2.4.4.[18] As predicted by the model, the time-series volatility decreases during recessions for the firm level. However, the relation is not very strong (the correlation coefficient between the volatility and the employment growth is insignificant). As argued by Hamermesh (1993), aggregation smooths away any non-convexity and heterogeneity of the firm level, i.e. the volatility is higher during recessions at higher aggregation levels. Hence, indeed, at higher aggregation levels, the pattern found in the cross-section disappears.

In sum, contrary to the stylized fact of counter-cyclical volatility of aggregate economic outcomes established in the literature[19], we document pro-cyclical volatility for employment growth in Belgium. And, the results are consistent with the predictions of the convex hiring rule mechanism. Interestingly enough, recent studies report pro-cyclical volatility and positive skewness for capital investment in the developed economies (Bachmann et al., 2013a; Bachmann and Bayer, 2014). And authors use the higher cost of decreasing capital compared to increasing capital as a reason behind this pattern.

2.4.3 Productivity Distribution

In this subsection, we study productivity distribution to make sure that the asymmetric responses are not driven by asymmetric shocks.

[18] Please see Figures 2.A.2 and 2.A.3 that display the evolution of the time-series volatility of the average across all four aggregation levels in Appendix.

[19] Please see for example Higson et al. (2002); Bachmann and Bayer (2013); Bloom et al. (2018) for cyclical patterns of output and productivity dispersion, Berger and Vavra (2018) for cyclicality in prices, and Bachmann et al. (2013b) for business forecasting and business cycles.

In case the only source of variation is TFP innovations, employment growth should display more cyclical volatility than the underlying shocks.

Table 2.4.5: Cross-sectional moments summary

Moment	TFP Innovation, z_{it}	Employment growth, n_{it}
Mean	0	0.024
Standard deviation	0.262	0.322
Interquartile range	0.273	0.054
Interdecile range	0.60	0.585
No. observations	1,934,406	2,034,026

The table presents summary statistics of dispersion for TFP innovations and employment growth rates. The numbers represent the averages across years.

Table 2.4.5 reports the summary statistics of cross-sectional moments for TFP innovations and employment growth. The mean of the TFP innovation is fixed to zero. The standard deviation of the TFP innovation is smaller than that of the employment growth. The average interquartile range of TFP innovation is greater than that of the employment growth, which can be explained by the fatter tails of the TFP distribution. Moreover, as it was mentioned in the earlier section, the Belgian economy is comprised of many small firms that adjust their employment by the incremental amount or not at all (Bijnens and Konings, 2020). As a result, the distribution of employment growth is highly concentrated around zero, making the IQR close to zero. Note that the SD and IQR of TFP innovation are close. A firm hit by a one standard deviation TFP shock generates around 26% more in value-added than the average firm. Although, other shocks are also relevant in explaining the volatility in employment growth, a comparison of the second moments of TFP innovation and employment growth distributions might be informative on observed dispersion in employment growth. The mere question is whether asymmetric responses are driven solely by the asymmetries in the underlying shocks. The higher standard deviation of the employment growth distribution suggests that other factors play role in determining its shape. Overall, the results indicate that the asymmetry in hiring and firing is not only because of the asymmetries in TFP shocks alone.

2.5 Sectoral Analysis

For designing proper policies, it is required to distinguish between the changes in employment that occur due to business cycles, that potentially affect all sectors of the economy and the ones that happen due to structural reallocation in production, that affect only particular sectors

(Rissman, 2009). Moreover, we might observe different curvatures of the hiring rule due to the composition of the workforce, joint committee agreements, and/or presence and strength of the labor unions in different sectors. Therefore, we will test whether the patterns found in the baseline results hold for broad categories of sectors in the economy: industry, services, and trade.[20]

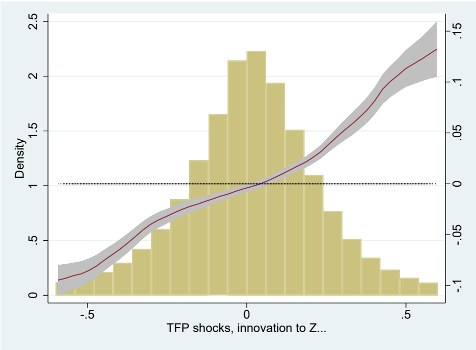
To this end, we estimate eq. (2.4.6) for each sector and plot the estimated regression lines in Figure 2.5.4. We observe a convex shape over the domain of TFP shocks for services. On average, one standard deviation positive TFP shock (+0.2) increases employment by 3.5%, while one standard deviation negative shock (-0.2) increases employment by 1.2%. For industry and trade, we observe more of a straight line. On average, employment in industry increases by 2.2% and decreases by 2.3% after one standard deviation (±0.2) positive and negative TFP shock, respectively. For trade, on average, employment increases by 3.3% and decreases by 2.1% after one standard deviation (±0.2) TFP shock.

The less convex shape in the industry sector could be related to the structural realignment in production. In a dynamic economy, some industries are shrinking, while others are expanding. As it was largely documented in the literature, the structural reallocation in production is taking place, in which the manufacturing sector is declining, while services are growing (Baily and Bosworth, 2014; Bernard et al., 2017; Fort et al., 2018). And labor naturally flows from declining sectors towards the expanding ones. This trend is evident in Belgium too (Bijnens, 2020; Karimov and Konings, 2020). Sectoral reallocation may coincide with the economic downturns (Bloom et al., 2018). However, since recessions are followed by booms, firms that contract during recessions tend to grow back during expansions, whereas structural changes tend to have a long-lasting effect on the employment composition of a firm in the contracting sector. Therefore, firms that are already on the edge of contracting or exiting are expected to undergo a structural reduction in employment, presumably contributing to a larger decline when a negative shock hits the already declining manufacturing sector.

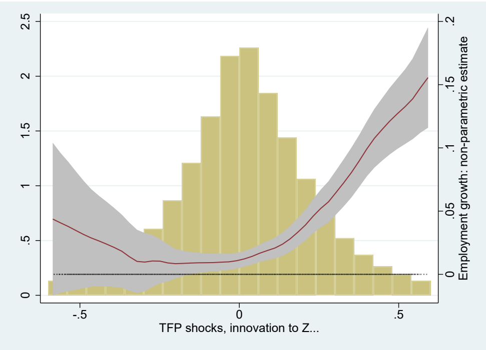
Similarly to the baseline case, further we explore the cyclical patterns of the employment growth volatility. Table 2.5.6 presents the average of cross-sectional moments for broad categories of sectors. Although the correlations of the moments with the aggregate employment growth are somewhat weak, we still observe pro-cyclical dispersion for trade and services sectors. The industry sector does not show any cyclical pattern. Overall, the patterns described in the

[20] Industry sector includes agriculture (NACE 1-3), mining and quarrying (NACE 5-9), manufacturing (NACE 10-33), and construction (NACE 41-43). The services sector is from NACE 49 to NACE 82 and the trade sector is NACE 45-47.

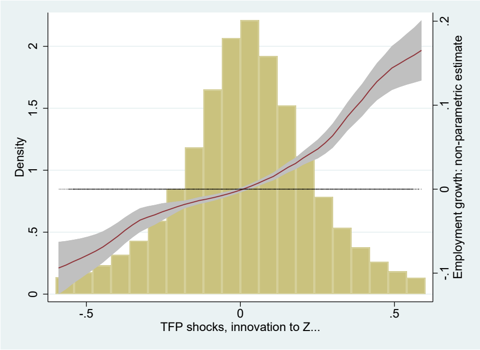
Figure 2.5.4: Employment growth and TFP innovations by sector



(a) Industry



(b) Services



(c) Trade

Table 2.5.6: Cross-sectional moments by sector

	Industry		**Services**		**Trade**	
	$SD_t(n_{it})$	$IQR_t(n_{it})$	$SD_t(n_{it})$	$IQR_t(n_{it})$	$SD_t(n_{it})$	$IQR_t(n_{it})$
Long-run average	.316	.081	.344	.068	.3	.023
Booms	.318	.086	.348	.076	.303	.03
Recessions	.32	.08	.341	.063	.299	.027
Great Recession, 2008-2009	.319	.083	.336	.042	.292	.02
Corr(dE_t^{aggr}, $Moment_t$)	.27	.275	.213	.488**	.454**	.202

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

The table displays summary statistics of cross-sectional dispersion of employment growth rates for broad categories of sectors. For each sector, the measures are the averages across years.

baseline results seem to hold for each of the sectors.

2.6 Further Evidence

This section intends to further convince the reader that the extent of market rigidity is reflected in the shape of the hiring rule function. To this end, first, we utilize the difference in the level of the labor market protection for blue-collar and white-collar workers, that was present during the time frame of the research. Second, we build the argument around the difference in the adjustment costs for adjusting the number of workers and adjusting the hours of work. Finally, we identify the shape of the hiring rule for some other European countries, namely, Ireland, Portugal, Sweden, and the United Kingdom.

2.6.1 Type of Labor Force

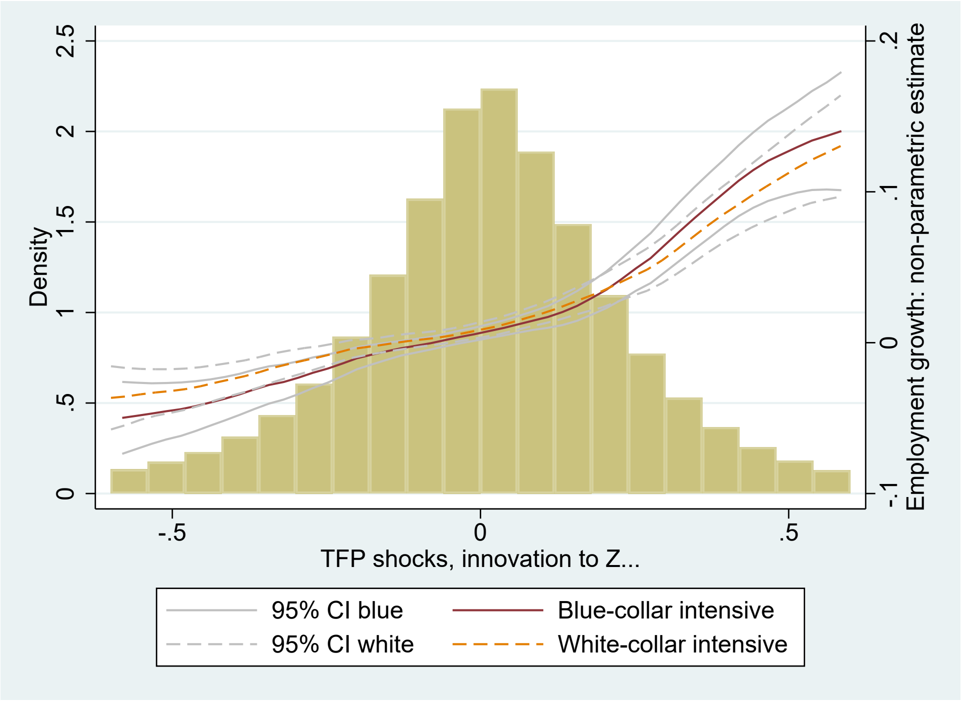
In the period we study, Belgium employment law was favoring white-collar workers more compared to blue-collar. White-collar workers were experiencing stronger labor market protections, i.e. firing costs for white-collar workers were higher than for blue-collar workers. Recent policy on harmonization of labor contracts of blue- and white-collar workers has increased adjustment costs for blue-collar intensive firms (Alpysbayeva and Vanormelingen, 2020). Moreover, Goux et al. (2001) show that the asymmetry between hiring and firing costs is more important for non-production workers, rather than production workers. In this regard, we differentiate between firms based on the production worker intensity. We define a firm to be blue-collar intensive if the share of blue-collar workers across the years is higher than 75%, and as a white-collar intensive firm if the share of blue-collar workers is lower than 25%. We focus only on firms that are identified as blue- or white-collar intensive firms throughout of its existence in the data[21]. As a result, we identify 36% of firms as blue-collar intensive and 35% as white-collar intensive firms. Table 2.6.7 presents some summary statistics based on the two sub-samples of firms.

Table 2.6.7: Summary: Type of labor intensity

	Total	**Blue-collar**	**White-collar**
$mean(z_{it})$	0.015	0.013	0.017
$SD(z_{it})$	0.216	0.210	0.224
Obs.	1,276,430	708,715	567,715
No. of firms	155,979	80,812	75,167

[21] 29% of firms change their type of labor intensity at least once. We ignore these firms.

Figure 2.6.5: Employment growth and TFP innovations: Type of labor force



We estimate eq. (2.4.6) for the two sub-samples and the results are depicted in Figure 2.6.5. Although we see some small differences for blue- (solid line) and white-collar (dashed line) intensive firms on average, the differences are more pronounced for larger shocks. We cannot conclude the asymmetry to be more or less important for one or the other type of the labor force because their confidence intervals overlap a lot.[22] Nevertheless, the average effects show the white-collar intensive firms to be less responsive to both positive and negative shocks. On average, after one standard deviation positive TFP shock, employment of a blue-collar intensive firm increases by 3.0%, while it increases by 3.6% for a white-collar intensive firm. After one standard deviation negative shock, the employment in a blue-collar intensive firm decreases by 0.7%, while it decreases by 0.2% in a white-collar intensive firm, on average.

2.6.2 Hours Worked

As argued by Decker et al. (2020), the decline in reallocation is the result of weaker responsiveness to shocks in the face of rising adjustment costs, rather than the declining dispersion of the shock. Abraham and Houseman (2009) provide evidence that when the shock hits, due to costly employment adjustment, in Germany, France and Belgium, in the short-run, hours worked are adjusted rather than the number of employees. Moreover, during the Great Recession, firms were allowed to costlessly hoard labor, which was reflected in the number of hours worked, but not necessarily followed by discarding employment. Van den bosch and Vanormelingen (2017) estimate the extent labor hoarding mitigates job reallocation in Belgium. In general, Belgium has a system of temporary unemployment, during recessions, for example, workers receive unemployment benefits, and they are called back to work when the economy recovers. Therefore, the number of full-time equivalents (FTE) used to calculate the employment growth rate is not ideal in reflecting the true amount of labor involved in the firm's production. Broadly, it ignores whether an employee is active or not. It abstracts from overtime, sick-leave, and maternity (paternity) leave. More importantly, it abstracts from labor hoarding. As a result, when using the number of workers, a smaller adjustment under a negative shock could have been generated by default. Considering these features of the labor market of Belgium, we expect the shape of the hiring rule to be less convex. Therefore, to make sure that the baseline results are not driven solely by labor-hoarding or the delayed effect of employment adjustment, we perform the same analysis using effective hours worked as an alternative measure of employment. Unfortunately,

[22] We perform a formal test for the statistically significant difference in asymmetries in response to shocks for blue- and white-collar worker intensive firms. Please see Section 2.C for details.

the usable part of the data on hours worked is limited to 1997-2014 (the later period is extremely poorly reported), which is smaller than the baseline time frame. Nevertheless, the period at hand captures all the recession periods experienced by the Belgian economy. We perform the same analysis as above with the employment growth measured as:

$$h_{it} \equiv \Delta log(H_{it}),$$

where H_{it} is effective hours worked. We estimate eq. (2.4.6) and the result is presented in Figure 2.6.6. As was anticipated, we observe a less convex shape, linear, if to be more precise. After a one standard deviation TFP shock hours of work increase by 3.7%, and decreases by -3.2% for one standard deviation negative shock, on average. This finding clearly indicates the importance of policies in adjusting the shape of the hiring rule and consequently affecting the cyclicality and skewness of employment distribution.

Figure 2.6.6: Employment growth and TFP innovations: Hours of work

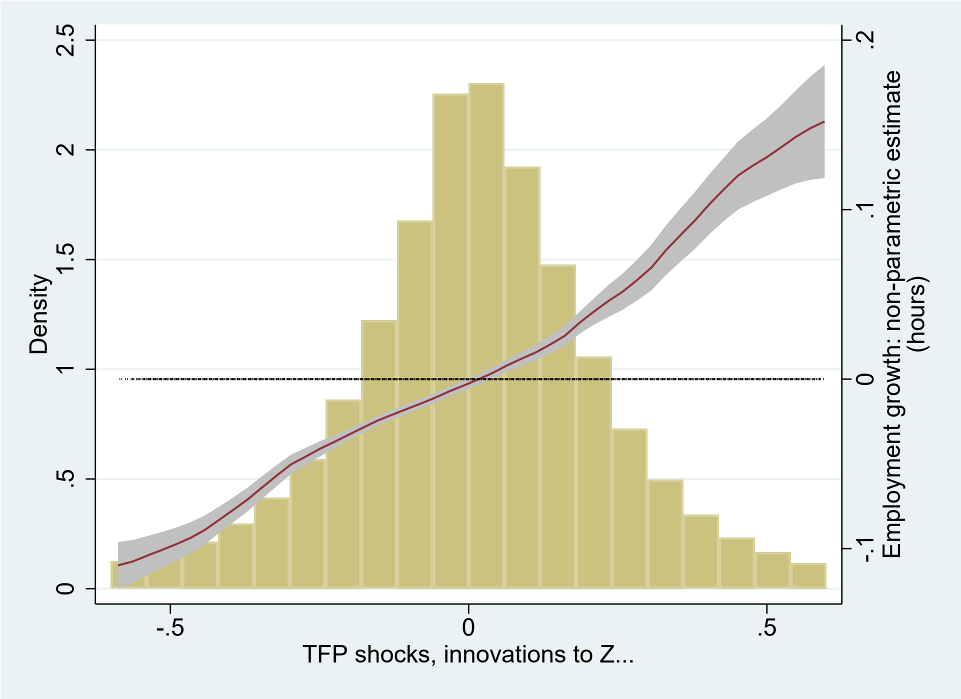


Table 2.6.8 presents the results for a formal test of linearity. We try to fit quadratic and non-monotonic models. The results suggest the hiring rule to be linear. The coefficient on z_{it}^2 is not statistically significant.

Table 2.6.8: Firm-level employment asymmetry: Hours of work

	(1) Quadratic	(2) Cubic
z_{it}	0.091***	0.063***
	(0.002)	(0.003)
z_{it}^2	0.008	0.009
	(0.006)	(0.006)
z_{it}^3		0.195***
		(0.017)
R^2	0.1117	0.1119
Obs.	1411763	1411763
Nr.Clust.	180184	180184

Standard errors in parentheses

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

Apart from the adjustment of hours of work being cheaper (costless), at least in the short run, Karimov (2019) document that Belgian firms tend to adjust their employment by little, and it is not the magnitude of adjusting the employment but rather the frequency of adjustment that plays a role in employment reallocation. Therefore, we speculate that the hiring rule is more linear for smaller shocks and has more curvature for larger shocks.[23] In this regard, we partition the data into small and large shocks. We focus on the shocks that are one standard deviation away from the mean of the TFP shock, which captures about 66% of the overall data. Table 2.6.9 presents the results. Indeed, we observe that for the sub-sample of small TFP shocks, the slope for positive TFP shock realizations is not statistically different from the negative shocks. Contrary, for the sub-sample of large shocks, the slope is higher for positive TFP shocks, i.e. asymmetric response. This implies that the response function for large shocks is convex, while for small TFP shocks it is linear.

Further, we explore the cyclicality of the volatility of the growth of hours of work. Table 2.6.10 displays the summary statistics of cross-sectional moments of TFP innovation and growth in hours worked. We observe similar patterns as in the baseline specification: the standard deviation and the interdecile range of TFP innovation are smaller than that of the growth of

[23] According to Hamermesh (1989), employment is unchanged in response to small shocks and moves in response to larger shocks.

Table 2.6.9: Firm-level employment asymmetry: Hours of work

	(1)	(2)
	Piece-wise linear	
	Small shock	*Large shock*
z_{it}	0.106***	0.050***
	(0.030)	(0.013)
$z_{it} \times 1\{z_{it} > 0\}$	-0.001	0.059**
	(0.052)	(0.024)
R^2	0.0754	0.0869
Obs.	386328	533830
Nr.Clust.	139834	134219

Standard errors in parentheses

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

The table reports the results of the firm-fixed effect regression of eq. (2.4.7). Standard errors are clustered at the firm level.

hours worked. The interquartile range of TFP innovations is greater than that of the growth of hours worked. Comparison of cross-sectional and time-series moments of TFP innovations and growth of hours worked indicate that asymmetric adjustments are not due to asymmetric TFP shocks.

Table 2.6.10: Cross-sectional moments summary: Hours of work

Moment	**TFP Innovation, z_{it}**	**Hours growth, h_{it}**
Mean	0	0.023
Standard deviation	0.250	0.348
Interquartile range	0.259	0.158
Interdecile range	0.572	0.660
No. observations	1,463,255	1,535,744

The table shows some summary statistics for TFP shocks and hours growth rates. The numbers represent the averages across years.

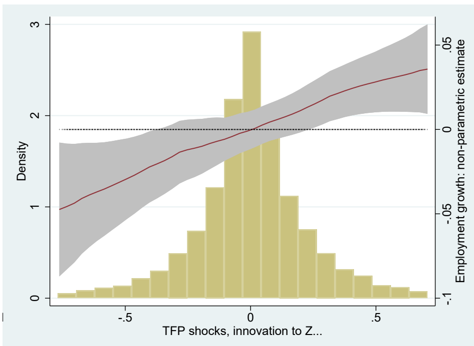
2.6.3 Other Countries

In this subsection, we focus on four other European countries: Ireland, Portugal, Sweden, and the United Kingdom. The analysis relies on firm-level data collected from Orbis Global. Although the limitations with the data coverage of the database are well-known, it still provides strong external validation of our baseline conclusions. The main reason for choosing specifically these four countries is that they differ across various dimensions - location, development, integration, to name a few, and most importantly, the labor market institutional settings. While

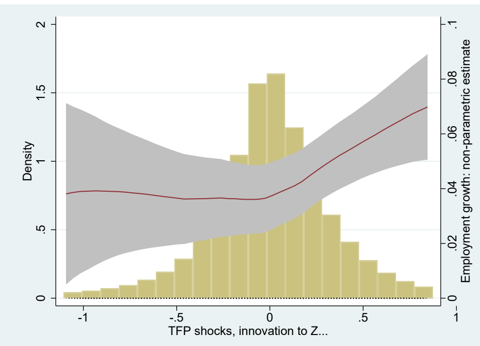
Ireland and the UK are believed to have a less rigid labor market compared to the Belgian market, Portugal and Sweden exert far more strong labor protection.[24] The time frame for Sweden and the UK is from 2000 to 2016, while for Ireland and Portugal - 2006-2016. We execute the same analysis for each country separately.[25]

The results of the non-parametric regression of eq. (2.4.6) are presented in Figure 2.6.7. While we observe the linear shape of the hiring rule for Ireland and the UK, Portugal and Sweden show a convex shape.

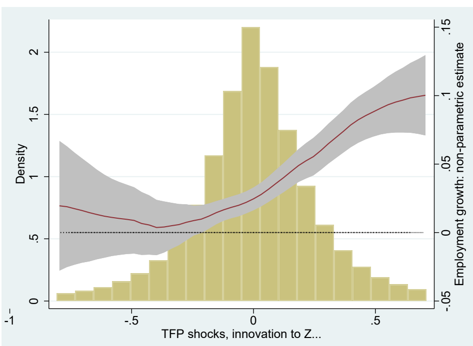
Figure 2.6.7: Employment growth and TFP innovations by country



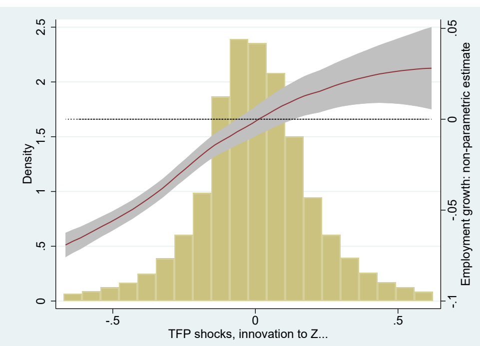
(a) Ireland



(b) Portugal



(c) Sweden



(d) United Kingdom

[24]For 2019, the EPL index for Ireland is equal to 1.23 and 1.35 for the UK. Portugal and Sweden are assigned higher values, 3.14 and 2.45, respectively.

[25]The only difference is that the production elasticities of labor and capital inputs are calculated at the NACE Rev.2 two-digit level for Portugal, Sweden, and the UK, and the NACE Rev.2 sector (1-digit) level for Ireland, due to the limited number of observations per more disaggregated industry definition.

Additionally, we perform a parametric regression analysis for a piece-wise linear case of eq. (2.4.7) for each country. Table 2.6.11 presents the results. Identical to the baseline case, a significant and positive estimated coefficient on the interaction term hints at a convex shape of the hiring rule, while a significant and negative estimated coefficient signals a concave hiring rule. A coefficient that is statistically not different from zero implies, on average, symmetric adjustment of employment, indicating a linear function. From Table 2.6.11, we confirm a convex hiring rule for Portugal and Sweden. We do not have enough evidence to conclude the concave or convex shape of the hiring rule for Ireland and the UK. The results broadly confirm our hypothesis that more (less) rigid labor market results in a more convex (concave) hiring rule, reaffirming the main conclusion from our baseline analysis.

Table 2.6.11: Firm-level employment asymmetry: Country

	(1) **Ireland**	(2) **Portugal**	(3) **Sweden**	(4) **UK**
z_{it}	0.014	-0.069***	0.001	0.030***
	(0.027)	(0.002)	(0.002)	(0.006)
$z_{it} \times 1\{z_{it} > 0\}$	-0.032	0.024***	0.010**	0.009
	(0.043)	(0.004)	(0.004)	(0.010)
R^2	0.1403	0.2260	0.1439	0.1056
Obs.	11890	1099261	1120431	206485
Nr.Clust.	3623	219186	168224	48119

Standard errors in parentheses

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

The table reports the results of the firm-fixed effect regression of the piece-wise linear case of the eq. (2.4.7) for each country. Standard errors are clustered at the firm level.

2.7 Conclusion

The literature on optimal adjustment behavior suggests that in the presence of adjustment costs, the responses to positive and negative shocks are asymmetric. Stronger labor market protection constrains firms to react to market fluctuations, i.e. when the negative shock hits, firms cannot easily adjust by firing employees due to high firing costs. With high firing costs, managers cannot easily fire workers during the downturns and are reluctant to hire during the booms. Hence, high adjustment costs slow the firm's reactions to shocks. It reduces investment and employment variability (Haltiwanger et al., 2014).

Contrary to most macroeconomic studies that focus on the volatility of productivity shock to explain the volatility in the aggregate employment growth, Ilut et al. (2018) propose an endogenous mechanism that shapes the distribution of employment growth generating countercyclical dispersion and negative skewness. They use the US microdata to document its applicability. Concave hiring rules are at the core of the mechanism. Basically, when a firm faces a firm-level shock, they respond more to bad shocks, than to good shocks, and the presence of the concave rule alone is able to generate countercyclical volatility in employment growth. One possible explanation for a concave shape could be that firing costs are lower than hiring costs. As a result, when a negative shock hits, the cheaper form of adjustment is to fire people.

Building on Ilut et al. (2018), this paper hypothesizes that stricter employment protection legislation results in (more) convex hiring rule generating pro-cyclical employment growth volatility. To test the hypothesis, we use firm-level data covering the annual accounts of Belgian firms from the National Bank of Belgium for the baseline analysis. The Belgian institutional setting is more typical of European institutions, more rigid labor market compared to the US. Therefore, it could be of considerable interest to study the Belgian case because while the result could be generalized to most of the European states with similar institutions, the differences in the optimal response to different shocks might arise from different institutional settings. Therefore, using firm-level data from ORBIS, we extend the analysis to four other European economies with different labor adjustment costs, namely, Ireland, Portugal, Sweden, and the United Kingdom. Compared to Belgium, Ireland and the UK are believed to exert far less strict labor market protection, while Sweden and Portugal are characterized by the stronger labor protection mechanism.

First, using both non-parametric and parametric regressions, we show that the hiring rule in Belgium is convex. According to the mechanism proposed by Ilut et al. (2018), the convex hiring rule induces pro-cyclical volatility of the aggregate employment growth. Therefore, next, we show that in line with the predictions of the mechanism, the volatility of employment growth in Belgium is pro-cyclical in cross-section and time-series. Second, we study the distribution of productivity innovation. We show that the distribution of TFP shocks is negatively skewed and has a longer tail compared to the distribution of the employment growth. Contrary to most studies that try to explain the cyclical patterns in the aggregate macroeconomic indicators by the variation in TFP shocks, we argue that given these differences, the asymmetric hiring and firing behavior cannot be attributed to the asymmetric TFP shocks alone. Finally, we focus on the four European countries with different levels of labor market protection. We confirm a convex hiring rule for both Portugal and Sweden, while we do not have enough evidence to conclude the shape of the hiring rule to be convex or concave for Ireland and the UK. This finding, confirms the hypothesis that the stricter employment protection legislation results in (more) convex hiring rule generating pro-cyclical employment growth volatility.

Nevertheless, there are some limitations and concerns that could potentially affect our results. One of the common concerns in the literature is the proper estimation of the total factor productivity (TFP) signal. The productivity shock that we estimate captures both measurement error and the true productivity innovations. We further use these estimated TFP shocks to identify the employment response of firms. As a result, there is some measurement error that creates the attenuation bias, which might potentially impact our conclusions on the shape of the hiring rule. However, since the bias is argued to be downward, it is mostly neglected in the literature Hausman (2001). Another concern is that we use a simple estimation model with only a few controls. Hence, there could potentially exist some variables that affect both productivity and employment that we omit and which are not captured by the firm and /or year fixed effects, generating omitted variable bias.

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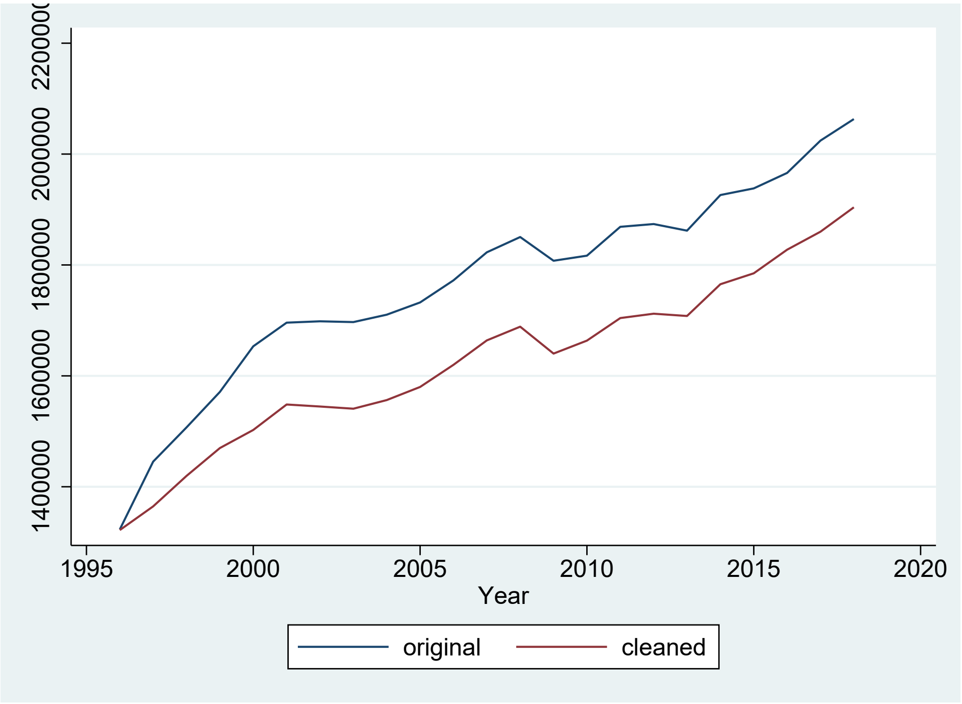
2.A Additional Figures and Tables

Figure 2.A.1: Aggregate employment



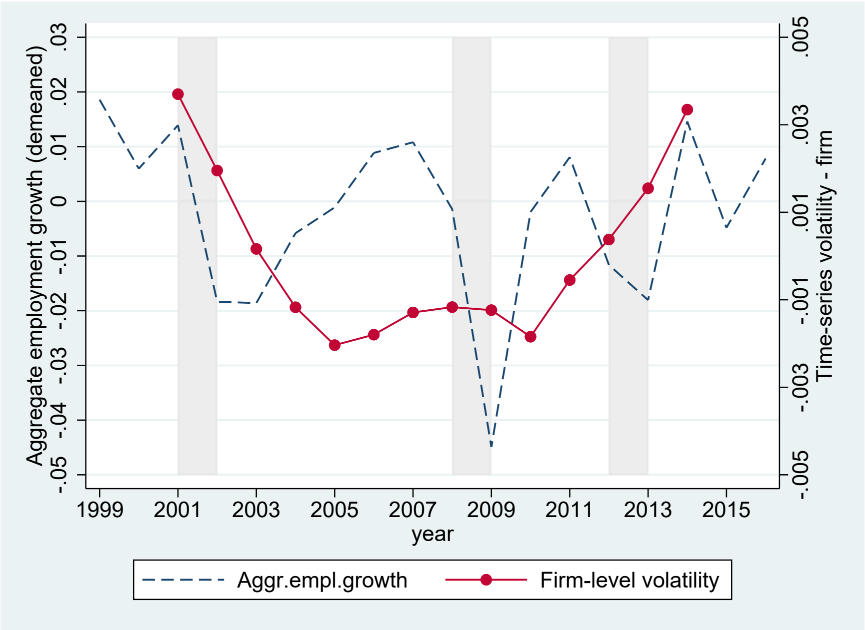
The figure presents the evolution of aggregate employment from the original data and after the cleaning introduced.

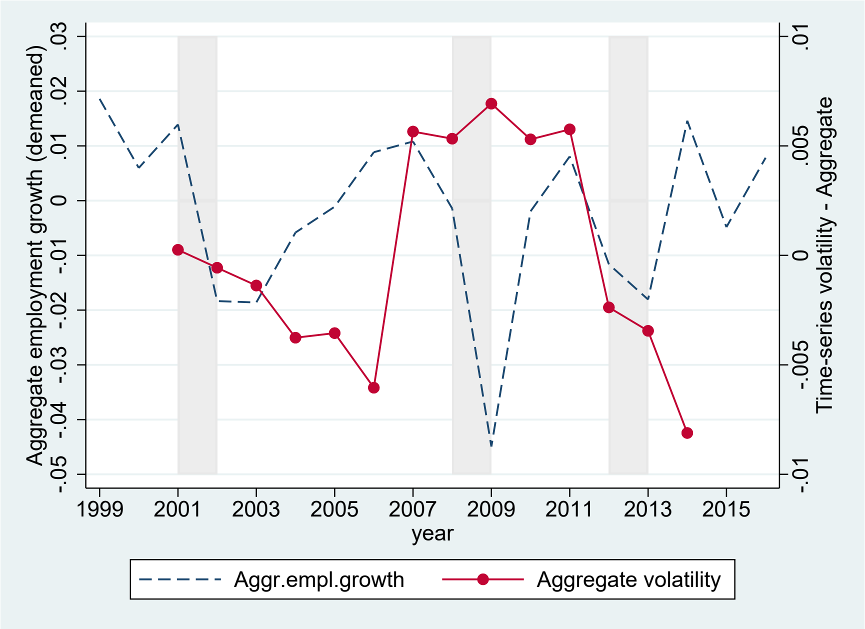
Table 2.A.1: Cross-sectional moments summary: Country

	Ireland		*Portugal*		*Sweden*		*United Kingdom*	
Moment	z_{it}	n_{it}	z_{it}	n_{it}	z_{it}	n_{it}	z_{it}	n_{it}
Mean	0	0.012	0	0.006	0	0.014	0	0.009
Standard deviation	0.247	0.246	0.353	0.319	0.271	0.268	0.221	0.228
Interquartile range	0.223	0.120	0.359	0.041	0.280	0.041	0.223	0.119
No. observations	12,378	12,797	1,144,583	1,271,429	1,166,627	1,353,401	214,995	221,723
Time frame	2006 – 2016		2006 – 2016		2000 – 2016		2000 – 2016	

The table displays summary statistics for moments of the TFP innovation and the employment growth rate distributions by country. The numbers represent the averages across years.

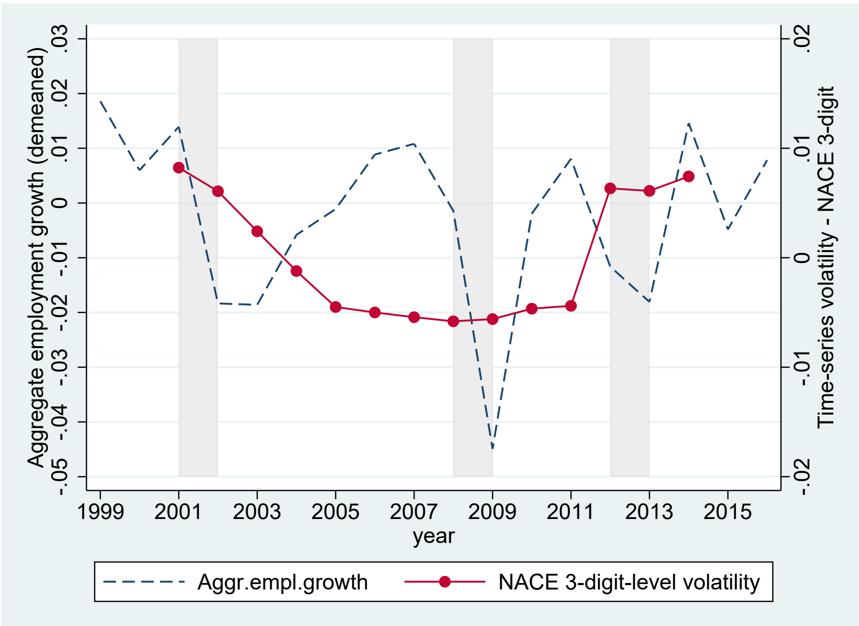
Figure 2.A.2: Time-series volatility

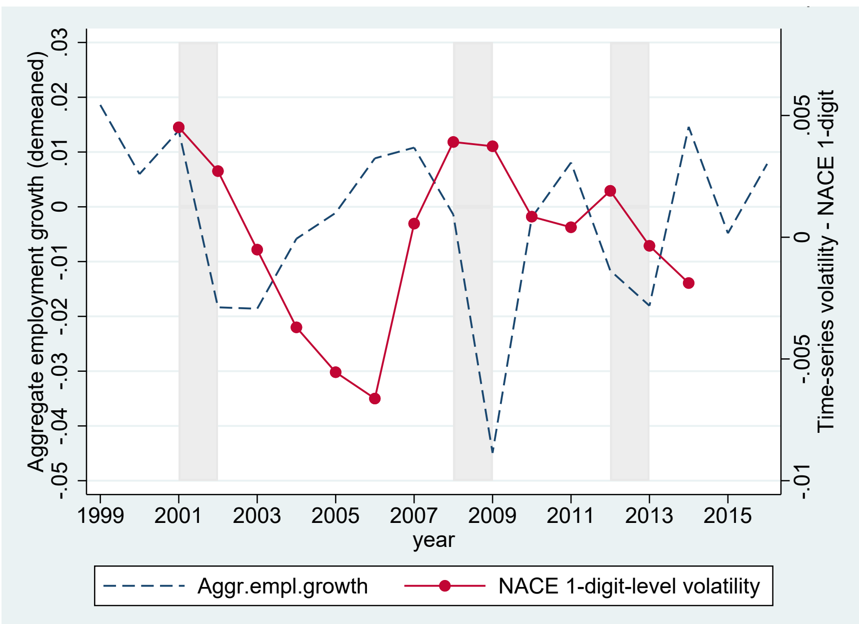




On the right axis, the figures display the evolution of the time-series volatility measure, Vol_t^i, of employment growth. The top figure shows the volatility at the firm level. The bottom figure shows the volatility at the aggregate level. On the left axis, the figures display demeaned aggregate employment growth evolution (gray dashed line). The vertical gray bars cover recession periods identified from OECD quarterly GDP growth data.

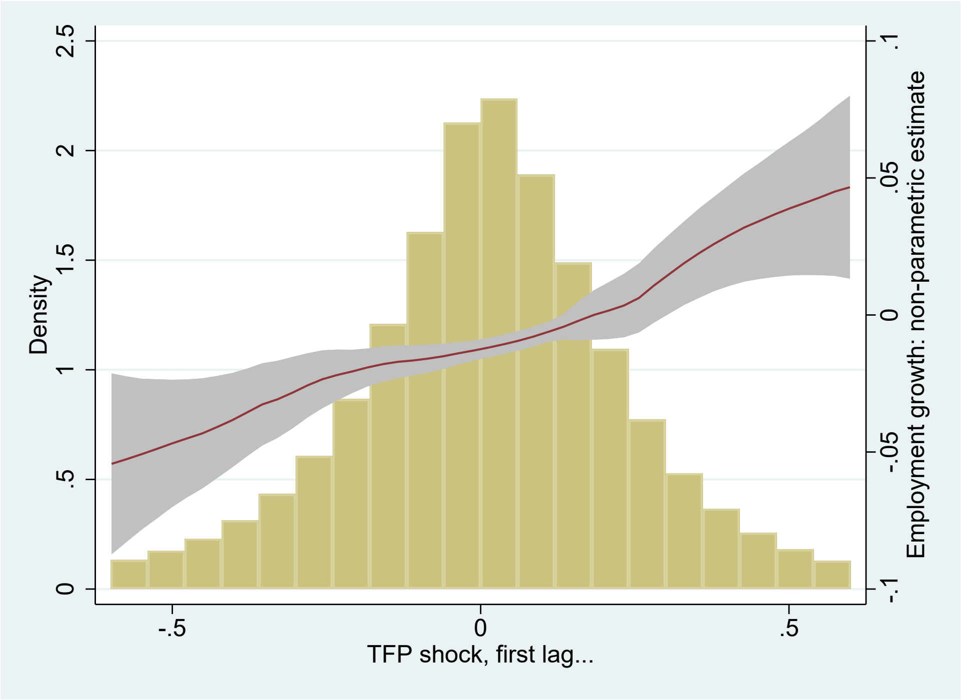
Figure 2.A.3: Time-series volatility





On the right axis, the figures display the evolution of the time-series volatility measure, Vol_t^i, of employment growth. The top figure shows the volatility at the NACE three-digit level. The bottom figure shows the volatility at NACE one-digit level. On the left axis, the figures display demeaned aggregate employment growth evolution (gray dashed line). The vertical gray bars cover recession periods identified from OECD quarterly GDP growth data.

Figure 2.A.4: Employment growth and TFP innovations, first lag



2.B Skewness

The mechanism also suggests that asymmetric adjustment induces skewness. For the concave (convex) hiring rule, the mechanism predicts negative (positive) skewness of employment growth distribution.

Calculate skewness using standard measures: the Fischer-Pearson coefficient and the Kelley skewness. The Fisher-Pearson skewness is based on the second and the third moments:

$$\gamma(x) = \frac{E[(x - E[x])^3]}{var(x)^{3/2}}. \tag{2.B.1}$$

The Kelley skewness on the other hand is calculated using the distribution percentiles:

$$\kappa(x) = \frac{x^{p90} + x^{p10} - 2x^{p50}}{x^{p90} - x^{p10}}, \tag{2.B.2}$$

where x^{pN} denotes the Nth percentile of the distribution of x. x is a random variable representing employment growth and TFP innovation. Note that the Kelley skewness coefficient is bounded between $[-1, +1]$. When the 90th percentile coincides with the median, then $\kappa(x) = -1$, and $\kappa(x) = +1$ if the median coincides with the bottom decile. From propositions in Ilut et al. (2018), for any aggregate shock the coefficient of skewness of the employment growth, $\gamma(n|a)$, is higher than the skewness of the underlying shocks, $\gamma(s|a)$. With regard to macro skewness, the skewness of the aggregate employment growth, $\gamma(E[n|a])$, is larger than the skewness of the aggregate signal realization, $\gamma(a)$. Similarly, for the Kelley skewness: $\kappa(n|a) > \kappa(s|a)$ and $\kappa(E[n|a]) > \kappa(a)$.

Note that the proposition does not predict any particular cyclical movements in skewness. This is because changes in skewness come from changes in the curvature of the signals, while changes in volatility are derived from changes in the slope of the response function. Hence, it is possible to have either pro-cyclical or counter-cyclical skewness, while having pro-cyclical volatility. This implies that during the negative realizations of the signal, the distribution can be less spread and at the same time be more or less positively skewed. In sum, the mechanism does not predict certain cyclical movements for the skewness of employment growth.

Figure 2.B.1 displays the evolution of the skewness calculated using eqs. (2.B.1) and (2.B.2).

Table 2.B.1 summarizes the cross-sectional skewness of employment growth distribution for both measures of skewness. As Table 2.B.1 shows, both of them are positive on average. This means that firms that contract shrink by less than firms that expand. From column (1), the long-run average of the skewness is 0.145. From column (2), the Kelley skewness is 0.187. For the

period of the Great recession, the Kelley skewness drops to 0.145. This indicates the distribution between the 10th and 50th percentiles is 75% ($\frac{1-0.145}{1+0.145}$) less spread compared to the distribution between the 90th and 50th percentile. The measures do appear to be pro-cyclical, albeit the model is silent about the cyclical behavior of the skewness. The correlation with aggregate employment is statistically significant.

Table 2.B.1: Cross-sectional skewness of employment growth

	Baseline		Robustness			
			weighted		DH	
	(1)	(2)	(3)	(4)	(5)	(6)
	$\gamma_t(n_{it})$	$\kappa_t(n_{it})$	$\gamma_t(n_{it})$	$\kappa_t(n_{it})$	$\gamma_t(n_{it})$	$\kappa_t(n_{it})$
Long-run average	.145	.187	2.991	.273	.112	.184
Booms	.2	.208	2.987	.307	.148	.205
Recessions	.049	.192	3.708	.204	.076	.189
Great Recession, 2008-2009	.015	.145	3.558	.109	.058	.143
Corr(dE_t^{aggr}, $Moment_t$)	.732***	.655***	-.07	.831***	.706***	.655***

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

These are the averages of the skewness measures of the cross-sectional employment distribution plotted in Figure 2.B.1. dE_t^{aggr} is the aggregate employment growth rate. Recessions are defined as years with two consecutive negative quarterly GDP growth rates. Booms are defined as years with two consecutive quarterly GDP growth rates above the trend. To identify boom and recession years we use quarterly GDP growth data from OECD. Columns (1)-(2) are the baseline results. Columns (3)-(4) are the weighted averages. Columns (5)-(6) are based on Davis and Haltiwanger (1992) employment growth measure.

The model predicts skewness of employment growth in cross-section and time-series, at the firm-level and higher levels of aggregation. Time-series skewness, $Asym_t$, of employment growth is computed at firms, NACE Rev.2 three-digit industries, NACE Rev.2 one-digit industries, and the aggregate economy levels. It is constructed within 5-year rolling windows:

$$Asym_{it} \equiv \frac{\frac{1}{4}\sum_{\tau=-2}^{2}(n_{it+\tau} - \bar{n_{it}})^3}{(Vol_{it})^3}, \tag{2.B.3}$$

where similarly to eq. (2.4.8) $\bar{n_{it}} \equiv \frac{1}{5}\sum_{\tau=-2}^{2} n_{it+\tau}$ is the average employment growth of firm i in the 5-year window around t, and Vol_{it} is the volatility calculated from eq. (2.4.8).

Figures 2.B.2 and 2.B.3 illustrate the evolution of time-series skewness at all aggregation levels. Table 2.B.2 presents the summary statistics for Figures 2.B.2 and 2.B.3. Similar to the time-series dispersion measure, the pattern found in the cross-section disappears. While at the firm-level the skewness is positive, it becomes negative at aggregate levels. At all levels of aggregation, the correlation between time-series skewness and employment growth is statistically insignificant. Hence, there is no cyclical pattern for skewness.

Table 2.B.2: Skewness of employment growth

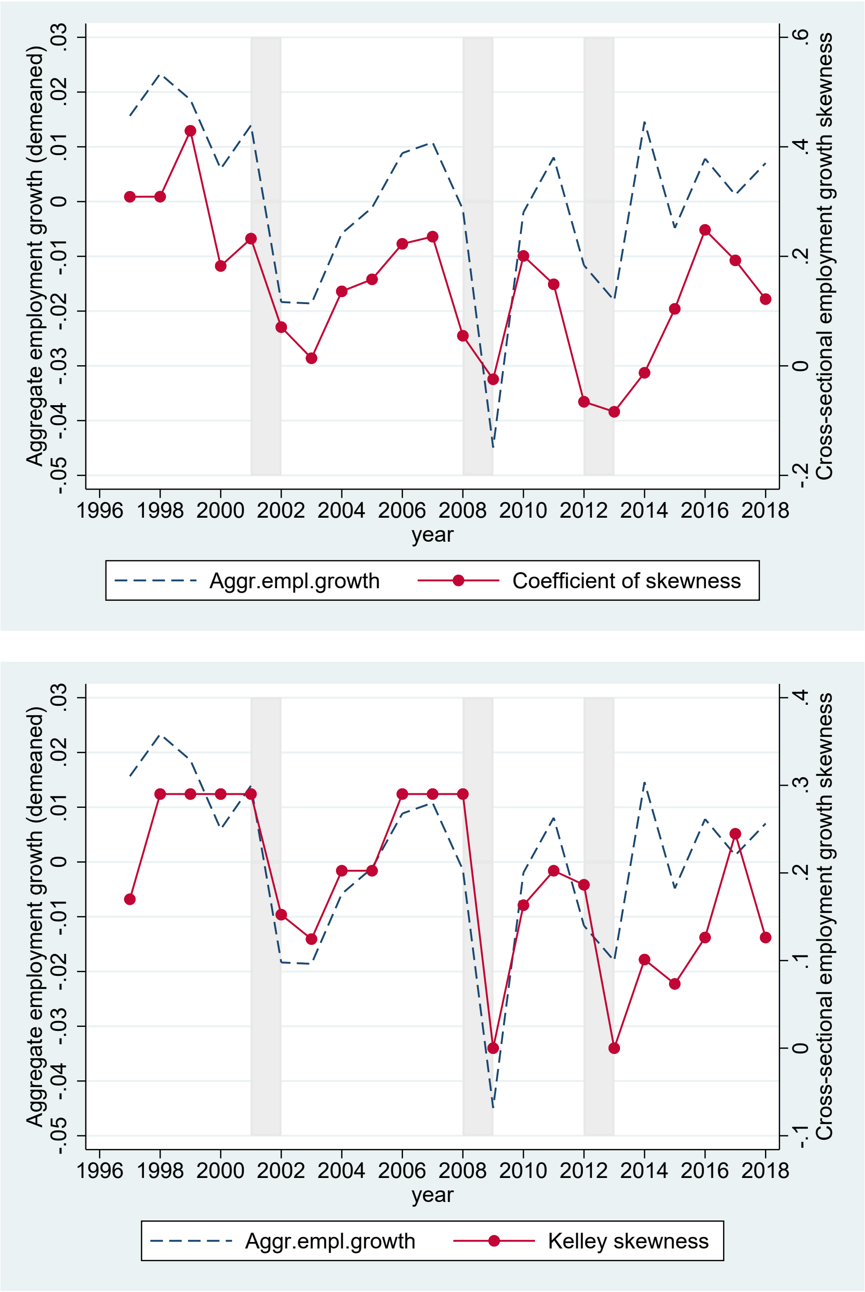
	Aggregation Level			
	Firm	**NACE 3-digit**	**NACE 1-digit**	**Aggregate**
Long-run average	.006	-.071	-.095	-.301
Booms	.009	-.111	-.208	-.441
Recessions	.027	-.017	.026	-.458
Great Recession, (2008-2009)	.02	-.185	-.295	-1.027
Corr($dE_t^{aggr}, Moment_t$)	.069	.02	.04	.044

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

The table displays the longitudinal asymmetry at various levels of aggregation. For the first column, we calculate the measures for each firm and report the average. For the second and third columns, we calculate the measures at the corresponding industry levels and report the averages. For the aggregate measure, we calculate the measures at the aggregate level and report the average.

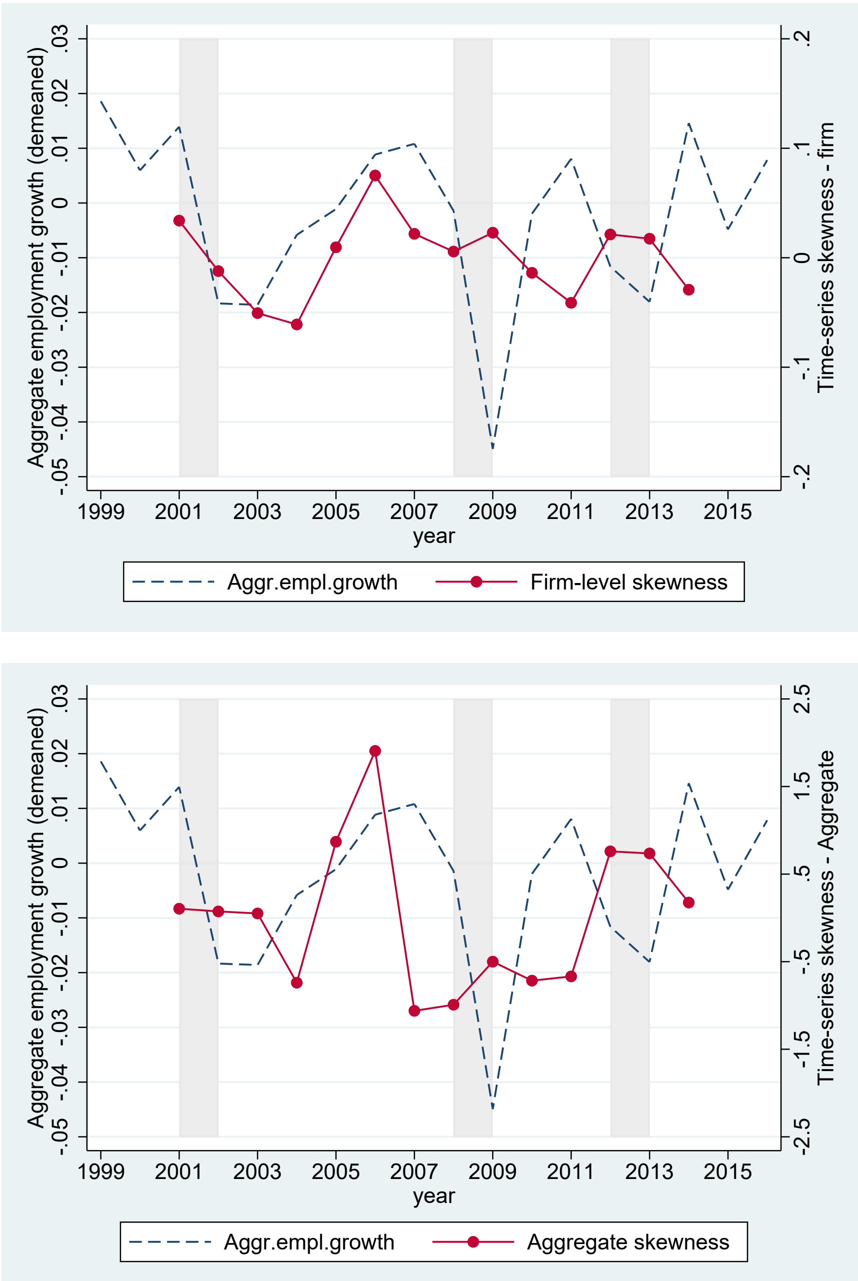
Overall, consistent with the predictions of the mechanism, employment growth rate distribution in Belgium is positively skewed in cross-section, and the skewness is not driven by the skewness of TFP shocks.

Figure 2.B.1: Skewness of the employment growth



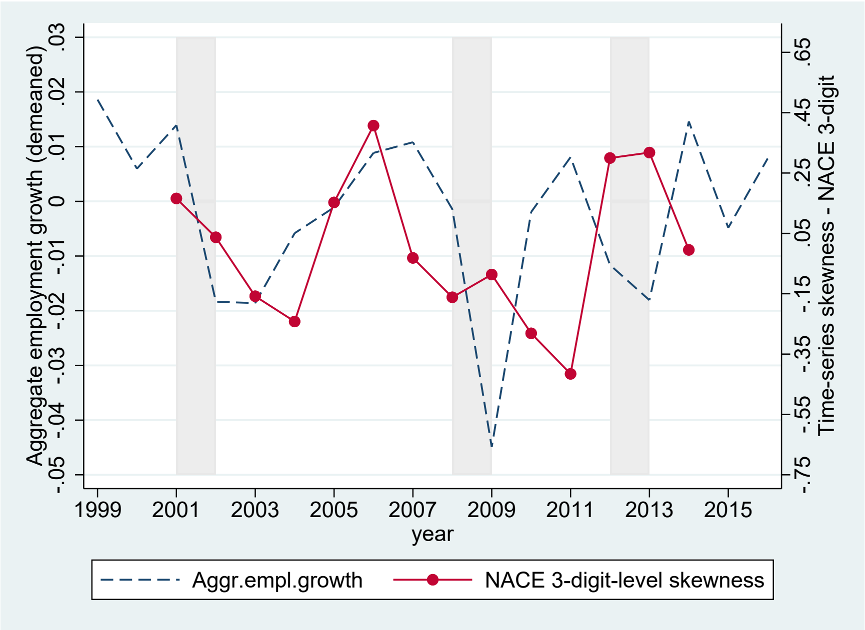
On the right axis, the figures display the evolution of the skewness measures, $\gamma(n_{it})$ (top) and $\kappa(n_{it})$ (bottom) of employment growth. On the left axis, the figure display demeaned aggregate employment growth evolution (gray dashed line). The vertical gray bars cover recession periods identified from OECD quarterly GDP growth data.

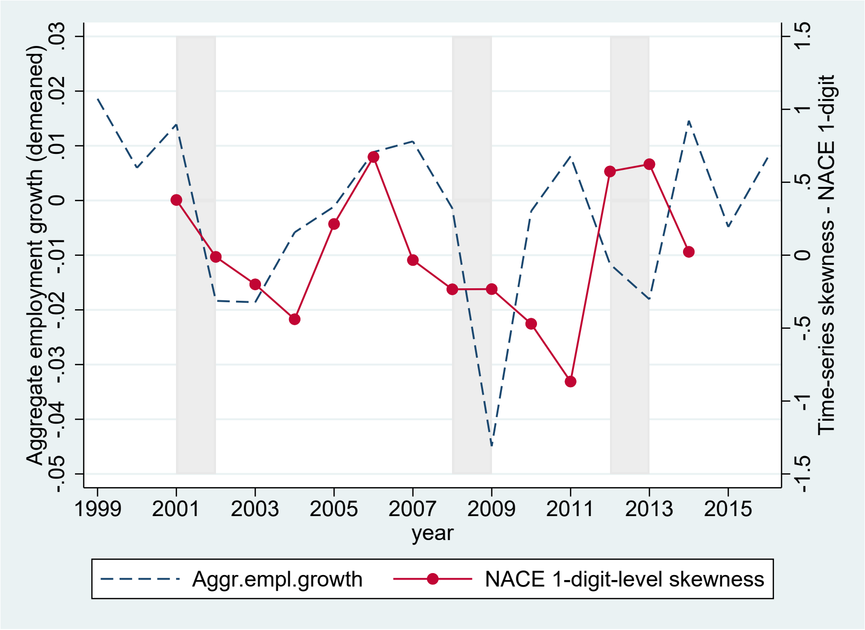
Figure 2.B.2: Time-series skewness



On the right axis, the figure displays the evolution of the time-series skewness, $Asym_t^i$, of employment growth. The top figure shows the skewness at the firm level. The bottom figure shows the skewness at the aggregate level. On the left axis, the figure display demeaned aggregate employment growth evolution (gray dashed line). The vertical gray bars cover recession periods identified from OECD quarterly GDP growth data.

Figure 2.B.3: Time-series skewness





On the right axis, the figure displays the evolution of the time-series skewness, $Asym_t^i$, of employment growth. The top figure shows the skewness at NACE three-digit level. The bottom figure shows the skewness at NACE one-digit level. On the left axis, the figure display demeaned aggregate employment growth evolution (gray dashed line). The vertical gray bars cover recession periods identified from OECD quarterly GDP growth data.

2.C Type of Labor: Parametric Estimation

To shed some light on the potential differences observed in Figure 2.6.5, we do a formal test for differences in slopes between blue- and white-collar intensive firms, and positive and negative TFP innovation. We extend the piece-wise linear specification of eq. (2.4.7) to include dummy variables on blue-collar intensive firms and positive TFP innovation:

$$\begin{aligned} n_{it} = \beta_0 + \beta_1 gt + \beta_2 Z_{it-1} + \beta_3 l_{it} + u_{it} \\ + \alpha_1 z_{it} + \alpha_2 b_i + \alpha_3 p_{it} + \alpha_4 z_{it} \times b_i + \alpha_5 z_{it} \times p_{it} + \alpha_6 b_i \times p_{it} + \alpha_7 z_{it} \times b_i \times p_{it}, \end{aligned} \tag{2.C.1}$$

where, similarly to eq. (2.4.7), gt is the time trend, Z_{it-1} is the lag of TFP, l is the log of employment, u_{it} is the iid error term. z_{it} is the TFP innovation, b_i is a dummy variable equal to 1 for firms with share of blue-collar workers of at least 75%, and 0 for which share of blue-collar workers does not exceed 25%, p_{it} is a binary variable equal to 1 for positive TFP innovation, and 0 - otherwise.[26]

Table 2.C.1: Firm-level employment asymmetry: Type of labor intensity

	(1)
z_{it}	0.088***
	(0.005)
p_{it}	-0.009***
	(0.001)
$z_{it} \times b_i$	-0.012*
	(0.007)
$z_{it} \times p_{it}$	-0.008
	(0.007)
$b_i \times p_{it}$	-0.001
	(0.002)
$z_{it} \times b_i \times p_{it}$	0.017*
	(0.010)
R^2	0.1456
Obs.	1276430
Nr.Clust.	155979

Standard errors in parentheses

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

The table reports the results of the firm-fixed effect regression of eq. (2.C.1). Standard errors are clustered at the firm level.

[26]Please note that the coefficient on b_i will be absorbed by firm-fixed effects.

Table 2.C.1 reports the results of the firm-fixed effects regression. α_5, the coefficient on $z_{it} \times p_{it}$, captures the difference in slopes between positive and negative shocks for white-collar intensive firms ($\frac{d}{dp_{it}}(n_{it}|b_i = 0) = \alpha_5 z_{it}$). Whilst the combination of estimated coefficients on $z_{it} \times p_{it}$ and $z_{it} \times b_i \times p_{it}$ captures the difference in slopes between positive and negative shocks for blue-collar intensive firms ($\frac{d}{dp_{it}}(n_{it}|b_i = 1) = (\alpha_5 + \alpha_7)z_{it}$). Both $\hat{\alpha_5}$ and $(\hat{\alpha_5} + \hat{\alpha_7})$ are statistically not different from zero (p-values are 0.267 and 0.202, respectively) implying that there is not enough evidence to conclude the difference in adjustments for blue- and white-collar intensive firms. This is consistent with the finding of the non-parametric estimation.

Chapter 3

The Impact of Pay Inequality on Firm Performance: Evidence from Kazakhstan[1]

3.1 Introduction

In the last few decades, rising wage inequality has become a central issue across the world and a widely researched topic. However, its causes are still not well understood. One of the possible reasons behind the diversity in the literature is that inequality has two dimensions: within firms and across firms. In accordance with a variety of theories, both within and between firm wage inequality influence worker and firm performance.[2] Due to increasing wage inequality among top earners (Piketty and Saez, 2003), a vast amount of research has focused on wage schemes that pay higher compensation to CEOs (see Edmans and Gabaix, 2016, for a detailed literature review). An important determinant of workers' effort is wage bargaining between employers and employees over the relative wages. Workers compare wages both within the organization and with the outside options (with workers in other firms). These comparisons could be made horizontally, meaning workers compare wages with fellow workers with similar tasks, education level, and occupations, or vertically, i.e. wages of workers across the hierarchical ladder. Intra-firm wage dispersion affects individual employees efficiency through adjusted effort and thus affecting firm performance. However, the literature focusing on this issue has not reached

[1]This chapter is joint work with Prof.dr.Jozef Konings, Prof.dr.Venkat Subramanian, and Dr.Aigerim Yergabulova. We gratefully acknowledge comments from Prof.dr.Stijn Vanormelingen, dr.Jakob Vanschoonbeek, and participants at VIVES and Nazarbayev University seminar series.

[2]Another strand of literature studies the relationship between productivity and wage differentials (Faggio et al., 2010; Bormans and Theodorakopoulos, 2020). These studies stress the importance of imperfect propagation of productivity shocks to wages (Comin et al., 2009; Card et al., 2016; Juhn et al., 2018). And these are out of the scope of this paper.

any consensus yet. On one hand, a variety of theories argue a higher wage differential to be productivity-enhancing, stressing the importance of higher pay differential to incentivize workers effort and/or to attract talented employees (Lazear and Rosen, 1981; Becker and Huselid, 1992). On the other hand, the growing gap between workers' wages is viewed as unethical and unfair, disturbing the work morale and cooperative working environment (Akerlof and Yellen, 1990; Levine, 1991), thus lowering performance.

More recent literature focuses on how differentiated pay structures are related to firm characteristics, such as firm size, reflecting the complexity of the organization, profitability, and the ability of firms to share profits, or the global nature of firms, reflecting international rent-sharing[3]. Linking pay to firm performance has long been a predominant method of rewarding executive managers. Several theoretical models have demonstrated that the relationship between CEOs compensation and firm size is consistent with the efficient allocation of CEOs in the market equilibrium (Gabaix and Landier, 2008; Tervio, 2008). Recent contributions (Lazear et al., 2015; Friebel et al., 2018; Hoffman and Tadelis, 2021) document that workplaces managed by "good" managers score better on workplace performance and employee turnover. This indicates the CEO characteristics to be an important element in firm performance (Bertrand and Schoar, 2003; Bennedsen et al., 2007; Bandiera et al., 2020). Management practices including performance targets, screening, and incentive provision are important factors of organizational performance (eg. Bloom and Van Reenen, 2007; Bloom et al., 2013; Van Reenen et al., 2014) and persistent productivity differences across firms (Syverson, 2011). Therefore, a CEO-firm match has a multiplicative effect on firm performance (Edmans and Gabaix, 2016; Mueller et al., 2017b).[4]

This paper focuses on the effect of vertical intra-firm pay inequality on firm performance.[5] To this end, we make use of hitherto unexploited firm-level data on Kazakhstan for the 2012-2015 year period. To measure within-firm vertical pay inequality, we calculate the pay ratio - the wage differential between the top- and the bottom-level job occupations - using the detailed firm-level data on wages by hierarchy levels. We begin our analysis by describing the relationship between wage inequality and firm size. We observe that wage inequality increases with firm size for upper hierarchies. The observation is consistent with a theoretical model stressing the allocative

[3]For instance, see Budd et al. (2005) and Kim and Konings (2019).

[4]The extent to which the CEO-firm match can boost firm performance depends not only on the parameters and characteristics of incentive schemes and firms *per se* but, also, on external factors, such as trade (Friedrich, 2021), corporate governance (Giroud and Mueller, 2010, 2011), and competitive market environment (Khashabi et al., 2020).

[5]Please note that this is different from studies focusing on the wage dispersion within the same hierarchical groups that stress the importance of worker characteristics, such as education and tenure, or research based on a broad definition of within-firm wage dispersion (mostly addressed using matched employer-employee data) (Bloom, 1999; Lallemand et al., 2004; Heyman, 2005; Ding et al., 2009).

efficiency of managerial positions (Gabaix and Landier, 2008; Tervio, 2008). Further, we analyze how wage inequality affects firm efficiency and profitability. Our analysis attempts to address potential endogeneity and omitted variable issues present in the previous empirical analyses. After controlling for firm-specific characteristics and implementing an instrumental variable analysis approach, we report a negative effect of pay inequality on firm performance. Note that we do not take a stand on which of the available theories is a source of or explains the negative relationship because the empirical approach used does not control for different explanations to rule one of them as being dominant. Nevertheless, our findings support the interpretation that a differentiated pay structure is viewed as compensation for unobserved effort and individual performance. Although a higher wage dispersion may serve as a signal to attract more productive or talented workers, we find no evidence to support the idea that incentive-based pay can boost overall firm performance. The paper, additionally, stresses the importance of addressing potential empirical concerns and their proper accountability.

While most of the literature has focused on wage inequality and firm performance in advanced economies, little work exists on this relationship in emerging or developing economies.[6] Yet, income inequality is often documented to be much larger in developing economies compared to developed economies (Roser and Ortiz-Ospina, 2013; Milanovic, 2016; Alvaredo et al., 2018), but this inequality is mostly attributed to institutional factors, such as the lack of modern labor legislation. As a result, many developing and emerging economies have no or very low minimum wages, limited employment protection legislation, or no union representation. Also, competition is often lacking, resulting in large differences in firm size, and its management is often closely linked to government practices. In contrast to advanced economies, it is thus far less clear to what extent firm characteristics matter for explaining wage inequality in emerging economies. Moreover, the existing empirical research on the efficient allocation of CEOs documents that pay inequality increases with firm size, and those, too, are largely focused on developed economies.[7] Our paper presents additional evidence by exploring the transition economy of Kazakhstan. Kazakhstan is the largest Central Asian economy with abundant natural resources, with its prime income reliant on oil and gas revenues. The country is one of the 15 former Soviet Union republics that gained independence during the 1990s. While most emerging market economies went through an intense process of restructuring, job destruction, and job

[6] A paper by Luo et al. (2020) look at the effect of pay gaps on firm performance for publicly listed firms in China and emphasize the importance of the state-ownership.

[7] For instance, see Brown and Medoff (1989) and Mueller et al. (2017b) for studies on the United Kingdom, Kim and Konings (2019) for South Korea, Song et al. (2019) for the US, and Friedrich (2021) for Denmark.

creation in the 1990s, Kazakhstan did not do so and was still able to sustain high levels of growth, primarily through the growth in the natural resources sector (Subramanian and Abilova, 2020). In 2006, Kazakhstan entered the group of upper-middle-income countries. While the gap in income inequality has declined between 2001 and 2017 (ADB, 2018), it is still high and around the average of the OECD economies. Kazakhstan is an interesting case to study because the firm size distribution is skewed towards the left as in most developed economies. There is heterogeneity in terms of both sales and employment, which are concentrated in a few large firms: 20 percent of firms account for more than 80 percent of all sales while the same fraction of firms employed around 60 percent of all workers in Kazakhstan in 2015 (Figure 3.A.1). If pay inequality increases with firm size, then shaping the firm size distribution can contribute to the trends in the aggregate wage inequality. This relates to the global phenomenon of the dominance of 'superstar firms' (Dorn et al., 2017; Abraham and Bormans, 2020; De Loecker et al., 2020) that dominate the market in terms of output, employment, and exports, worsening the uneven distribution of wages. Nevertheless, pay incentives, which partly cause wage inequality, work in motivating employees and contribute to better firm performance (Kerr, 1975; Faleye et al., 2013; Mueller et al., 2017b; Khashabi et al., 2020). So, does wage inequality necessarily hamper output?

The rest of the paper is organized as follows. Section 3.2 summarizes theoretical background and previous empirical findings. Section 3.3 describes the data used. Section 3.4 analyzes the relationship between pay inequality, firm size, and firm performance. Some concluding remarks are presented in Section 3.5.

3.2 Literature Overview

There are many studies that analyze the effect of within-firm pay inequality on firm performance. These studies are based on two conflicting viewpoints that predict positive or negative relationships. One argument is based on incentive effects (tournament models) and the other one stresses fairness and cooperation (relative deprivation theories), respectively.

The tournament model developed by Lazear and Rosen (1981) predicts that a more differentiated wage structure based on workers performance is beneficial for a firm.[8] The model suggests that rewarding workers according to their relative productivity stimulates their effort. The wage difference between different job occupations is regarded as the tournament award in the form of bonuses or/and promotions. A higher pay difference thus incentivizes workers to perform better,

[8] The model has been extended by McLaughlin et al. (1988) highlighting the importance of worker competition in the presence of multiple workers, and by Frey (2000) to include intrinsic motivation as a source of workers effort.

i.e. optimal level of effort increases with wage dispersion. Thus, the model predicts a positive relationship between pay dispersion and firm performance.

The prediction of the tournament model has been tested by several studies. Based on survey data, Main et al. (1993) study the pay dispersion among the top management team in 200 US firms. They find a positive and significant effect of wage dispersion among executives on return on assets. However, when stock market returns are used as an alternative proxy for firm performance, they find no significant effect. Other studies that focus on other developed economies also find supporting empirical evidence for tournament theory include Baixauli-Soler and Sanchez-Marin (2015) who focus on Spanish firms and by Eriksson (1999) on Danish firms, and Heyman (2005) on Swedish firms.

Another strand of research highlights the importance of firm size in driving within-firm inequality (Brown and Medoff, 1989; Mueller et al., 2017b; Kim and Konings, 2019). These studies find that within-firm pay inequality rises as firms grow larger. The relationship between size and pay inequality may vary across firms for several reasons. The main theoretical models to explain this relationship include the talent assignment model and rent extraction models. These models predict that larger firms exhibit higher pay inequality. According to the competitive talent assignment model, the most skilled CEOs should match with larger firms and earn higher wages (Gabaix and Landier, 2008; Edmans et al., 2009). The underlying idea is that large firms reflect a large span of control meaning that the value created by CEOs is multiplicative in talent and scales with firm size. Hence, more talented managers should match with larger firms. Under the assumption that managers are paid according to their marginal product, wage dispersion between the top and low-level occupations should increase with firm size (Tervio, 2008; Edmans and Gabaix, 2011; Eisfeldt and Kuhnen, 2013).

The rent extraction theory suggests that there is more rent to extract at larger firms and those can be extracted by workers at the top positions (Bebchuk and Fried, 2003; Bebchuk et al., 2011). As workers in lower level hierarchies may not be able to extract significant rents, pay inequality at lower levels should be largely invariant to firm size (Mueller et al., 2017b).

Although the talent assignment and rent-seeking behavior theories described above suggest a positive relationship between pay inequality and firm size, they diverge in their prediction with regard to the effect of pay inequality on firm performance.

The talent assignment model predicts that larger firms attract more talented managers and this scales up their managerial talent. As Rosen (1982, p. 311) puts it: "Assigning persons of superior talent to top positions increases productivity by more than the increments of their abilities because greater talent filters through the entire firm by a recursive chain of command technology." Talent assignment also affects managerial behavior as managers allocate more of their effort towards the most able workers and fire the least able (Bandiera et al., 2007). Hence, firms with more inequality should perform better than firms with less inequality according to this theory. In the rent extraction model, managers in larger firms are able to extract more rents without contributing to firm performance. If rent extraction is a reflection of more inequality, then we expect firms to have lower operating performance.

Alternative to these models, a relative deprivation theory by Martin (1981) and Akerlof and Yellen (1990) predicts a negative effect of a dispersed wage structure on firm performance. Their prediction is based on the premise that employees react negatively (damaged labor relations, reduced cooperation, negative attitude and behavior, reduced effort) when they find that their relative wages are lower and below the fair wage they expect for the amount of effort they put. Hence, according to the theory, wages should be distributed so that the combination of effort and wages is perceived as fair. Otherwise, an unfair treatment will lead to negative consequences for the firm through decreasing worker effort or excess turnover. Thus, the model predicts a negative relationship between pay inequality and firm performance.

Using the list of the 100 best companies to work for in America, a study by Edmans and Gabaix (2011) measures employee satisfaction and its link to firm value. The study finds that employee morale or satisfaction is an intangible that can foster worker productivity and hence increase firm performance. This suggests that a lower wage dispersion or more compressed wages works towards increasing firm performance. A recent study by Green and Zhou (2019) also finds a negative effect of base pay inequality on return on assets and Tobins Q.

In sum, on the one hand, tournament and talent assignment models predict a positive effect of inequality on firm performance, on the other hand, deprivation and rent-seeking models predict an opposite result. Table 3.A.1 provides a summary of the main theoretical and empirical studies. Please note that we focus on these four major theories, but admit that the list is not exhaustive. Our paper relates to this literature in several ways. First, it contributes to the research that focuses on the role of pay inequality on firm performance. While existing empirical evidence looks mainly at profitability measures, namely return on assets, Tobin's Q or EBITDA, this paper also studies efficiency measures, such as total factor productivity and labor productivity. Furthermore, we do not limit the focus to CEOs but look at various hierarchy and their corresponding wage dispersion. Finally, not every article that study the relationship between pay inequality and firm performance addresses the endogeneity issue. A firm that performs well is also likely to reward their workers. Due to increasing wage inequality among top earners, this means that pay incentives affect managers decisions to exert effort, which in turn may affect firm performance. Following previous literature, we address this issue using the instrumental variables approach.

3.3 Data

3.3.1 Descriptive Statistics

We exploit two firm-level datasets obtained from the Bureau of National Statistics of the Republic of Kazakhstan.[9] The first dataset is collected based on production reports filed by legal entities with more than 50 employees, excluding the public sector (i.e. organizations of education, health, banking, pension funds, public funds, and associations). It covers 40,193 firms between 2012-2018 and includes information on firm inputs, such as employment, material costs, fixed assets, and firm output as sales.

The second dataset is collected based on the labor report filed by legal entities with more than 50 employees and a 30 percent sample of small firms[10]. The sample contains 410,299 observations over the 2008-2015 period. It includes information on the number of employees (measured by the actual number of workers in a company per year), the total salary fund (wages + bonuses)[11] by occupation for each firm in a given year by industrial activities and regions. When we combine these two datasets, our final sample contains 19,605 firms over the period 2012-2015.[12] In terms of coverage of the data, Table 3.A.2 of the Appendix compares the number of employees in our dataset (both employment and final data) with the total number of paid employees (excluding self-employed) from the official statistics. Our employment dataset covers more than 95% of all paid workers. Note that, public sector accounts for around 50 percent of all workers, which is not covered by the production data. Furthermore, we also do not cover small firms and individual entrepreneurs. Therefore, the final data cover around 15% of all workers. Nevertheless, we capture on average 30% of all workers in each of the private sectors.

The labor report includes employment and wages by job classifications for every firm. The

[9] Access to the dataset is restricted.

[10] Small firms are defined as firms with less than 50 employees. The set of small firms is randomly drawn every year and is excluded from the final data as the production data do not cover these firms.

[11] Please note that we do not observe bonuses separately from wages in our data. Rather the average wages that we see are total salary bill (which includes both salary and bonuses) over number of workers by occupation.

[12] As mentioned earlier, due to a sample selection, a subset of small firms is excluded from the study, thereby creating a selection bias. Nevertheless, our sample covers medium and large private firms in Kazakhstan compared to studies that focus only on publicly listed firms. We admit that by excluding small firms, we truncate the left tail of the wage inequality distribution under the assumption that there is less pay inequality in small firms, on average, compared to large firms. This creates an overestimation of the actual pay inequality as we keep firms that are mostly on the right side of the distribution thus increasing the average pay inequality.

raw data include nine job classifications grouped into four broad categories based on the international standard classification of education[13]. The first category includes qualification level that corresponds to the basic general education and the secondary (general) education. The second category includes those with the initial vocational education, while the third one includes those with secondary vocational education. The fourth category contains workers with higher and postgraduate vocational education. This qualification criterion is used to identify all types of labor activity and the formation of large groups, except for the 'Heads (representatives) of government and administrative bodies at all levels, including heads of organizations', i.e. managers and CEOs, since in terms of qualification it is not possible to associate this group with any one of the defined education levels. Moreover, the second category includes five job classifications of which four are industry-specific, such as workers in agriculture or art, and miss about 95 to 99 percent values in the original data. Hence, we drop these four job classifications within the second category, leaving five classifications altogether, including the heads of organizations.

Table 3.3.1 shows the descriptions of job classifications (column 2) and examples of job positions (column 3) associated with each of them. The job classifications are presented in ascending order of education level: from unskilled workers (level 1) to administrative workers (level 2), mid-specialists (level 3), senior specialists (level 4), and heads (level 5). A variety of professions are sorted into these five job classifications. For instance, cleaners and taxi drivers are in the category of unskilled workers, whereas IT specialists and lawyers are in the classification level 4 and characterized as senior specialists. Managers, directors, and heads of organizations are in the highest classification level 5.

We further combine these five classifications into three distinct groups (column 1) so that job positions can be identified based on hierarchical order. For instance, the hierarchy level 1 captures low-level job occupations and includes unskilled workers and assistant positions. Hierarchy level 2 includes mid-level job occupations and combines both mid- and senior-level specialists. The top hierarchy level 3 contains managers, CEOs, and the head of the departments. Hence, unless stated otherwise, we focus our analysis based on three hierarchy levels. This grouping allows us to abstract from the differences in salaries between different professions, and focus on differences in hierarchical positions. Additionally, it makes it similar to the hierarchical classifications found in the standard literature.

Table 3.3.2 provides the summary statistics for employment and wages by hierarchy levels for the 2012-2015 year period. From the table, the average firm in our sample employs 111 workers

[13] International Standard Classification of Education (ISCED).

Table 3.3.1: Hierarchy levels, job titles and descriptions

Hierarchy level (1)	**Job classification** (2)	**Examples of job position** (3)	**Job description according to the SCO (State Classifier of Occupations)** (4)
1	1. Unskilled workers	Cleaner, cloakroom attendant, taxi driver	Unskilled workers perform simple mechanical work, mainly associated with the use of hand tools and the cost of some effort. Most of the professions in this classification group are characterized by a low level of qualifications, corresponding, as a rule, to the presence of basic general or secondary general education or secondary general education and individual training in the workplace.
	2. Employees engaged in the preparation of information, paperwork, accounting and maintenance	Secretary, typewriter, postal worker	The employees of this enlarged group mainly perform functions related to information support of various fields of activity, keeping records of inventories, cash and transportation, and customer service. Their implementation presupposes appropriate professional experience or practical training. For most of the occupations (professions) of this enlarged group, the required qualifications are achieved through individual training or special training according to the established program on the basis of secondary general education.
2	3. Middle-level specialists	Technician, Midwife, Sales manager	The functions of mid-level specialists of an average qualification level are to perform simple and medium level of complexity of engineering and technical works, as well as works of similar complexity. Their implementation presupposes the presence of a certain theoretical training and skills in the practical application of principles and methods from the field of special knowledge.
	4. Senior-level specialists	IT specialist, Lawyer, Engineer	Senior-level specialists carry out the development and research of scientific theories and concepts, contributing to the enrichment and increase in the amount of knowledge accumulated by society in various fields of activity, their practical application and systematic dissemination through training. Most of the occupations (professions) united by this classification group are distinguished by a high degree of complexity of the work performed and require a level of qualification corresponding to higher vocational education (the fourth qualification level), as well as its higher levels, determined by additional special knowledge and skills and characterized by the presence of an academic degree.
3	5. Heads (representatives) of authorities and management of all levels, including heads of organizations.	Department head, HR director, chief marketing officer	Heads (representatives) of authorities and management at all levels, including heads of organizations, develop and make managerial decisions, regulate, implement, coordinate and control their implementation.

Adapted from: National Classification of the Republic of Kazakhstan and pays around 130,000 KZT (*tenge*)[14] per worker per month. The number of workers varies at each hierarchy level, ranging from 16 workers in hierarchy level 3 to almost 60 workers in hierarchy level 2. Naturally, average wages are increasing with each hierarchy level. For instance, on average, if a cleaner receives around 68,000 tenge per month, the head of the organization receives 309,000 tenge per month.

Table 3.3.2: Summary statistics

	count	mean	sd	min	max
Employment	20906	111.03	196.73	1	6696
1 - Unskilled worker	20906	37.84	75.84	0	1990
2 - Specialist	20906	57.20	108.59	0	2237
3 - Manager	20906	15.99	63.83	0	3261
Wage/worker/month	20906	130155.66	124095.23	22146.64	759337.06
1 - Unskilled worker	17702	67715.87	51397.88	17652.10	385797.19
2 - Specialist	20218	130598.66	118274.21	20833.30	891027.81
3 - Manager	20723	308798.58	375265.58	25740.70	2351587.50

Please note that the wages in the data are gross wages. Working with the net wages is more accurate in identifying the wage differentials because, naturally, most government policies use income taxes to redistribute from higher to lower-earning workers, resulting in lower wage inequality in reality. However, unlike most developed countries with progressive taxes, the tax system in Kazakhstan is flat, which makes analysis in gross and net wages to be similar.

3.3.2 Distribution of Pay Ratios

Within a firm and a year, we observe 3 hierarchy levels and their associated wages. For our measure of within-firm pay inequality - relative wage differentials between the top- and the bottom-level jobs - we construct 3 hierarchy-level pairs and compute their corresponding ratio of wages. Thus, we calculate pay ratios, denoted as r_{jk}[15], which compare associated wages between higher and lower hierarchy levels as

$$r_{jk} = \frac{\text{Average wage for rank } k}{\text{Average wage for rank } j}, \qquad \text{for each } k > j \text{ in firm } i \text{ at time } t, \tag{3.3.1}$$

[14] From the National Bank of Kazakhstan (2020), the average exchange rate of the US dollar to the Kazakhstani tenge (USD/KZT) for the period from January 1, 2012, to August 20, 2015, was 1 USD = 164.57 KZT and from August, 21 to December, 31 of 2015 - 1 USD = 286.09 KZT. After the collapse of the oil prices, the government of the country decided to move from a fixed-exchange-rate regime to a free-float in August 2015. This led to a sharp depreciation of the national currency and a steep increase in the inflation rate. See, for instance, Colicev et al. (2021) who look at how the depreciation of the national currency in Kazakhstan affected the cost of living of people.

[15] We suppress the it in the subscript for simplicity.

where j and k are hierarchy ranks. For example, r_{12} is the wage ratio of a specialist to an unskilled worker, and r_{13} is the ratio of the average wage of a manager to the average wage of an unskilled worker.

Table 3.3.3 presents the distribution of pay ratios for all three combinations of hierarchy-level pairs. We see an increase in pay ratios as we move along the hierarchy level, i.e. pay ratio 12 is lower than pay ratio 13, and pay ratio 23 is lower than pay ratio 13. This means that the pay difference between, for example, a manager and an unskilled worker (r_{13}) is larger than between a specialist and an unskilled worker (r_{12}). For an unskilled worker and a specialist (r_{12}) the average pay ratio of 1.95 means that a middle-level worker, on average, earns almost 95 percent more than an unskilled worker, while a manager earns 334 percent more than an unskilled labor ($r_{13} = 4.34$).

Table 3.3.3: Distribution of pay ratios

r_{jk}	obs	avg.wage	10%	25%	50%	75%	90%
12	17248	1.952	1.096	1.358	1.727	2.24	2.965
23	20057	2.308	1.203	1.463	1.887	2.595	3.754
13	17621	4.338	1.744	2.339	3.291	4.893	7.592

This table presents the distribution of pay ratios for hierarchy-level pairs. The pay ratio is calculated using the ratio of higher-rank wages to lower-rank wages, eq. (3.3.1). Hierarchy codes are described in Table 3.3.1.

Note that the measure of within-firm pay inequality in eq. (3.3.1), might be affected by changes in both of the rank wages (changes in the nominator and denominator of the ratio simultaneously), or changes in one of the elements of the ratio (either the nominator or the denominator). To shed some light on which part of the equation dominates in driving the distribution of the pay ratios, i.e. whether the pay ratio primarily moves because higher ranks are paid more or because lower ranks are paid less, we recalculate our actual pay ratios by (i) fixing the higher rank wages to its mean value across firms and allowing lower rank wages to change, and (ii) vice-versa. Formally, we calculate the following counterfactual pay ratios:

$$\widehat{r_{jk}} = \frac{\text{Average wage for rank } k_{it}}{\sum_i \text{Average wage for rank } j_{it}/N}, \qquad \widetilde{r_{jk}} = \frac{\sum_i \text{Average wage for rank } k_{it}/N}{\text{Average wage for rank } j_{it}}, \qquad (3.3.2)$$

where N is the number of firms. Fixing one of the wages allows us to explore the relative importance of each variable in driving the variation in the actual pay ratio. The general idea is that the distribution of the actual pay ratio r_{jk} should closely resemble the distribution of (i) $\widehat{r_{jk}}$ if it is primarily driven by wages of the higher rank (nominator), and of (ii) $\widetilde{r_{jk}}$ if wages of the lower rank (denominator) are the primary source of pay inequality measure. We plot the density distributions of actual and counterfactual pay ratios for each hierarchy-level pair in Figure 3.A.2. According to the plot, the distribution of r_{jk} and $\widehat{r_{jk}}$ are similar for each hierarchy-level pair, hinting those pay ratios primarily move because top positions are paid more and not because bottom positions are paid less.

We further explore whether wages associated with lower occupations are invariant to firm size, or do wages in all hierarchy levels change at a similar rate? Table 3.3.4 reports the results of firm-fixed effect regression of log wages by occupation on firm size (proxied by the log of fixed assets) and year fixed effects. From the table, wages, on average, are positively associated with firm size. Interestingly enough, the wages of unskilled workers and specialists seem to increase at a similar rate (in columns (1) and (2), the confidence intervals overlap a lot), while the wages for managers increase by more as a firm grows larger. This observation broadly indicates that larger firms compensate their managers more presumably to attract a better one. Additionally, it implicitly suggests that the variation in pay ratios is primarily driven by the wages of managers.

Table 3.3.4: Wages and firm size

	(1) Unskilled b/ci95/se	(2) Specialist b/ci95/se	(3) Manager b/ci95/se
ln(size)	0.043	0.036	0.081
	[0.027,0.059]	[0.021,0.051]	[0.063,0.099]
	(0.008)	(0.008)	(0.009)
Constant	10.163	10.867	10.885
	[9.923,10.404]	[10.649,11.085]	[10.623,11.148]
	(0.123)	(0.111)	(0.134)
R^2	0.150	0.142	0.097
Obs.	17696	20206	20711

This table shows the results of firm-fixed effect regression analysis of the wages (in logs) associated with a given hierarchy level on firm size (proxied by the log of fixed assets) and year dummies. The first number represents the estimated coefficient. 95% CI in squared parentheses. Robust standard errors in parentheses.

Ideally, comparing differences in hourly wages is more accurate in dealing with inequality. So, one possible limitation of the data at hand is that we observe monthly wages (calculated as the ratio of total salary fund to the number of workers), which abstracts from the hours worked, possibly biasing the inequality measure. Inability to account for hours worked makes the pay ratio reflect both differences in hours worked across occupations as well as pay differences. Presumably, part-time work increases in lower job hierarchies because the opportunity cost of not working is lower. Hence, by using the average wages, we implicitly assume the equality of hours worked, which risks overestimating the pay ratios for higher hierarchies. Nevertheless, unlike in most developed countries, working part-time is not common in Kazakhstan. According to the World Bank statistics, on average, part-time workers accounted for around 9% of total employment in Kazakhstan in 2015, whereas it is more than 30% for OECD member countries (the World Bank statistics).

3.4 Results

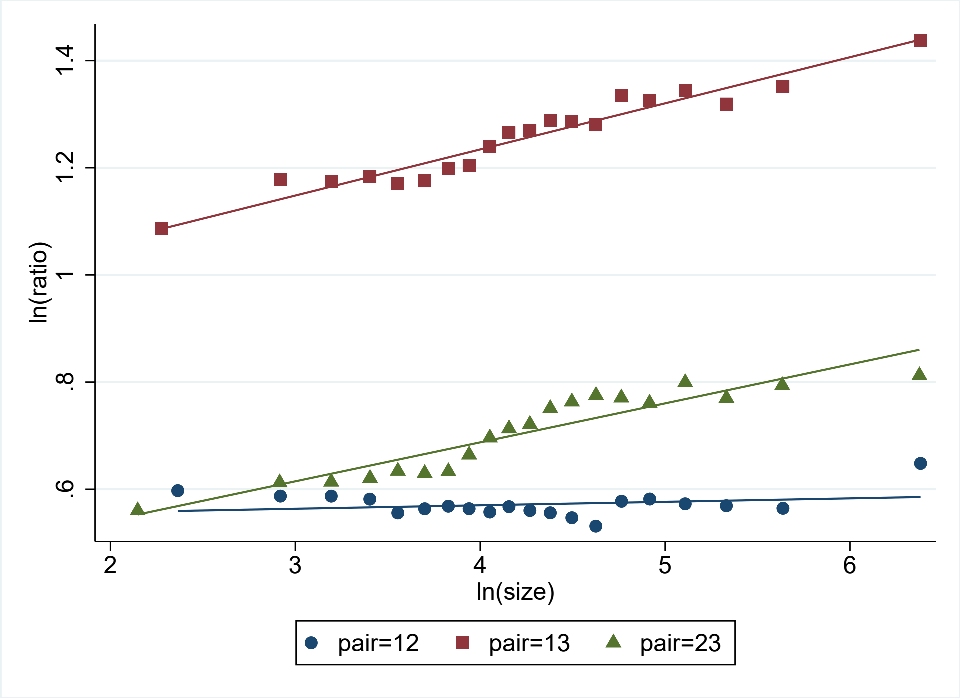
3.4.1 Pay Inequality and Firm Size

To observe the relationship between pay inequality and firm size, we generate a binned scatterplot, depicted in Figure 3.4.1. First, the data is divided into equal-sized bins based on firm size proxied by a log of employment (x-axis). For each bin, we plot the average value of a log of ratio for each hierarchy-level pair (y-axis). The fitted line corresponds to the best linear approximation of the conditional expectation function. According to Figure 3.4.1, there is a clear positive relationship between firm size and pay inequality between hierarchy level-pairs 13 and 23.[16] While, if we compare lower hierarchy levels (1 and 2) to each other, an increase in firm size has no clear relationship with within-firm pay inequality. These patterns are consistent with Mueller et al. (2017b) and Kim and Konings (2019) that took a regression-based approach in examining the UK and Korean data, respectively. Moreover, the figure implicitly confirms our observations of Table 3.3.4 and suggests that pay ratios primarily move because managers are paid more, rather than lower hierarchy workers being paid less.

Overall, Figure 3.4.1 supports the view that large firms exhibit higher pay inequality which reflects the differences in pay for top-level hierarchy. This relates back to the theories which highlight the importance of firm size in driving within-firm pay inequality. In particular, as predicted by talent assignment model (Rosen, 1981; Tervio, 2008; Gabaix and Landier, 2008), more talented managers should match to larger firms. Naturally, as senior-level workers' actions filter through the entire firm, their talent scales with firm size, whereas for lower-level workers talent is less scalable (Mueller et al., 2017b). If more talented managers are allocated to larger firms, then within-firm pay inequality rises with firm size (Brown and Medoff, 1989; Mueller et al., 2017a,b; Kim and Konings, 2019), conditional on the fact that workers are paid according

[16] Please note that we do not claim a causal relationship between the two variables.

Figure 3.4.1: Pay inequality and firm size



This graph depicts binned scatterplots of log of pay ratios on firm size (proxied by the log of employment) by hierarchy-level pair. The line traces the linear fit.

to their marginal product.

The result also relates to the rent extraction model (Bebchuk and Fried, 2003; Bebchuk et al., 2011) which also predicts that larger firms exhibit higher pay inequality. As there is more rent to extract at larger firms, managers presumably have an incentive to target these firms without contributing to performance. To assess the plausibility of these theories, we further analyze how pay inequality is related to firm performance. If rent extraction is a reflection of more inequality, then we expect firms to have lower operating performance. In contrast, if managerial talent is a reflection of more inequality, firms with more inequality should perform better than firms with less inequality.

3.4.2 Pay Inequality and Firm Performance

Following Mueller et al. (2017b), we construct a measure of pay inequality at the firm level to study the relationship between pay inequality and firm performance. First, we make two broad groups of pay ratios: top-bottom-level (pay ratios 13 and 23) and bottom-level (12) pay ratios. The groups are related to firm sizes (Figure 3.4.1). We focus our attention on top-bottom level pay ratios that compare the top hierarchy level (3) with lower hierarchy levels (1 and 2).[17] We, then, compute the percentile rank for each top-bottom pay ratio within the associated distribution for all years. Next, we average the percentile ranks of each pay ratio for every firm-year observation and use it as the measure of firm-level pay inequality in our analysis.[18] A higher average percentile rank reflects higher pay inequality. Finally, we estimate the following baseline equation to analyze the impact of pay dispersion on firm performance:

$$y_{it} = \beta_0 + \beta_1 PI_{it} + \beta_2 ln(size)_{it} + \mu_s + \gamma_t + \varepsilon_{it}, \tag{3.4.3}$$

where, y_{it} is the performance indicator, such as firm efficiency and profitability. We use two measures of efficiency including total factor productivity (TFP) and labor productivity (LP). Similarly, firm profitability measures include return on assets (ROA) and EBITDA margin.[19] PI_{it} is the pay inequality. To control for firm size, $ln(size)$, we use the log of fixed assets as a proxy. μ_s is NACE Rev.2 two-digit level *sector*-fixed effect. γ_t is *year*-fixed effect and ε_{it} is i.i.d.

[17] We exclude bottom-level ratio because a firm with high top-bottom level pay ratio may be misclassified as low-inequality firm as they might have very low levels of bottom-level pay ratio.

[18] Alternatively, we also (i) solely focus on pay ratio 13 and use (ii) weighted averages of pay ratios of level 3 with levels 2 and 1 (where the weights reflect employment share of level 1 and 2) as measures of firm-level pay inequality. The baseline results are robust to these alternatives (see Tables 3.B.2 and 3.B.3).

[19] To infer total factor productivity, we use a Tornqvist index (Törnqvist,1936). Labor productivity by definition is output per worker calculated as the ratio of real value-added over average employment. Return on assets is calculated as net income over total assets. The EBITDA margin is the ratio of net income plus depreciation over the total revenue.

error term. This specification allows us to determine whether the firms that exercise higher pay inequality perform better as predicted by the tournament theory or worse as suggested by the rent extraction theory.

Note that our results *a priori* might be driven by the positive association between firm size and performance. As shown in Section 3.4.1, firms exercising higher wage inequality are usually large firms. Hence, we need to make sure that we are not picking up a mere correlation between size and performance rather than the true effect of wage inequality on performance. To this end, we estimate the model controlling for firm size. We also plot the distributions of wage inequality for different size categories to show that even within the same size category, wage inequality levels are different. See Figure 3.A.3 in Appendix.

We start by following the standard organizational literature, we estimate eq. (3.4.3) using ordinary-least squares (OLS). However, there are some potential issues with applying the simple OLS technique to the model specified in eq. (3.4.3). First, given the panel structure of the data, the model is misspecified if we omit unobserved firm-level characteristics. Usually, OLS estimates suffer from upward bias, and including firm-fixed effect to control for (un)observed firm characteristics would drive the impact of pay inequality on performance down. Think of, for example, the ownership structure of a firm. Private firms are argued to perform better compared to publicly owned firms (Ehrlich et al., 1994; Konings et al., 1997; De Loecker and Konings, 2006). Moreover, they are expected to exercise a higher pay differential compared to public firms, where wages are more likely to be lower and regulated (Aitken et al., 1996). Hence, omitting ownership variable will result in a positive bias for OLS estimations.[20]

Moreover, a firm that performs well is also likely to reward its employees, including the CEOs. This might potentially introduce endogeneity issues to the model specification. Therefore, OLS could result in biased and inconsistent estimates. To address the issue, we use the instrumental variable (IV) two-stage least-squares (2SLS) estimation technique, where pay inequality is instrumented via its first and second lags. The requirement is that the instruments satisfy instrument exogeneity ($Cov(PI_{it-1}, \varepsilon) = 0$ and $Cov(PI_{it-2}, \varepsilon) = 0$) and instrument relevance ($Cov(PI, PI_{it-1}) \neq 0$ and $Cov(PI, PI_{it-2}) \neq 0$) conditions. We verified the instrument relevance from the first stage of the 2SLS estimation and the validity of instruments using Hansen's overidentification restrictions (Hansen, 1982). Under the null hypothesis, the instruments are not correlated with the error term ($H_0 : E(\varepsilon, X) = 0$, where X is a vector of instruments), i.e. instruments are valid. The decision rule is to fail to reject the null, i.e. the p-value is greater than the common significance levels.

[20] Formally: $Corr(private, y_{it}) > 0$ and $Corr(private, PI_{it}) > 0 \Rightarrow Bias(\tilde{\beta}_1) > 0$.

Table 3.4.5: Pay inequality and firm performance

	(1)	(2)	(3)	(4)	(5)	(6)
A. Efficiency						
		TFP			*Labor Productivity*	
	OLS	FE	IV	OLS	FE	IV
Pay inequality	0.247***	-0.035	-0.083	0.343***	-0.116***	-0.437*
	(0.046)	(0.041)	(0.248)	(0.046)	(0.043)	(0.243)
ln(size)	-0.010	0.006	0.039	0.183***	0.152***	0.097***
	(0.009)	(0.022)	(0.049)	(0.007)	(0.017)	(0.035)
Constant	-0.046	-0.042	-0.556	5.132***	6.601***	7.486***
	(0.140)	(0.317)	(0.718)	(0.120)	(0.212)	(0.491)
Obs.	17088	17088	6230	17451	17451	6359
Hansen test (p-value)			0.049			0.509
Year FE	yes	yes	yes	yes	yes	yes
Sector FE	yes	no	no	yes	no	no
Region FE	yes	no	no	yes	no	no
Firm FE	no	yes	yes	no	yes	yes
B. Profitability						
		ROA			*EBITDA*	
	OLS	FE	IV	OLS	FE	IV
Pay inequality	0.011***	-0.003	-0.037*	0.029**	0.005	0.034
	(0.003)	(0.004)	(0.020)	(0.011)	(0.010)	(0.063)
ln(size)	-0.002***	-0.000	0.018***	0.007***	0.008**	0.008
	(0.000)	(0.002)	(0.004)	(0.002)	(0.004)	(0.010)
Constant	0.018**	0.027	-0.234***	0.143***	0.244***	0.216
	(0.007)	(0.031)	(0.062)	(0.028)	(0.055)	(0.140)
Obs.	19406	19406	7022	18800	18800	6842
Hansen test (p-value)			0.124			0.481
Year FE	yes	yes	yes	yes	yes	yes
Sector FE	yes	no	no	yes	no	no
Region FE	yes	no	no	yes	no	no
Firm FE	no	yes	yes	no	yes	yes

Standard errors in parentheses

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

This table shows the results for the OLS, firm-fixed effect, and IV regression analyses where the dependent variables are the firm's total factor productivity in logs (TFP), labor productivity in logs (LP), return on assets (ROA), and EBITDA margin (EBITDA). Log of fixed assets is used as a size control. For IV, we use the first and second lags of the endogenous variable (pay inequality) as instruments.

Table 3.4.5 presents the results of the relationship between firm performance and pay inequality using OLS (columns (1) and (4)), firm-fixed effect (columns (2) and (5)) and IV (columns (3) and (6)) estimation techniques. Panel A presents two measures of productivity: total factor productivity[21] and labor productivity, whereas Panel B presents two measures of profitability: return on assets (ROA) and EBITDA margin. The OLS estimation coefficients on pay inequality suggest a positive and significant relationship between firm performance and pay inequality. This identifies firms that exhibit higher pay inequality as better performers compared to those with less pay inequality. If we believe these findings, the results support the talent assignment and incentive pay structures. It is consistent with the empirical evidence that firms that provide pay incentives for workers (bonuses and premiums) perform better (Lazear, 2000; Gerhart et al., 2009). However, once we control for unobserved firm-level characteristics (columns (2) and (5)), the impact of pay inequality on firm performance weakens, suggesting OLS be positively biased. In fact, the effect of pay inequality on firm performance disappears or becomes negative and significant. Although a higher wage dispersion may serve as a signal to attract more productive or talented workers, we find no evidence to support the idea that incentive-based pay can boost overall firm performance, once firm-specific characteristics are taken into account. We further explore the relationship by addressing the potential endogeneity problem (columns (3) and (6)). The coefficients of FE estimations are going down further with the IV estimation technique. For labor productivity and return on assets we even observe a negative and significant effect of pay inequality. Formally, for instance, moving from the 25th to 75th percentile of the pay inequality distribution[22] decreases the labor productivity by 19.3 percentage points. Similarly, moving from the 25th to 75th percentile of the pay inequality distribution rises the return on assets (ROA) by 1.64 percentage points.

The reverse impact seems to support the prediction of the rent extraction theory, where within-firm pay inequality is negatively related to firm performance. Since we do not directly control for all the possible explanations of the relationship between pay inequality and firm performance, we cannot claim with certainty that the negative conditional correlation found in the analysis is fully attributable to the rent-seeking behavior of managers. Nevertheless, our findings support the interpretation that a differentiated pay structure is viewed as compensation for unobserved effort and individual performance. Although a higher wage dispersion may serve as

[21]To infer total factor productivity, we use a Tornqvist index (Törnqvist, 1936). We also infer TFP using two-stage ACF estimation technique (Ackerberg et al., 2015) and adding pay inequality to the control function similar to Amiti and Konings (2007); De Loecker and Warzynski (2012), which control for firm import and export status, respectively. The results are robust and presented in Table 3.B.1 of the Appendix.

[22]The difference between the 25th and 75th percentile of the pay inequality distribution is equal to 0.443.

a signal to attract more productive or talented workers, we find no evidence to support the idea that incentive-based pay can boost overall firm performance.

Alternative explanations for the negative conditional correlation between pay inequality and firm performance also include institutional factors such as unionization and/or labor laws. Pay inequality in developing economies is often explained by the lack of modern labor legislation reflected in no or very low minimum wages, limited employment protection legislation, or no union representation. Also, competition is often lacking, resulting in large differences in firm size, and its management structure is often closely linked to government practices. These in turn may widen the wage dispersion and potentially hamper firm performance.

Moreover, there is a possibility that the two opposing effects are taking place simultaneously. If both rent-seeking and allocative-efficiency mechanisms are at play in the data, the results would cancel each other out, rendering the regression results unclear. Alternatively, the negative relationship may not necessarily imply rent-seeking behavior, because a better manager might be allocated to an inherently low-performing firm. Similarly, a positive relationship does not necessarily suggest allocative efficiency as rent-seeking managers may not fully extract the rents. Therefore, the results should be interpreted with extreme caution. And, to be able to support one of the theories with certainty, one should account for these alternatives.

Additionally, it is important to note that standard inequality literature models the relationship between inequality and growth in linear terms. However, this approach was strongly criticized by Banerjee and Duflo (2003). Using a non-parametric approach the authors present a non-linear relationship between inequality and growth. Despite a large number of studies, the evidence on the trade-off between the two is inconclusive. We briefly check for the non-linear relationship between the pay inequality and firm outcomes to see how the quadratic approximations match with the underlying data (see Figure 3.A.4). There is indeed a non-linear relationship between the two. Hence, we extend the model specified in eq. (3.4.3) to include the quadratic term of the pay inequality measure to capture the possible non-linearities. The results are presented in Table 3.4.6. The OLS estimates suggest that indeed the conditional correlation between pay inequality and firm performance to be non-linear. The quadratic term is positive and significant implying a U-shaped relationship. The results are in line with findings of Luo et al. (2020) that observe a U-shaped relationship for pay gaps and firm performance for Chinese publicly listed firms. They suggest that the U-shape is the result of two opposing effects being in place, namely, tournament theory (which suggests a positive correlation between inequality and performance) and relative deprivation theory (which predicts the negative effect of inequality on firm perfor-

Table 3.4.6: Pay inequality and firm performance

	(1)	(2)	(3)	(4)	(5)	(6)
A. Efficiency						
		TFP			*Labor Productivity*	
	OLS	FE	IV	OLS	FE	IV
Pay inequality	-0.353**	0.110	0.309	-0.170	0.013	0.781
	(0.169)	(0.138)	(0.693)	(0.165)	(0.146)	(0.664)
Pay inequality^2	0.597***	-0.146	-0.397	0.510***	-0.130	-1.251*
	(0.162)	(0.131)	(0.660)	(0.157)	(0.138)	(0.649)
ln(size)	-0.010	0.006	0.041	0.183***	0.152***	0.099***
	(0.009)	(0.022)	(0.049)	(0.007)	(0.017)	(0.035)
Constant	0.063	-0.066	-0.659	5.220***	6.579***	7.245***
	(0.143)	(0.319)	(0.739)	(0.122)	(0.214)	(0.506)
Obs.	17088	17088	6230	17451	17451	6359
Hansen test (p-value)			0.035			0.042
Year FE	yes	yes	yes	yes	yes	yes
Sector FE	yes	no	no	yes	no	no
Region FE	yes	no	no	yes	no	no
Firm FE	no	yes	yes	no	yes	yes
B. Profitability						
		ROA			*EBITDA*	
	OLS	FE	IV	OLS	FE	IV
Pay inequality	-0.022**	-0.017	-0.017	-0.067	-0.010	-0.024
	(0.010)	(0.011)	(0.056)	(0.042)	(0.035)	(0.182)
Pay inequality^2	0.034***	0.014	-0.019	0.096**	0.015	0.057
	(0.010)	(0.011)	(0.054)	(0.041)	(0.033)	(0.175)
ln(size)	-0.002***	-0.000	0.018***	0.007***	0.008**	0.008
	(0.000)	(0.002)	(0.004)	(0.002)	(0.004)	(0.010)
Constant	0.024***	0.029	-0.239***	0.160***	0.246***	0.228
	(0.007)	(0.031)	(0.063)	(0.028)	(0.055)	(0.144)
Obs.	19406	19406	7022	18800	18800	6842
Hansen test (p-value)			0.179			0.458
Year FE	yes	yes	yes	yes	yes	yes
Sector FE	yes	no	no	yes	no	no
Region FE	yes	no	no	yes	no	no
Firm FE	no	yes	yes	no	yes	yes

Standard errors in parentheses

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

This table shows the results for the OLS, firm-fixed effect, and IV regression analyses where the dependent variables are the firm's total factor productivity in logs (TFP), labor productivity in logs (LP), return on assets (ROA), and EBITDA margin (EBITDA). Log of fixed assets is used as a size control. For IV, we use the first and second lags of the endogenous variable (pay inequality) as instruments.

mance). However, once we account for possible bias in OLS estimations, we fail to observe any impact of pay inequality on firm performance.

3.5 Conclusion

In this study, we sought to investigate the impact of vertical within-firm pay inequality on firm performance using unexploited firm-level data on Kazakhstan. To measure pay inequality at a firm level, we constructed pay ratios using the wage differentials between the top- and bottom-level hierarchies. First, we found that wage inequality increases with firm size for upper hierarchies. Second, we reported a negative effect of pay inequality on firm performance after controlling for firm-specific characteristics and implementing an instrumental variable analysis approach. The paper, hence, stressed the importance of addressing potential empirical concerns and their proper accountability.

The results we observed suggest that no single theory can fully explain how pay differential relates to firm performance. Although our results provided support for rent-seeking behavior theory they should be interpreted with caution because that is not the only plausible explanation. In order to claim one of the theories to be the only consistent explanation, one should exploit exogenous variations and/or control for other potential explanations. Nevertheless, our findings supported the interpretation that a differentiated pay structure is viewed as compensation for unobserved effort and individual performance. Although a higher wage dispersion may serve as a signal to attract more productive or talented workers, we found no evidence for the idea that incentive-based pay can boost overall firm performance. This study also highlighted the need for more research on how context moderates the effects of pay differentials. Moreover, one should not neglect the effect of wage inequality on the distribution of consumption and total welfare, which was out of the scope of this paper.

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3.A Additional Figures and Tables

Table 3.A.1: Theoretical and empirical literature

Theory	Prediction for the relationship between pay inequality and firm performance	Empirical findings	Firm performance measure	Endogeneity addressed
Tournament Lazear and Rosen (1981)	Positive	Eriksson (1999) Heyman (2005) Lee et al. (2008) Kale et al. (2009)	Log profit/sales Tobin's Q Profit per worker ROA, Tobin's Q	No No Yes Yes
Deprivation Martin (1981) Akerlof and Yellen (1990)	Negative	Edmans (2011) Edmans et al. (2014) Liu et al. (2017) Green and Zhou (2019)	Tobin's Q Stock market returns Equity returns ROA, Tobin's Q	No No Yes Yes
Talent assignment Tervio (2008) Gabaix and Landier (2008)	Positive	Tervio (2008) Gabaix and Landier (2008) Mueller et al. (2017b)	Tobin's Q Tobin's Q ROA, Tobin's Q	No No No
Rent-seeking Bebchuk and Fried (2003)	Negative	Bebchuk et al. (2011)	ROA, Tobin's Q	Yes

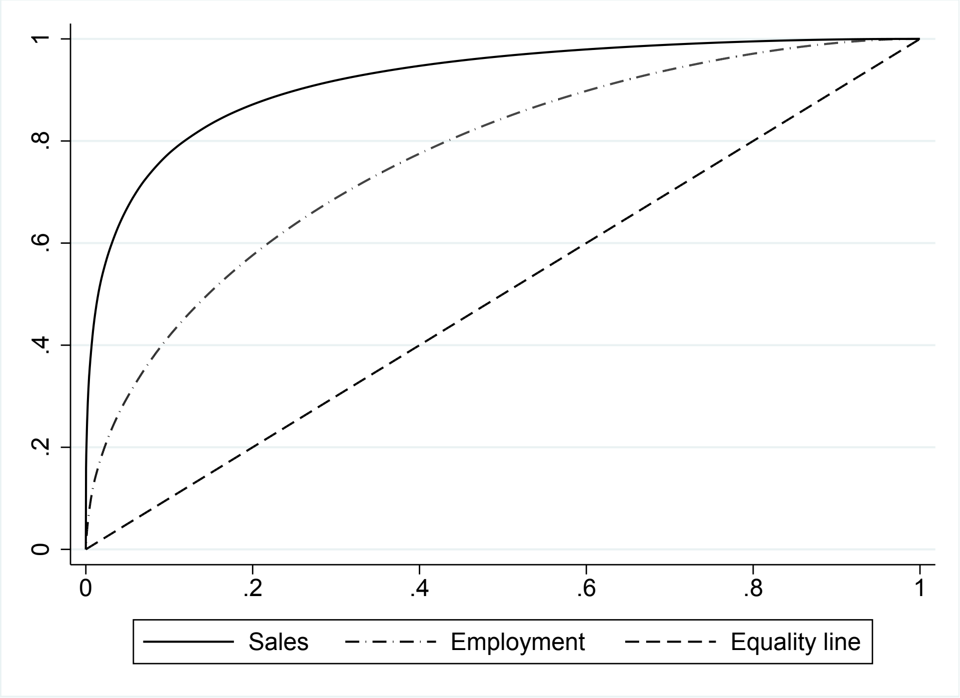
This table shows the summary of the main theoretical and empirical papers on pay inequality and firm performance with the limitation on if papers address the endogeneity issues.

Table 3.A.2: Sample coverage, 2012

	Official statistics	Employment data		Final data	
Total employment	3650900	3477200	95%	564500	15%
By sector					
Agriculture	115300	96300	83.5%	41500	36%
Manufacturing (incl. mining)	576400	549900	95.4%	160400	28%
Electricity, gas, and water supply	154800	150500	97.2%	50000	32%
Construction	214300	197000	91.9%	68300	32%
Trade	178200	171800	96.4%	68900	39%
Services	695300	671700	96.6%	175300	25%
Public sector & other services	1716600	1640000	95.5%	-	-

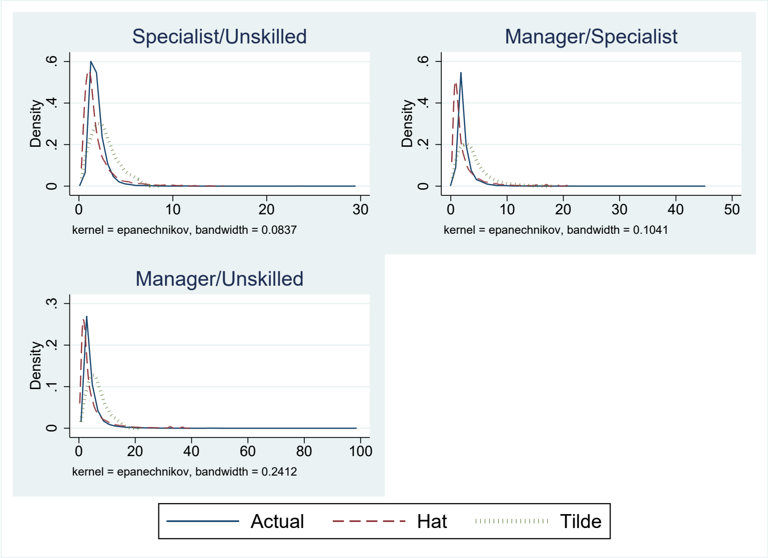
This table shows the sample coverage by sector using employment for the year 2012. The number of workers in employment and final datasets are compared with the aggregate statistics.

Figure 3.A.1: Firm size distribution, 2015



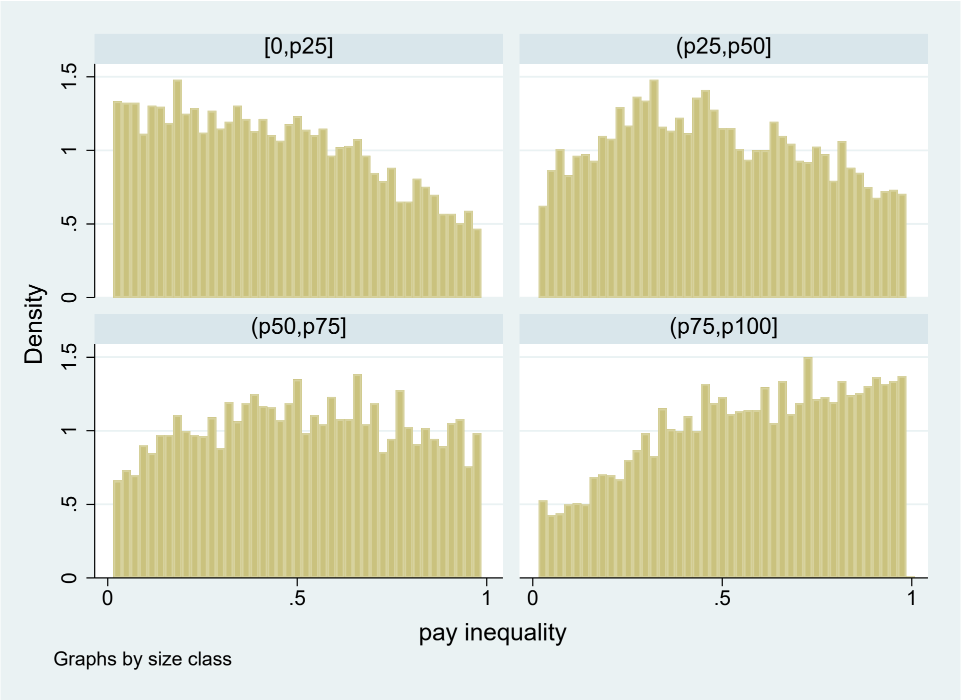
This graph plots the share of a firm (i) sales and (ii) employment against the share of firms in 2015. The 45-degree line presents the line of equality when sales or employment distribution is evenly spread.

Figure 3.A.2: Distribution of actual and counterfactual pay ratios



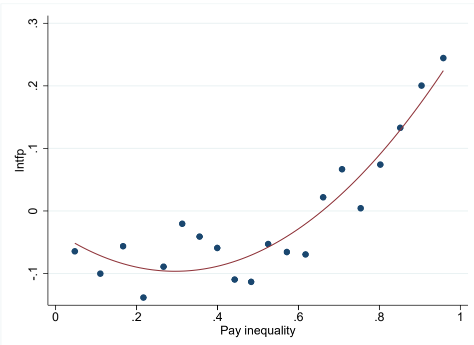
This graph plots the Kernel densities of actual and counterfactual pay ratios for each hierarchy-level pair, jk. "Actual" refers to the pay ratio calculated from eq. (3.3.1). "Hat" refers to the pay ratio in which the denominator of the ratio is fixed to the average wage of rank j across all firms. "Tilde" is the pay ratio in which the numerator of the ratio is fixed to the average wage of rank k across all firms, eq. (3.3.2).

Figure 3.A.3: Wage inequality distribution by size

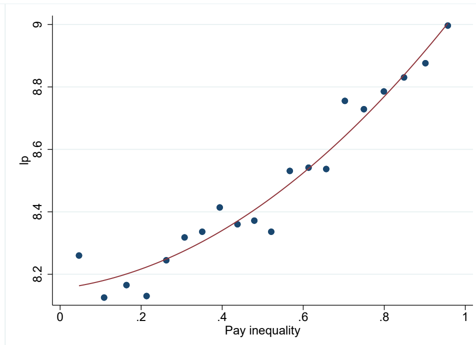


The size classes are determined by fixed assets.

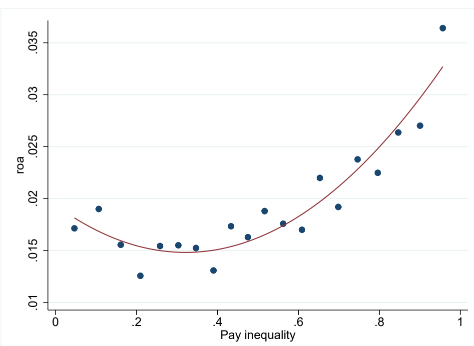
Figure 3.A.4: Performance and pay inequality



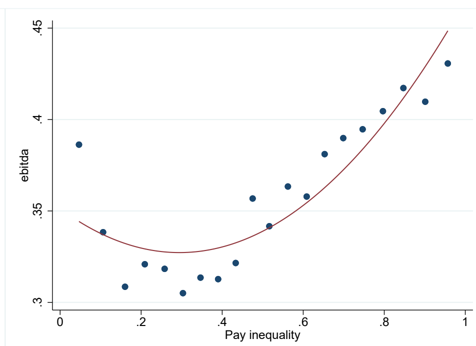
(a) TFP



(b) Labor Productivity



(c) ROA



(d) EBITDA

These graphs depict binned scatterplots of (a) log of TFP; (b) log of labor productivity; (c) ROA; and, (d) EBITDA margin on pay inequality. The line traces the quadratic fit line.

3.B Robustness Checks

Table 3.B.1: Pay inequality and firm productivity: Control function approach

	(1) OLS	(2) FE	(3) IV	(4) OLS	(5) FE	(6) IV
Pay inequality	0.260***	-0.064	-0.212	-0.172	0.064	0.048
	(0.040)	(0.040)	(0.250)	(0.152)	(0.134)	(0.706)
ln(size)	0.136***	0.131***	0.090*	0.136***	0.131***	0.092*
	(0.008)	(0.021)	(0.051)	(0.008)	(0.021)	(0.051)
Pay inequality^2				0.430***	-0.129	-0.269
				(0.145)	(0.130)	(0.665)
Constant	4.694***	6.932***	7.701***	4.771***	6.912***	7.616***
	(0.172)	(0.399)	(0.981)	(0.174)	(0.401)	(1.004)
Obs.	17115	17115	6230	17115	17115	6230
Hansen test (p-value)			0.333			0.030
Year FE	yes	yes	yes	yes	yes	yes
Sector FE	yes	no	no	yes	no	no
Region FE	yes	no	no	yes	no	no
Firm FE	no	yes	yes	no	yes	yes

Standard errors in parentheses

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

This table shows the results for the OLS, firm-fixed effect and IV regression analyses where the dependent variable is the firm's total factor productivity in logs (TFP) inferred using the 2-stage control function approach (ACF). Log of fixed assets is used as a size control. For IV, we use the first and second lags of the endogenous variable (pay inequality) as instruments.

Table 3.B.2: Pay inequality and firm performance: PI based on rank 13

	(1)	(2)	(3)	(4)	(5)	(6)
A. Efficiency						
	TFP			*Labor Productivity*		
	OLS	FE	IV	OLS	FE	IV
Pay inequality	0.352***	0.081**	-0.288	0.482***	0.082**	-0.446*
	(0.045)	(0.041)	(0.272)	(0.045)	(0.041)	(0.246)
ln(size)	-0.012	-0.002	0.004	0.179***	0.170***	0.032
	(0.009)	(0.024)	(0.058)	(0.008)	(0.018)	(0.041)
Constant	-0.039	-0.028	0.010	5.150***	6.205***	8.282***
	(0.148)	(0.352)	(0.847)	(0.125)	(0.229)	(0.581)
Obs.	14740	14740	5147	15118	15118	5283
Hansen test (p-value)			0.016			0.959
Year FE	yes	yes	yes	yes	yes	yes
Sector FE	yes	no	no	yes	no	no
Region FE	yes	no	no	yes	no	no
Firm FE	no	yes	yes	no	yes	yes
B. Profitability						
	ROA			*EBITDA*		
	OLS	FE	IV	OLS	FE	IV
Pay inequality	0.012***	0.003	-0.013	0.023**	0.011	0.089
	(0.003)	(0.003)	(0.020)	(0.011)	(0.011)	(0.061)
ln(size)	-0.001***	0.000	0.013***	0.011***	0.010**	-0.004
	(0.000)	(0.002)	(0.005)	(0.002)	(0.005)	(0.011)
Constant	0.018**	0.021	-0.174**	0.093***	0.205***	0.332**
	(0.008)	(0.034)	(0.069)	(0.028)	(0.060)	(0.151)
Obs.	16834	16834	5860	16346	16346	5717
Hansen test (p-value)			0.212			0.226
Year FE	yes	yes	yes	yes	yes	yes
Sector FE	yes	no	no	yes	no	no
Region FE	yes	no	no	yes	no	no
Firm FE	no	yes	yes	no	yes	yes

Standard errors in parentheses

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

This table shows the results for the OLS, firm-fixed effect, and IV regression analyses where the dependent variables are the firms total factor productivity in logs (TFP), labor productivity in logs (LP), return on assets(ROA), and EBITDA margin (EBITDA). Pay inequality is computed based on the pay ratio 13. Log of fixed assets is used as a size control. For IV, we use the first and second lags of the endogenous variable (pay inequality) as instruments.

Table 3.B.3: Pay inequality and firm performance: PI based on weighted average

	(1)	(2)	(3)	(4)	(5)	(6)
A. Efficiency						
	TFP			*Labor Productivity*		
	OLS	FE	IV	OLS	FE	IV
Pay inequality	0.012	-0.016**	-0.047	0.012	-0.031***	-0.063
	(0.008)	(0.007)	(0.053)	(0.008)	(0.007)	(0.046)
ln(size)	0.001	0.002	0.016	0.192***	0.169***	0.046
	(0.009)	(0.025)	(0.060)	(0.008)	(0.018)	(0.040)
Constant	-0.109	-0.008	-0.195	5.166***	6.336***	8.026***
	(0.151)	(0.356)	(0.854)	(0.128)	(0.234)	(0.555)
Obs.	14395	14395	5002	14772	14772	5137
Hansen test (p-value)			0.797			0.120
Year FE	yes	yes	yes	yes	yes	yes
Sector FE	yes	no	no	yes	no	no
Region FE	yes	no	no	yes	no	no
Firm FE	no	yes	yes	no	yes	yes
B. Profitability						
	ROA			*EBITDA*		
	OLS	FE	IV	OLS	FE	IV
Pay inequality	0.002***	0.001	-0.002	0.007***	0.003	0.012
	(0.000)	(0.001)	(0.004)	(0.002)	(0.002)	(0.012)
ln(size)	-0.001***	-0.001	0.012**	0.010***	0.010**	-0.003
	(0.000)	(0.002)	(0.005)	(0.002)	(0.005)	(0.011)
Constant	0.014*	0.040	-0.152**	0.091***	0.202***	0.329**
	(0.008)	(0.033)	(0.070)	(0.029)	(0.061)	(0.152)
Obs.	16437	16437	5686	15980	15980	5558
Hansen test (p-value)			0.788			0.163
Year FE	yes	yes	yes	yes	yes	yes
Sector FE	yes	no	no	yes	no	no
Region FE	yes	no	no	yes	no	no
Firm FE	no	yes	yes	no	yes	yes

Standard errors in parentheses

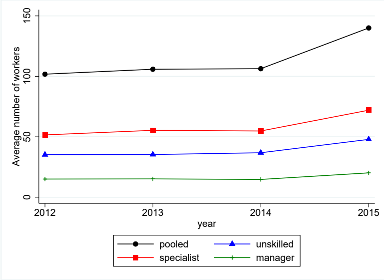
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results for the OLS, firm-fixed effect, and IV regression analyses where the dependent variables are the firms total factor productivity in logs (TFP), labor productivity in logs (LP), return on assets(ROA), and EBITDA margin (EBITDA). Pay inequality is computed as a weighted average of pay ratios of level 3 with levels 2 and 1 where the weights reflect employment share of level 1 and level 2. Log of fixed assets is used as a size control. For IV, we use the first and second lags of the endogenous variable (pay inequality) as instruments.

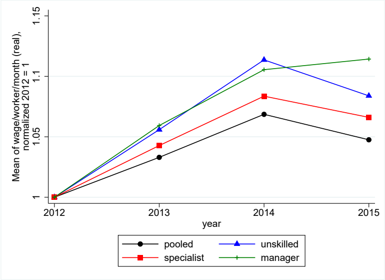
3.C Supplementary Materials

Figure 3.C.1: Evolution of wages and employment by hierarchy level

(a) Evolution of employment



(b) Evolution of wages



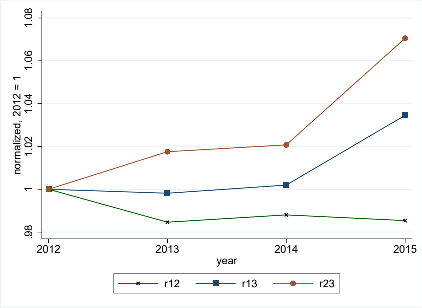
These graphs plot the evolution of (i) employment, and (ii) average real wages by hierarchy levels. Wages are normalized to 1 in 2012 for better visualization.

Table 3.C.1: Distribution of wages by hierarchy level

	obs	avg.wage	10%	25%	50%	75%	90%
Unskilled worker	17702	67716	26557	36145	52324	79406	125187
Specialist	20218	130599	42198	62466	93815	152753	254429
Manager	20723	308799	68646	105773	180000	349250	677864

This table shows the distribution of wages for each job position across all firm-year observations. Wages are in KZT (*tenge*).

Figure 3.C.2: Evolution of pay ratios



The graph plots the evolution of pay ratios by hierarchy-level pairs. The ratios are normalized to 1 in 2012 for better visualization.

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