Labor Market Rigidities and Misallocation: Evidence from a Natural Experiment *

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Abstract

This paper estimates the impact of labor market rigidities on labor misallocation. 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. Using a rich data set of the universe of Belgian firms, preliminary evidence shows that this policy change had a measurable impact on labor (mis)allocation and productivity.

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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 with which this conversion occurs, has received special attention by 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, Haltiwanger and Krizan (2001), and more recently Petrin and Levinsohn (2012) and Collard-Wexler and De Loecker (2015), among others.

A strand of literature has emerged to study possible misallocation of resources across firms in slowing down the 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 TFP. Particularly, they found that policies driving differences in input prices faced by producers result in 30-50 percent decrease in output and TFP. Hsieh and Klenow (2009) proposed that within-sector dispersion in the marginal product of inputs can be used as a measure of misallocation and potential productivity gains. They have estimated that fully equalizing revenue productivity (TFPR) across plants in each industry would increase the aggregate productivity in manufacturing by 86%-115% in China, 100%-128% in India and by 30%-43% in the United States.

Inspired by these papers, a recent body of work, studying the sources of misallocation and their relation to aggregate productivity growth emerged. 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. Other studies investigate the impact of financial crises on resource misallocation (Sandleris and Wright, 2014), the introduction of the euro (Gopinath et al., 2017) and internationalization (Berthou and Manova, 2016). See also Restuccia and Rogerson (2013) for an overview. Other papers 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 (Kherig and Vincent, 2016).

In related work, Petrin and Levinsohn (2012) showed that when aggregate productivity growth (hereinafter, APG) is defined in terms of changes in final demand, a unit increase in any input increases APG by that input's corresponding value of marginal product-input cost gap. Petrin and Sivadasan (2013) built on their methodology and proved that the difference in the value of the marginal product of an input and its marginal cost is exactly equal to a change in the aggregate output that would occur if that input's use is changed by one unit. Consequently, the mean absolute gap across plants for any input is, ceteris paribus, an approximate measure of the gain to society that would occur if every plant had changed that input use by one unit in the efficient direction.

Our paper contributes to the literature by evaluating the effect of labor adjustment costs and misallocation on aggregate productivity growth in Belgium. A large literature has documented 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)). Critiques have claimed that high adjustment costs, which results from strong protection rights, prevents employers from adjusting their labor input to economic fluctuations or changes in demand, i.e. during the downturns employers are less likely to fire and they are less inclined to hire during the booms. Regulations that impose notice and severance pay requirements are considered to affect the adjustment decisions the most (Abraham and Houseman, 1993). Historically, in Belgium, the working conditions, including severance payments, differed largely between white-collar and blue-collar workers.

In 2014, the two types of labor contracts were harmonized, thereby increasing employment protection for blue-collar workers and reducing it for white-collar workers. This policy change makes Belgium an ideal case-study to evaluate the effect of labor adjustment costs on aggregate productivity growth.

This paper has two goals. First, following Petrin and Sivadasan (2013), we begin our analysis by documenting the evolution of labor misallocation measure in Belgium. 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 to infer the value of lost output from allocative inefficiency. Moreover, we look for an impact on allocative efficiency of the recent change to the labor law: harmonization of labor contracts for blue- and white-collar workers introduced in 2014. This policy change gives us a chance to evaluate the effect of labor adjustment costs on aggregate productivity growth. Second, in a later stage, we will build up a dynamic model of labor demand incorporating hiring and firing costs. We can then structurally estimate the parameters of the model, including the different labor adjustment costs, and determine to what extent the model can explain the observed misallocation.

This paper contributes to the literature in several ways. First, the paper improves our understanding of how much distortions matter for aggregate productivity growth. While most recent work focuses on misallocation in the capital market, the project will focus on labor market distortions. 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). Moreover, as highlighted by Bassanini et al. (2009) and van Ark et al. (2008), the lack of convergence between the US and 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 systematic evidence 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 aggregate performance.

The research covers all private sectors[1] for the period 1996-2016. Preliminary results document an increase in the potential gain from labor reallocation across the Belgian economy for the sampling period. Furthermore, the findings indicate that the policy lowered allocative efficiency for blue-collar workers relative to white-collar workers. Particularly, after the harmonization of labor contracts, a one standard deviation increase in the share of blue-collar workers increases the labor gap by 2000 euro after the policy change, implying that allocative efficiency of blue collar labor decreased relative to white collar labor following the harmonization of the labor contracts.

The rest of the paper is organized as follows. Section 2 focuses on the Employment Protection Legislation of Belgium. Section 3 discusses the framework of Petrin and Sivadasan (2013) and, within a standard panel regression model, explores the observed changes in labor misallocation. Section 4 describes the data. Results are discussed in section 5. Section 6 presents the results of placebo experiments. Section 7 concludes.

2 Belgian Employment Protection Legislation

Historically, Belgian workers were enjoying a strong employment protection. Traditionally, job security was provided through the means of the advance notice periods upon dismissal and severance payments. However, the labor law in Belgium had treated white and blue-collar workers differently.[2] 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.[3] As a result, the notice periods were gradually

[1]excluding construction

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

[3]It is important to note that sectors such as construction industry (limitless) and diamond industry (temporarily) are allowed to have shorter notice periods for their blue-collar workers. The reason for allowing a temporary exemption is that these sectors could potentially be seriously

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).[4] 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. So, in a situation of dismissal without an appropriate notice period, severance payment is equivalent to the amount of salary that should have been received during the notice period.[5] 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 and 13-22 weeks' salary for a white-collar worker. In comparison to the previous regime, the new contract favors blue-collar workers, while it is more detrimental for white-collar employees, especially those 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 (Allen & Overy (2014), Loyens & Loeff (2014), OECD (2013), American Chamber of Commerce in Belgium (nd)).

Another aspect of the labor law that affects adjustment costs is an elimination of the *carensdag/jour de carence* ("waiting day"). Previously, the first day of absence due to illness was not paid to blue-collar workers. With the enforcement of the new legislation, blue-collar workers are paid from the first day of their sick leave. And, the associated costs are borne by firms (Allen & Overy (2014), Loyens & Loeff (2014)).

disrupt 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 social protection of these employees (Allen & Overy (2014)).

[4] If a worker's gross annual remuneration is not over €32,254 then the notice period was 3 months (13 weeks), and 150 days ($\approx$ 21.4 weeks) otherwise.

[5] 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. Therefore, the severance payment for the blue-collar worker from the example described is $2500 \times \frac{3}{13} \times 33 = 19,038.46$ euros under the new policy. The notice period was 56 days (8 weeks) under the previous regime, therefore the payment would have been $2500 \times \frac{3}{13} \times 8 = 4,615.38$ euros.

Moreover, the trial period clause was abolished[6], during which both an employer and an employee had a possibility to terminate the contract with a shorter notice period (7 days) than normal. So now, firstly, an employer can dismiss an employee after a period of employment of less than one month, provided that a statutory 2 weeks' notice is met, whereas, under the former regime, an employer was not allowed to terminate the contract of a white-collar worker during the first month of employment. However, secondly, in the case of dismissal after an employment of, for example, 9 months, an employer will have to observe a notice period of 7 weeks, instead of 7 days under the previous regime. As a result, termination of the contract after an employment of several months involves a higher dismissal cost for employers.[7] Additionally, employment contracts of definite duration can be terminated with a notice period as applicable to contracts of indefinite duration. Therefore, employment contracts of definite duration can be terminated during its first half, as this half does not exceed 6 months (Allen & Overy (2014), Loyens & Loeff (2014)).

It has been argued that since the compensation will 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/firing behavior. Therefore, since labor costs have a direct impact on firms' growth, investment and production decisions, and, as a result, productivity, we attempt to study the effect of the policy change on aggregate productivity.

3 Methodology

3.1 Measuring Lost Output due to Allocative Inefficiency

To determine aggregate productivity growth (APG), defined as the difference between a change in the value of aggregate demand and a change in the total expenditure on inputs, and to derive the reallocation terms, we follow the methodology

[6]Contracts for temporary work and contracts for students can still include a trial period. Existing trial periods, which commenced before January 1, 2014, are still valid.

[7]Under the old regime, while the notice period was fixed to 7 days, the probation period for blue-collar workers was up to two weeks. 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 otherwise.

developed by Petrin and Levinsohn (2012), Petrin and Sivadasan (2013). Readers familiar with the literature can skip directly to implementation in Section 3.3.

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 is a vector of primary inputs, M_i is a vector of intermediate inputs (output of firm j) 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 forgone 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 serves as an intermediate input within a firm and other firms. Given the differential of final demand, $dY_i = dQ_i - \sum_j M_{ji}$, and assuming that prices are uniquely determined by Q, given as P_i, a change in aggregate final demand is

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

APG is then

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

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. Unavailability of output data does not enable us to calculate APG using equation (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 our initial equation and calculate APG[8]:

$$APG(t) = \sum_i dVA_i - \sum_i \sum_k W_{ik} dX_{ik}. \tag{2}$$

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

$$\begin{aligned} APG &= [TE] + [F] + [RE] \\ &= \left[\sum_i P_i d\omega_i\right] + \left[-\sum_i P_i dF_i\right] + \\ &\quad \left[\sum_i \sum_k \left(P_i \frac{\partial Q_i}{\partial X_k} - W_{ik}\right) dX_{ik} + \sum_i \sum_j \left(P_i \frac{\partial Q_i}{\partial M_j} - P_j\right) dM_{ij}\right], \end{aligned} \tag{3}$$

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, $\frac{\partial Q_i}{\partial X_k}$ is a partial derivative of production function with respect to the kth primary input, $\frac{\partial Q_i}{\partial M_j}$ 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. 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 reallocation terms are based on the value of marginal product (VMP) for every input (X_k) at firm i, generically given as

$$VMP_{ik} \equiv P_i \frac{\partial Q_i}{\partial X_k}, \tag{4}$$

and include a VMP term and input cost terms of primary and intermediate inputs

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

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

for every firm.[10]

3.2 Linking the Gaps to Allocative Efficiency

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

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

Thus, aggregate final demand increases without any changes to technical efficiency or aggregate input use if an input moves from a low marginal value activity to a higher one.

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

$$\frac{1}{N} \sum_{i=1}^{N} \left(P_i \frac{\partial Q_i}{\partial L} - W \right) D_i = \frac{1}{N} \sum_{i=1}^{N} \left| P_i \frac{\partial Q_i}{\partial L} - W \right|, \tag{5}$$

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

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

Thus, equation (5) gives a simple lower bound approximation to a possible efficiency gains from reallocating labor resources for "one step" in the direction of more efficiency.[11]

For counterfactuals, let E0 and E1 be the two states. For example, if E0 is a state with some firing costs, E1 denotes a state of the economy with no costs. So, we use the reallocation of inputs, outputs and prices from E0 to E1 over the interval $t \in [0, 1]$. The reallocation terms define a change in aggregate productivity due to

[10] From equation (3) input cost terms are W_{ik} and P_j for primary and intermediate inputs, respectively.

[11] Assuming that reallocation is not constrained.

changes in the allocative efficiency term:

$$\Delta AE \equiv \int_0^1 \sum_i \sum_k \left(P_{it} \frac{\partial Q_{it}}{\partial X_k} - W_{ikt} \right) dX_{kt} + \int_0^1 \sum_i \sum_j \left(P_{it} \frac{\partial Q_{it}}{\partial M_j} - P_{jt} \right) dM_{jt}. \tag{6}$$

This implies that the average absolute gap across firms between labor's value of marginal product and wage equals the average productivity gain from adjusting labor by one unit in the optimal direction at every firm, holding all else constant.[12]

As a simple example, consider a single-input (labor) firm facing a perfectly elastic supply curve. The situation is illustrated in figure D.1. Imagine a firm in an environment of E0, where it faces a positive gap between the value of the marginal product and the wage. This gap could be due to any frictions in the market, such as firing costs, markups, taxes, and others. Elimination of the gap moves the firm to the socially optimal level of labor (L^*). The gain from allocative efficiency would be equal to the area below the VMP and above the labor supply (= competitive wage) curves. So, the gap is used as an approximation for a potential gain in productivity from reallocating the input to an efficient direction.

3.3 Estimating The Gap

In this section we will discuss how VMP gaps can be calculated using a firm-level data. In order to estimate the marginal product we start with the Cobb-Douglas production function specification:[13]

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

where Q_{it} is output,[14] A_{it} is a productivity/efficiency, L_{it} and K_{it} are labor and capital inputs, respectively, for firm i at time t.

[12] Can be applied to any input.

[13] Given that elasticities from the Cobb-Douglas production function are industry specific, one can argue that variation in the marginal products come solely from a variation in output to labor ratio. To address the concern, we provide the analysis using a translog production function specification, which allows input elasticities to vary by firm, in Appendix A.1. The results still hold.

[14] In this paper, due to data limitations, deflated value added is used instead of output.

Re-write the function in natural logarithms:

$$q_{it} = \beta_{sp}^{k} k_{it} + \beta_{sp}^{l} l_{it} + \varepsilon_{it} \tag{7}$$

where small letters represent log-transformation of their capital counterparts and ε_{it} is a productivity shock given as

$$\varepsilon_{it} = \omega_{it} + \eta_{it},$$

with ω_{it} as a transmitted (predictable) component and η_{it} being a measurement error.

A wide variety of production function estimators are in the disposal of a researcher given a panel structure of the data. We employ the approach proposed by Ackerberg et al. (2015) (hereafter, ACF) that addresses issues in methods introduced by Olley and Pakes (1996) and Levinsohn and Petrin (2003). Knowing that job security reforms introduce adjustment costs to 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[15] to grant variation in elasticities. Moreover, we allow the estimates to change by certain time intervals, to capture adjustments in production processes and, hence, input elasticities.[16] Elasticities of labor and capital are indexed with sp highlighting the industry and period specific estimation, respectively. We discuss different estimation procedures in more detail in Appendix B.

Given the estimates of the production function and observed levels of inputs used, marginal product of labor is given by

$$\frac{\partial Q_{it}}{\partial l} = \beta_{sp}^{l} \frac{Q_{it}}{L_{it}}, \tag{8}$$

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.

[15] We classify industries by NACE two-digit level specification. Appendix C.3 provides information on classification.

[16] We split the sample into 5 periods: [1996-2000), [2000-2004), [2004-2008), [2008-2012), [2012-2016]. Figure B.1 illustrates the evolution of average capital and labor coefficients. We observe an increasing trend for labor coefficient and a decreasing trend for capital.

Multiplying this marginal product by firm's output price gives the value of marginal product:[17]

$$VMP_{it}^{l} = P_{it}\frac{\partial Q_{it}}{\partial l}. \tag{9}$$

Methodologies of production function estimation assume that variable inputs are chosen conditional on observing the transmitted component, ω_{it}. Therefore, we expect firms to equate the marginal product conditional on ω_{it} to input prices. Marginal revenue conditional on $\hat{\omega}_{it}$, as a result, is given by

$$\beta_{sp}^{l}\frac{Q_{it}e^{(\omega_{it})}}{l_{it}e^{(\varepsilon_{it})}}.$$

In order to eliminate the unpredictable part of the productivity term we run the first stage regression of value added on variable inputs and a polynomial in the capital and the proxy variable (materials). Then, we linearly predict the level of value added ($\hat{y}_{it}$), which yields value added corrected for the unpredictable part of the error term.

The absolute value of the gap between the marginal product of labor and the marginal input price for labor is, then, given by

$$G_{it}^{l} = |VMP_{it}^{l} - W_{it}^{l}|, \tag{10}$$

where W_{it}^{l} denotes the average wage. The gap measures deviation from the social optimum, where the marginal revenue is equated to the marginal cost and there are no frictions in the economy.

To obtain the absolute real gap, we deflate the nominal value by consumer price

[17] Most of the firm-level datasets report firm-level revenues, but not prices and quantities. When estimating 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:

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

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.

index (CPI), to make the gap comparable over time:

$$RG_{it}^{l} = \frac{G_{it}^{l}}{CPI_t}.$$

3.4 Relating the Gaps to the Harmonization of Labor Contracts

Finally, we want to relate the gaps to the labor market characteristics. Particularly, we want to assess the effect of the harmonization of labor contracts. A straightforward way to do this would be to calculate the gaps for blue and white-collar workers separately. However, estimating the gaps for each type of worker requires the marginal cost of labor (approximated using the average wage) for each type. Unfortunately, the data at hand do not differentiate the wage bill for different types of laborers. Nevertheless, 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:

$$RG_{it}^{l} = \beta_b s_i + \beta_p policy_t + \alpha\ s_i \times policy_t + \mu_{ijt} + \epsilon_{it}, \tag{11}$$

where RG_{it}^{l} is the real absolute gap for labor input of firm i at time t, s_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, [2014-2016], μ_{ijt} is firm, industry and year specific fixed effects and their interactions, ϵ_{it} is iid error term.

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, the coefficient α should be positive and β_b negative, i.e. we anticipate $\alpha > 0$ and $\beta_b < 0$. α is the coefficient of interest, which indicates the labor gap differential for blue-collar workers compared to white-collar employees attributable to the harmonization of labor contracts.

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 not to be representative of the changes that occur to 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 and captures the period of "announcement" for following-up changes in the labor law, which allowed firms to decide their input use in the production process.

We find our approach to be more accurate in a certain way, compared to the straightforward way of calculating the gap for the two types of workers. Production units in the Cobb-Douglas production function are assumed to be imperfect substitutes. So, estimating the production function using both types of labor as separate units in the production process requires to drop 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 a 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.

4 Data

We will use a dataset containing the annual accounts of Belgian firms from the National Bank of Belgium. The data cover the 1996-2016 year period and include information on all the necessary variables for calculating the production function estimates and the gap, such as value-added (in thousand euros), tangible fixed assets (proxy for capital) (in thousand euros), average number of employees (FTE), material costs (in thousand euros), and remuneration (in thousand euros) per firm. The data also include NACE Rev.2 two-digit level codes for each firm.[18] Firms with limited liabilities are required to submit 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. Since the short form is restricted to value-added reports and only 7.3% 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"

[18] We exclude all non-private sectors of the economy and construction industry because they got smaller notice periods for their blue-collar workers. Please visit http://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF for more detailed information on the statistical classification of economic activities in the European Community. Please see Appendix C.3 for classification used in this paper.

dataset, that 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).

To obtain real values we use NACE two-digit level deflator[19] retrieved from the National Bank accounts, the year 2010 is taken as a base year. Capital is deflated by the economy gross capital formation index from the UNECE Statistical Database.

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.[20] Hence, our productivity measure resembles residual profitability rather than true productivity estimate. This implies that gain in productivity from reallocation is, by construction, gain in revenue productivity.

Labor gap calculation requires data on the marginal input price for labor, which is the marginal wage. In our 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. For each year and firm, we divide a total wage bill by number of workers (FTE) to get the average wage. And we use the average wage as an approximation for the marginal wage. Figure D.2 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 trend in the average wage across the sampling period. Except for the first and last two years of the sample, the calculated average wage closely tracks the reported one, indicating that the data are representative at aggregate level.

The main constraint on the data comes from the use of log-linear variables. Therefore we are limited to a sample where firms do not have missing and non-negative data points. Moreover, in estimating the production function we employ the technique proposed by Ackerberg et al. (2015) with materials as a proxy variable. We

[19]Please see Appendix C.2 for more detail on construction of the deflator.

[20]For those interested in the issue and possible solutions, we suggest looking at De Loecker and Goldberg (2014).

use materials over investment, because of the well-known zero-investment problem and lumpiness of the data.[21] 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. After cleaning the data we are left with 741 181 observations with positive values for all the factor inputs. The sample constitutes around 66% of the initial total value added and 69% of the total employment. Table C.4.1 presents summary statistics of key variables.

We estimate production function on NACE two-digit level classification[22] splitting the time span of 21 years into 5 samples.[23] So the input elasticities have 185 unique values for the Cobb-Douglas production function specification (37×5).

5 Results

The first step towards measuring the labor gap is to estimate the production function coefficients. Table B.1 documents the input coefficients. On average, the capital coefficient is equal to 0.18, the labor coefficient on average is 0.82, and the average returns to scale is 1.00.

After estimating the elasticities, we have calculated the wedge between the value of marginal product of labor and its marginal cost using equations (9) and (10). Table 1 presents the average absolute labor gap by industry. For the Belgian economy across the 1996-2016 year period the average absolute gap is equal to 24.6 thousand euros. The dispersion, captured by the coefficient of variation (CV), is quite high both within and across different industries. Across the economy 69% of observations have positive gaps. The sign of the gap helps to identify the direction of misallocation. Positive labor gap implies that some product and/or labor market imperfections do not allow firms to expand.

Figure 1 examines the year-to-year evolution of the labor gap. The figure plots the coefficients of year indicators of the fixed-effect regression of the absolute value of the gap on yearly and year times industry specific indicators. We observe that the gap is increasing over time.

[21] Details are discussed in Appendix B.

[22] Please refer to Appendix C.3 for details.

[23] [1996-2000), [2000-2004), [2004-2008), [2008-2012), [2012-2016]

The unconditional mean (median) gaps in real terms for labor are around 24 (16) thousand euros in the period prior and after the reform.[24] The gaps are nearly half of the average wage.

Figure 2 presents the kernel density estimate of the gap, plotting the two periods defined by the introduction of the new labor policy. The plot is indicative of an increase in the probability of observing a positive gap after the reform.

Following Petrin and Sivadasan (2013), in table 3 we present the change in the gap across two periods, base period - 1996-2013 - the pre-policy period, and the second period - 2014-2016 - the period after the policy implementation, from a fixed-effects regression of the absolute value of the labor gap against period indicators. As suggested by Petrin and Sivadasan (2013), from equation (5) the average absolute gap for a labor input in any period is an approximate measure of the potential gain in productivity from a unit reallocation of that input in the optimal direction by all firms. Hence, in the base period the potential gain from a unit adjustment in labor was 27 thousand euros. After the the reform this potential gain increased by 7 thousand euros. The sample is restricted to those firms appearing in the panel at least one year prior and after the reform. Overall, the results suggest that gains from efficient reallocation of labor input increased after the policy.

Finally, we study the effect of 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. Table 4 presents the results of the model that captures the difference between the two types of labor force (equation (11)). The results suggest that on average the labor gap will be higher for firms that decide to increase their share of blue-collar workers compared to white-collar workers. From model 2, one standard deviation increase in the share of blue-collar workers increases the labor gap by 2 152 euros per year after the policy. This implies that on average, adjustment costs for blue-collar workers have increased compared to white-collar workers after the policy implementation. The results are in-line with the implications of the harmonization of labor contracts.

Overall. the values reported indicate that the potential gain from labor reallocation increased over the sampling period. Moreover, the harmonization of labor

[24] Summary statistics of the labor gap is presented in table 2.

contracts increased the allocative inefficiency of the labor input for firms increasing the value of lost output through rising adjustment costs for blue-collar workers. The results are robust to different production function specification and per hour gap estimations.[25]

TO BE COMPLETED

6 Placebo Test

We want to provide further evidence that results shown are related to the introduction of harmonization of the labor contracts and not to any other factors that may have impacted the evolution of the revenue-cost wedge for the labor input. Therefore, we perform a placebo experiment in which i) the evolution of the gap for construction industry is compared to the rest of the Belgian economy, and, ii) we pretend the policy have occurred in 2005-2007.

6.1 Construction Industry

As it was mentioned before, some industries of the economy were exempted from increased notice period for the blue-collar workers. The diamond industry has received a temporary exemption, to allow firms in the sector to introduce changes gradually, while the construction industry was allowed to have shorter notice periods for their blue-collar workers permanently.

Given that the construction industry was not affected by exactly this policy, 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. So, we implement the same analysis for construction industry.

After calculating the elasticities from the Cobb-Douglas production function and calculating the wedges, we plot the year-to-year evolution of the labor gap in figure 3. Contrary to what we saw in the evolution of the labor wedge for the rest of the economy, we can clearly observe a declining trend in the gap after the policy implementation.

[25] Results on robustness checks are presented in Appendix A.

Figure 4 presents the kernel density of the distribution of the labor gap in construction industry plotting the two periods identified by the policy implementation. The plot demonstrates that there are no noticeable difference in the distribution of the labor gap for the two periods.

In table 5 we present the change in the gap across two periods, base period - 1996-2013 - the pre-policy period, and the second period - 2014-2016 - the period after the policy implementation, from a fixed effects regression of the absolute value of the gap against period indicators. We can see that the post-policy gap is not statistically different from the pre-policy gap for the construction industry. Overall, these results suggest that after the policy implementation, the gains from efficient reallocation of labor input did not change significantly for the construction industry.

Finally, we study the effect of harmonization of labor contracts on return-cost wedges. The policy was argue to increase the adjustment costs for blue-collar workers compared to white-collar employees. Table 6 shows the results of the model in equation 11. Contrary to the results that we got for the rest of the economy and to the anticipated consequences of the policy, the results in the table suggest that on average the labor gap will be lower or not different for firms that decide to increase the share of the blue-collar workers compared to white-collar workers. This implies that on average, adjustment costs for blue-collar workers did not change after the policy implementation. The results are in-line with the implications of the harmonization of labor contracts for the construction industry, i.e. no effect.

Overall, we see that the policy had no effect on the construction industry. Given that we see substantial changes in the gap for the rest of the economy in Belgium, we can argue the changes to be attributable to the harmonization of labor contracts, which resulted in an increase in the loss in total value added for the economy from allocative inefficiencies.

6.2 Another period

Another experiment to test for the importance of the policy would be to imagine a policy had occurred at a different period. We chose the 2005-2007 period, because it is further away from the original policy, and before the crisis period. We perform the same analysis as before, with period dummy being equal to 1 for 2005-2007 years.

We present the results of the Cobb-Douglas production function, nevertheless, we get the same results with the translog specification.

In table 7 we present the change in the gap for the hypothetical period of the policy - 2005-2007. We can see that the policy did not have any statistically significant effect on the labor gap. We can also observe it from the kernel density of the distribution of the labor gap (figure 5). We see that the distribution for 2005-2007 is similar to the rest of the sample, and it is more concentrated around the mean.

Finally, we study the effect of harmonization of labor contracts on the labor return-cost wedges. Table 8 shows the results. Contrary to the original case, we see that the coefficient of interest is negative, which contradicts the anticipated consequences of the policy.

7 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 1996-2016 period. We also focused on the recent labor reform introduced to harmonize labor contract for blue- and white-collar workers, which increased the firing costs of blue-collar workers. We found sizable gaps for labor even prior to the increase in costs of dismissing employees. The average gap for the sampling period is estimated to be 24 thousand euros per year, which is approximately 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 one standard deviation increase in the share of blue-collar workers after the harmonization of labor contracts increases the gap by 2 thousand euros compared to white-collar employees. The findings suggest that the Belgium labor reform did affect the allocative efficiency of the labor input.

References

Abraham, K. G. and S. N. Houseman (1993). Does employment protection inhibit labor market flexibility? Lessons from Germany, France, and Belgium. *NBER Working Paper No. 4390*.

Ackerberg, D. A., K. Caves, and G. Frazer (2015). Identification properties of recent production function estimators. *Econometrica 83*(6), 2411–2451.

Allen & Overy (2014). The reform of dismissal rules in Belgium. Accessed: February 7, 2018.

American Chamber of Commerce in Belgium (n/d). Harmonization. http://www.amcham.be/policy/labor-market/harmonization Accessed: February 7, 2018.

Asker, J., A. Collard-Wexler, and J. De Loecker (2014). Dynamic inputs and resource (mis)allocation. *Journal of Political Economy 122*(5), 1013–1063.

Autor, D. H., J. J. Donohue III, and S. J. Schwab (2004). The employment consequences of wrongful-discharge laws: Large, small, or none at all? *American Economic Review 94*(2), 440–446.

Baily, M. N., C. Hulten, and D. Campbell (1992). Productivity dynamics in manufacturing plants. *Brookings Papers on Economic Activity. Microeconomics*, 187–267.

Bassanini, A., L. Nunziata, and D. Venn (2009). Job protection legislation and productivity growth in OECD countries. *Economic Policy 24*(58), 349–402.

Berthou, A. and K. Manova (2016). Productivity, misallocation and trade.

Collard-Wexler, A. and J. De Loecker (2015). Reallocation and technology: Evidence from the US steel industry. *American Economic Review 105*(1), 131–171.

Collard-Wexler, A. and J. De Loecker (2016). Production function estimation with measurement error in inputs. *NBER Working Paper Series No.22437*.

Criscuolo, C., P. N. Gal, and C. Menon (2014). The dynamics of employment growth: New evidence from 18 countries. *OECD Science, Technology and Industry Policy Papers* (14).

De Loecker, J. and P. K. Goldberg (2014). Firm performance in a global market. *The Annual Review of Economics 6*, 201–227.

Gopinath, G., S. Kalemli-Ozcan, L. Karabarbounis, and C. Villegas-Sanchez (2017). Capital allocation and productivity in South Europe. *The Quarterly Journal of Economics 132*(4), 1915–1967.

Hsieh, C. and P. Klenow (2009). Missallocation and manufacturing TFP in China and India. *Quarterly Journal of Economics 124*(4), 1403–1448.

Kherig, M. and N. Vincent (2016). Do firms mitigate or magnify capital misallocation? evidence from plant-level data.

Levinsohn, J. and A. Petrin (2003). Estimating production functions using inputs to control for unobservables. *Review of Economic Studies 70*(2), 317–341.

Loyens & Loeff (2014). Belgium - new dismissal rules as of January 1, 2014. Accessed: April 13, 2018.

Midrigan, V. and D. Y. Xu (2014). Finance and misallocation: Evidence from plant-level data. *American Economic Review 104*(2), 422–458.

OECD (2013). Belgium. https://www.oecd.org/els/emp/Belgium.pdf Accessed: March 29, 2018.

Olley, G. and A. Pakes (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica 64*(6), 1263–1297.

Petrin, A. and J. Levinsohn (2012). Measuring aggregate productivity growth using plant-level data. *The RAND Journal of Economics 43*(44), 705–725.

Petrin, A. and J. Sivadasan (2013). Estimating lost output from allocative inefficiency, with an application to Chile and firing costs. *The Review of Economics and Statistics 95*(1), 286–301.

Restuccia, D. and R. Rogerson (2008). Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic Dynamics 11*, 707–720.

Restuccia, D. and R. Rogerson (2013). Misallocation and productivity. *Review of Economic Dynamics 16*(1), 1–10.

Sandleris, G. and M. L. J. Wright (2014). The costs of financial crises: Resource misallocation, productivity, and welfare in the 2001 argentine crisis. *The Scandinavian Journal of Economics 116*(1), 87–127.

Syverson, C. (2011). What determines productivity? *Journal of Economic Literature 49*(2), 326–365.

van Ark, B., M. O'Mahony, and M. Timmer (2008). The productivity gap between europe and the united states: Trends and causes. *The Journal of Economic Perspectives 22*(1), 25–44.

Van Beveren, I. (2012). Total factor productivity estimation: A practical review. *Journal of Economic Surveys 26*(1), 98–128.

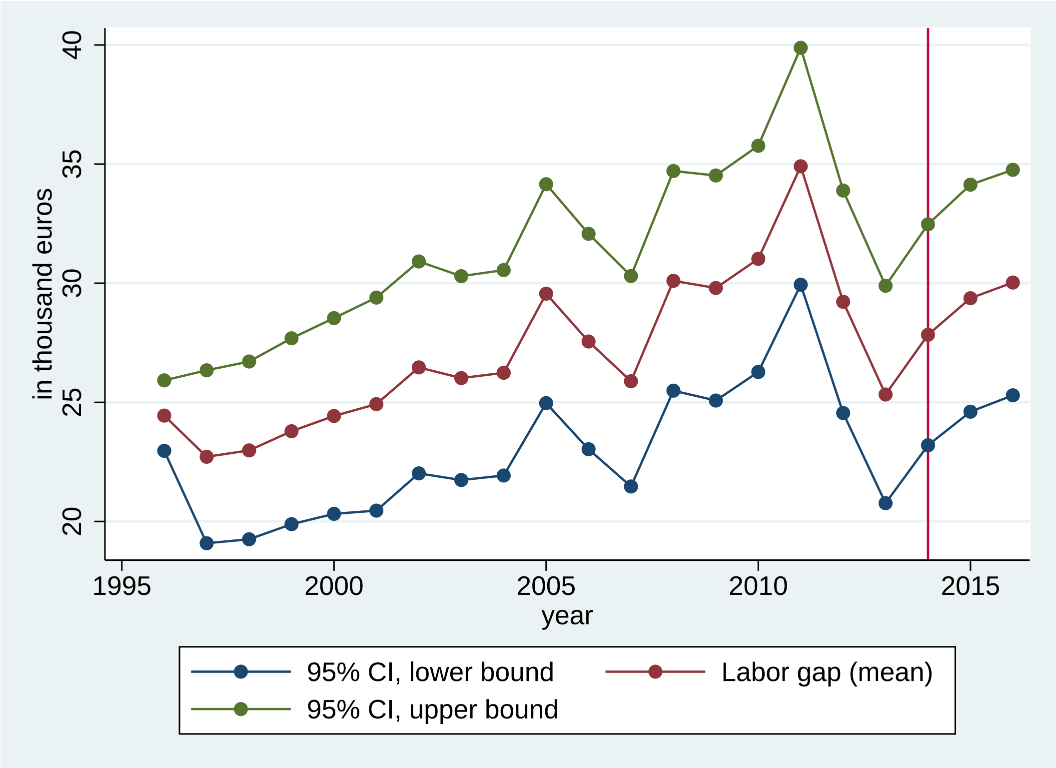
Van Biesebroeck, J. (2007). Robustness of productivity estimates. *The Journal of Industrial Economics 55*(3), 529–569.

Wooldridge, J. M. (2009). On estimating firm-level production functions using proxy varibles to control for unobservables. *Economics Letters 104*, 112–114.

8 Tables and Figures

8.1 Baseline Model

Figure 1: Absolute Gap: 95% Confidence Interval for Change in Gap



Note: Gap estimates are in thousand euros. The figure plots the coefficients from the regression of the absolute value of the labor gap on yearly and year × industry indicator variables, and firm-fixed-effects. Standard errors are clustered at the firm level.

Table 1: Absolute Gap, by industry

NACE	Description	Mean	CV	Pos %	Obs
1-3	Agriculture, forestry, and fishing	20.79	0.97	63.65	8651
5-9	Mining and Quarrying	22.32	1.01	71.96	1109
10-12	Manufacturing Food products; Beverages; Tobacco products	17.55	1.03	65.85	24267
13-15	Manufacturing Textiles; Wearing apparel; Leather and related products	12.15	1.11	49.00	9329
16	Manufacturing Wood, products of wood and cork, except furniture; ...	15.16	1.12	52.76	5591
17	Manufacturing Paper and paper products	20.22	1.06	63.31	2698
18	Manufacturing Printing and reproduction of recorded media	16.63	0.93	55.26	10179
19-21	Manufacturing Coke and refined petroleum products; Chemicals and chemical products; Basic pharmaceutical products and preparations	33.91	0.96	81.45	6856
22	Manufacturing Rubber and plastic products	17.19	1.01	57.33	5999
23	Manufacturing Other non-metallic mineral products	18.75	1.02	77.83	8964
24	Manufacturing Basic metals	25.84	1.24	60.10	1857
25	Manufacturing Fabricated metal products, except machinery and equipment	14.39	0.99	64.11	24090
26	Manufacturing Computer, electronic and optical products	19.99	0.95	39.72	2827
27	Manufacturing Electrical equipment	15.98	0.98	60.15	3049
28	Manufacturing Machinery and equipment	16.57	1.07	64.58	8746
29	Manufacturing Motor vehicles, trailers and semi-trailers	16.58	1.24	54.08	1607
30	Manufacturing Other transport equipment	19.99	0.95	59.29	646
31-32	Manufacturing Furniture and Other manufacturing	14.70	1.12	72.99	10746
33	Manufacturing Repair and installation of machinery and equipment	18.50	0.93	77.40	2482
36-39	Water supply, sewerage, waste management and remediation activities	40.74	0.92	82.24	5704
45	Wholesale and retail trade; repair of motor vehicles and motorcycles	19.22	1.05	77.79	49171
46	Wholesale trade, except motor vehicles and motorcycles	33.49	0.98	75.11	136250
47	Retail trade, except motor vehicles and motorcycles	15.96	1.15	66.33	113327
49	Land transport and via pipelines	13.96	1.14	59.23	36545
50-53	Water and air transport; Warehousing and support activities for transportation; Postal and courier activities	33.91	0.99	68.88	15352
55-56	Accommodation; Food and beverage services activities	12.41	1.26	54.51	57384
58	Publishing activities	24.43	0.96	69.31	3496
59-60	Motion picture, video and television, ...; Programming and broadcasting activities	39.19	0.91	82.14	3265
61	Telecommunications	61.46	0.95	58.55	1392
62-63	Computer programming, consultancy and related activities; Information service activities	26.55	0.95	67.07	17486
64-66	Financial and Insurance activities	47.21	0.78	87.54	37476
68	Real estate activities	52.50	0.96	74.30	20255
69-75	Professional, scientific, and technical activities	29.48	0.92	73.57	67173
77	Rental and leasing activities	49.64	1.09	74.27	6058
78	Employment activities	20.02	1.23	43.00	2742
79	Travel agency, tour operator reservation service and related activities	24.58	0.93	65.69	4734
80-82	Security and investigation activities; Services to buildings and landscape activities; Office administrative, office support and other business support activities	20.04	1.09	63.67	23224
	Total	24.64	1.15	69.09	740727

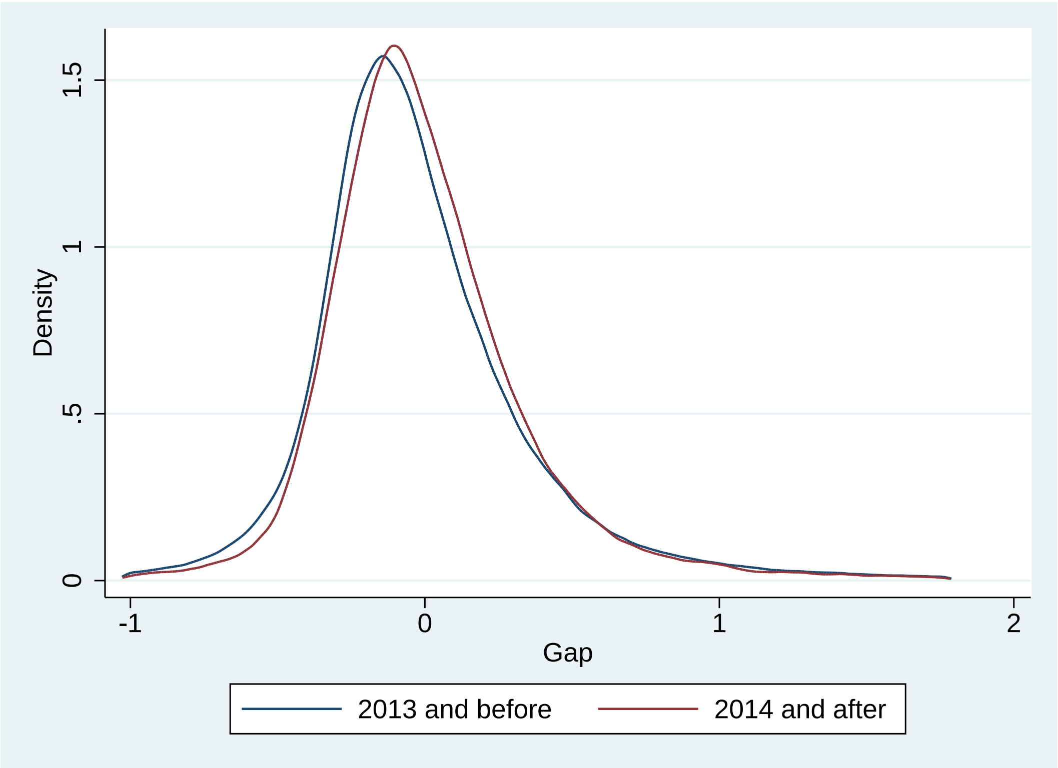
Note: Average absolute labor gap was calculated by $\overline{RG^l_s} = \frac{\sum_{i \in s} RG^l_{it}}{N_s}$, reported in thousand euros. Coefficient of variation is $CV_s = \frac{sd_s}{\overline{RG^l_s}}$. Percent of positive labor gap is defined as $Pos = \frac{N_s^+}{N_s} \times 100$.

Table 2: Summary of the labor gap

	RG^l_{it}			RG^+_{it}			RG^-_{it}		
	mean	median	obs.	mean	median	obs.	mean	median	obs.
Total	24.638	15.729	740727	28.459	19.574	511750	16.098	9.762	228977
	(28.396)			(30.197)			(21.564)		
year $\leq$ 2013	24.760	15.755	643963	28.645	19.636	442446	16.232	9.846	201517
	(28.511)			(30.366)			(21.615)		
year $>$ 2013	23.824	15.542	96764	27.273	19.185	69304	15.117	9.177	21460
	(27.605)			(29.062)			(21.164)		

Standard errors in parentheses

Figure 2: Gap Distribution



Note: The figure presents the kernel density (standardized) of the gap for labor for two periods defined by the labor reform. It omits top and bottom 1% of the distribution.

Table 3: The Absolute Value of the Gap

	Labor gap
Change in gap, 2014-2016	7.104***
	(1.920)
Base period, 1996-2013	27.060***
	(0.618)
year	yes
year × nace	yes
N	534347
R^2	0.081

Note: The sample is restricted to firms that operate at least one year prior and after the reform. Gap estimates are in thousand euros. The reported values are the estimated coefficients from a firm fixed-effects regression. Standard errors in parentheses are estimated after 499 bootstraps.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

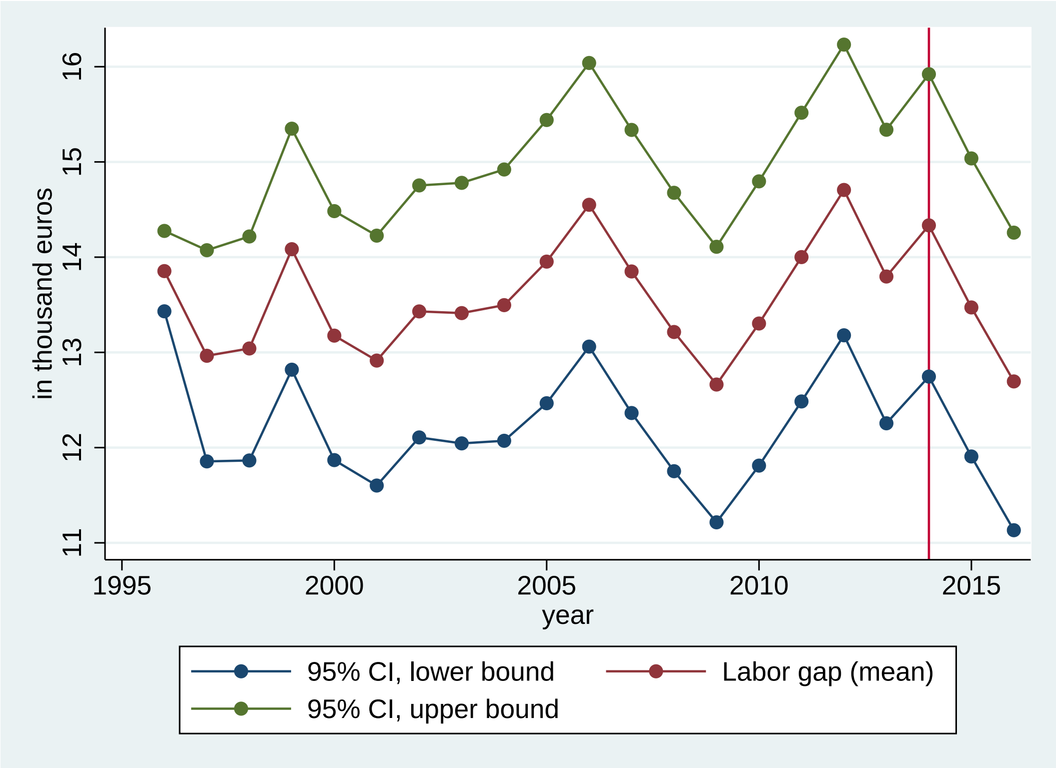
Table 4: Estimation Results

	Model 1	Model 2	Model 3	Model 4	Model 5
s	-11.857***	-12.222***	-1.299***	-	-
	(0.315)	(0.321)	(0.457)		
s × policy	-0.118	2.152***	2.169***	1.863***	-0.309
	(0.136)	(0.240)	(0.236)	(0.215)	(0.311)
year	-	yes	yes	yes	yes
nace	-	-	yes	-	-
year × nace	-	-	-	-	yes
firm	-	-	-	yes	yes
N	576569	576569	576569	576569	576569
R^2	0.030	0.032	0.175	0.010	0.079

Note: Coefficients are in thousand euros. Standard errors in parentheses are estimated after 499 bootstraps.

8.2 Placebo test: Construction Industry

Figure 3: Absolute Gap: 95% Confidence Interval for Change in Gap



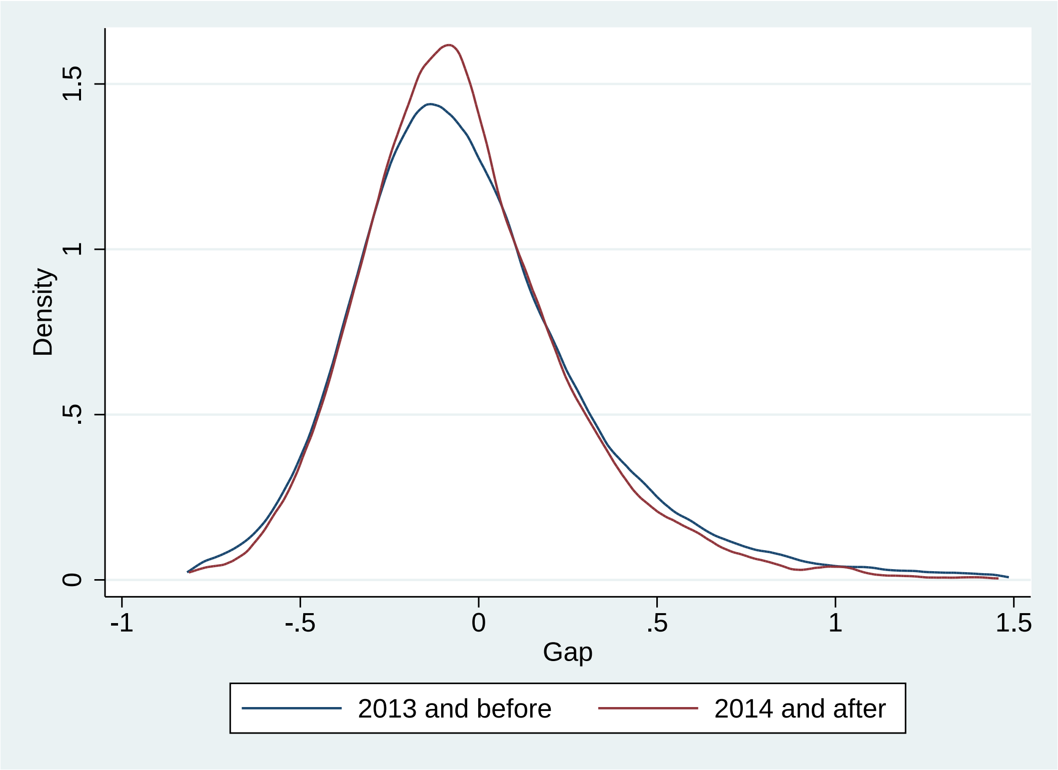
Note: Gap estimates are in thousand euros. The figure plots the coefficients from the regression of the absolute value of the labor gap on yearly and year × industry indicator variables, and firm-fixed-effects. Standard errors are clustered at the firm level.

Table 5: The Absolute Value of the Gap

	Labor gap
Change in gap, 2014-2016	-1.067
	(0.662)
Base period, 1996-2013	13.842***
	(0.268)
year	yes
year × nace	yes
N	96850
R^2	0.019

Note: The sample is restricted to firms that operate at least one year prior and after the reform. Gap estimates are in thousand euros. The reported values are the estimated coefficients from a firm fixed-effects regression. Standard errors in parentheses are estimated after 499 bootstraps.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 4: Gap Distribution



Note: The figure presents the kernel density (standardized) of the gap for labor for two periods defined by the labor reform. It omits top and bottom 1% of the distribution.

Table 6: Estimation Results

	Model 1	Model 2	Model 3	Model 4	Model 5
s	-10.781***	-10.602***	-10.570***	-	-
	(0.850)	(0.857)	(0.846)		
s × policy	-0.907***	-2.061***	-2.026***	-0.644	-0.561
	(0.128)	(0.671)	(0.668)	(0.602)	(0.602)
year	-	yes	yes	yes	yes
nace	-	-	yes	-	-
year × nace	-	-	-	-	yes
firm	-	-	-	yes	yes
N	104933	104933	104933	104933	104933
R^2	0.041	0.045	0.046	0.010	0.018

Note: Coefficients are in thousand euros. Standard errors in parentheses are estimated after 499 bootstraps.

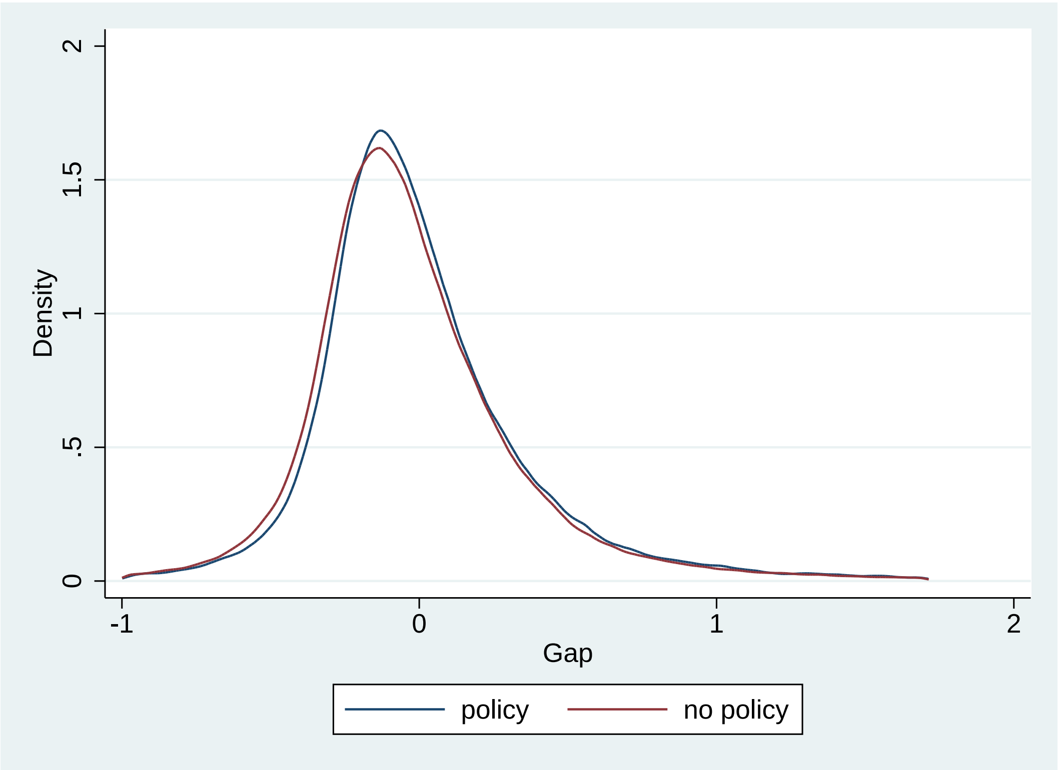
8.3 Placebo Test: Different Period

Table 7: The Absolute Value of the Gap

	Labor gap
Change in gap, 2005-2007	1.188
	(1.494)
Base period, 1996-2013	27.068***
	(0.704)
year	yes
year × nace	yes
N	495281
R^2	0.059

Note: The sample is restricted to firms that operate at least one year prior and after the reform. Gap estimates are in thousand euros. The reported values are the estimated coefficients from a firm fixed-effects regression. Standard errors in parentheses are estimated after 499 bootstraps.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 5: Gap Distribution



Note: The figure presents the kernel density (standardized) of the gap for labor for two periods defined by the labor reform. It omits top and bottom 1% of the distribution.

Table 8: Estimation Results

	Model 1	Model 2	Model 3	Model 4	Model 5
s	-11.758***	-11.488***	0.413	-	-
	(0.532)	(0.529)	(0.670)		
s × policy	-0.456***	-1.990***	-1.848***	-2.095***	-0.217
	(0.127)	(0.293)	(0.290)	(0.267)	(0.358)
year	-	yes	yes	yes	yes
nace	-	-	yes	-	-
year × nace	-	-	-	-	yes
firm	-	-	-	yes	yes
N	294795	294795	294795	294795	294795
R^2	0.020	0.028	0.178	0.029	0.097

Note: Coefficients are in thousand euros. Standard errors in parentheses are estimated after 499 bootstraps.

Appendix

A Robustness Check

A.1 Translog Production Function Specification

From equations (9) and (10) variability in the measure of the labor gap comes from the variability in the value of marginal product of labor, which in turn depends on the labor input coefficient and output to labor ratio. Given that input coefficients in the Cobb-Douglas production function have limited diversity (industry specific coefficients)[26], one may argue that our gap estimation results are driven solely by the variation in output over labor ratio. To address the concern, we will repeat the same procedure for the alternative functional form of production function. To add variability to both terms of the marginal product estimates, we use the translog production function specification, which is a generalization of the Cobb-Douglas production function. It does not impose separability between the inputs of the production function by including interaction terms between inputs. The translog analogue of equation (7) is given by:

$$y_{it} = \beta_t^l l_{it} + \beta_t^k k_{it} + \beta_t^{ll} l_{it}^2 + \beta_t^{kk} k_t^2 + \beta_t^{lk} l_{it} k_{it} + \omega_{it} + \epsilon_{it}. \tag{12}$$

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

$$\begin{aligned} \hat{\theta}_{it}^l &= \hat{\beta}_t^l + 2\hat{\beta}_t^{ll} l_{it} + \hat{\beta}_t^{lk} k_{it} \\ \hat{\theta}_{it}^k &= \hat{\beta}_t^k + 2\hat{\beta}_t^{kk} k_{it} + \hat{\beta}_t^{lk} l_{it}. \end{aligned} \tag{13}$$

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

With the alternative specification the general conclusions from the baseline case hold. Table A.1 presents the summary of the absolute labor gap across different industries. For the Belgian economy across the 1996-2016 year period the average absolute gap is equal to 19.5 thousand euros. As in the baseline case, for almost all sectors for the majority of the firms we find positive gaps.

[26]Note that in our baseline analysis coefficients are industry and sample-period specific.

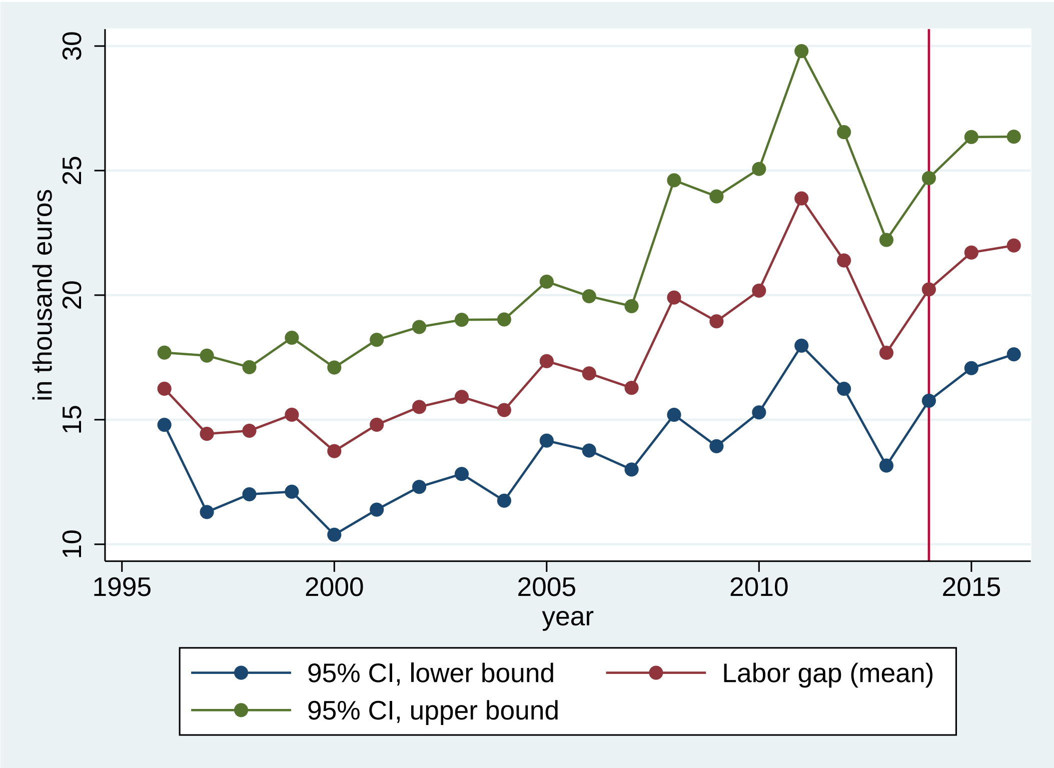
Table A.1: Absolute Gap, by industry

NACE	Description	Mean	CV	Pos %	Obs
1-3	Agriculture, forestry, and fishing	16.13	0.88	64.11	8538
5-9	Mining and Quarrying	22.08	1.00	66.79	1105
10-12	Manufacturing Food products; Beverages; Tobacco products	15.23	0.99	67.20	23895
13-15	Manufacturing Textiles; Wearing apparel; Leather and related products	11.02	1.08	54.66	9208
16	Manufacturing Wood, products of wood and cork, except furniture; ...	13.39	0.98	63.98	5344
17	Manufacturing Paper and paper products	17.94	1.03	71.42	2442
18	Manufacturing Printing and reproduction of recorded media	13.32	0.90	56.82	10048
19-21	Manufacturing Coke and refined petroleum products; Chemicals and chemical products; Basic pharmaceutical products and preparations	26.77	0.86	88.56	6478
22	Manufacturing Rubber and plastic products	15.46	0.94	63.38	5833
23	Manufacturing Other non-metallic mineral products	15.16	0.87	82.15	8841
24	Manufacturing Basic metals	24.50	1.18	64.03	1843
25	Manufacturing Fabricated metal products, except machinery and equipment	11.96	0.93	72.19	23200
26	Manufacturing Computer, electronic and optical products	19.48	0.90	43.67	2739
27	Manufacturing Electrical equipment	14.24	0.95	68.07	2931
28	Manufacturing Machinery and equipment	16.18	0.98	79.55	8436
29	Manufacturing Motor vehicles, trailers and semi-trailers	13.35	1.11	61.72	1434
30	Manufacturing Other transport equipment	19.67	0.79	71.11	533
31-32	Manufacturing Furniture and Other manufacturing	13.25	1.00	78.66	10653
33	Manufacturing Repair and installation of machinery and equipment	17.54	0.85	84.20	2367
36-39	Water supply, sewerage, waste management and remediation activities	31.48	0.79	89.74	5538
45	Wholesale and retail trade; repair of motor vehicles and motorcycles	17.62	0.89	89.08	46625
46	Wholesale trade, except motor vehicles and motorcycles	29.62	0.87	97.97	117144
47	Retail trade, except motor vehicles and motorcycles	12.01	0.97	69.48	111689
49	Land transport and via pipelines	10.51	1.02	60.54	36126
50-53	Water and air transport; Warehousing and support activities for transportation; Postal and courier activities	27.34	0.79	99.44	12778
55-56	Accommodation; Food and beverage services activities	9.76	1.09	59.61	57002
58	Publishing activities	24.14	0.89	91.03	2954
59-60	Motion picture, video and television, ...; Programming and broadcasting activities	34.42	0.80	103.88	2761
61	Telecommunications	45.88	0.87	73.97	1191
62-63	Computer programming, consultancy and related activities; Information service activities	23.82	0.86	99.29	13582
64-66	Financial and Insurance activities	37.61	0.66	111.72	30866
68	Real estate activities	25.22	0.88	86.74	18164
69-75	Professional, scientific, and technical activities	24.10	0.82	90.51	59183
77	Rental and leasing activities	30.43	1.02	80.98	5857
78	Employment activities	20.29	1.13	42.53	2732
79	Travel agency, tour operator reservation service and related activities	20.84	0.78	75.84	4209
80-82	Security and investigation activities; Services to buildings and landscape activities; Office administrative, office support and other business support activities	16.60	1.02	71.08	21978
	Total	19.54	1.03	72.24	686247

Note: 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 $Pos = \frac{N^+_s}{N_s} \times 100$.

While figure A.1 plots the evolution of the labor gap for the sampling period, table A.2 presents the summary statistics. According to the figure, the labor gap is increasing over time. According to the table the unconditional mean (median) gaps in real terms for labor are around 19.5 thousand euros in the period prior and after the reform.

Figure A.1: Absolute Gap: 95% Confidence Interval for Change in Gap



Note: Gap estimates are in thousand euros. The figure plots the coefficients from the regression of the absolute value of the labor gap on yearly and year × industry indicator variables, and firm-fixed-effects. Standard errors are clustered at the firm level.

Table A.2: Summary of the labor gap

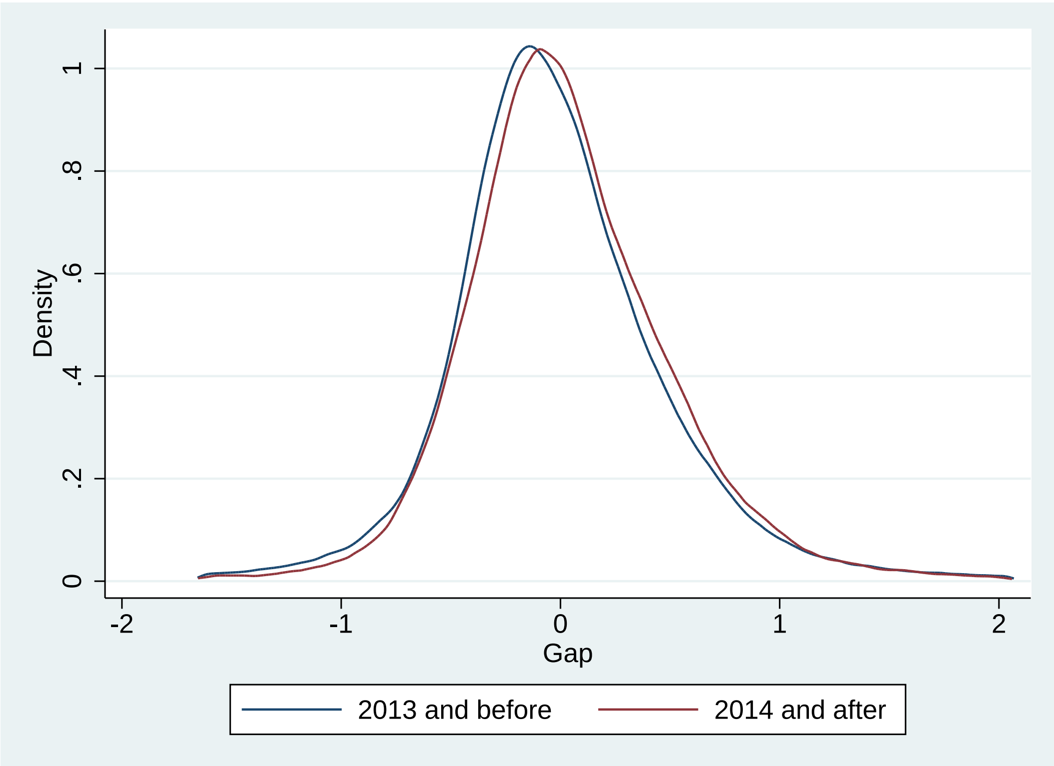
	RG^l_{it}			RG^+_{it}			RG^-_{it}		
	mean	median	obs.	mean	median	obs.	mean	median	obs.
Total	19.541	13.758	686247	21.561	16.352	495720	14.285	8.237	190527
	(20.097)			(20.082)			(19.164)		
year $\leq$ 2013	19.563	13.733	601170	21.546	16.310	432149	14.492	8.302	169021
	(20.172)			(20.107)			(19.438)		
year $>$ 2013	19.387	13.944	85077	21.665	16.636	63571	12.655	7.804	21506
	(19.556)			(19.906)			(16.764)		

Standard errors in parentheses

Figure A.2 presents the kernel density estimate of the gap, plotting the two periods defined by the introduction of the new labor policy. The plot is indicative of an increase in the probability of observing a positive gap after the reform. In table

A.3 we present the change in the gap across two periods, base period - 1996-2013, and the second period - 2014-2016 - the period after the policy implementation, from a fixed-effects regression of the absolute value of the labor gap against period indicators for firms that were operating at least one year before and after the policy introduction. According to the table, in the base period the potential gain from a unit adjustment in labor was 21 thousand euros. After the the reform the potential gain is 28 thousand euros. Consistent with the baseline model, the results suggest that gains from adjusting the labor input increased after the policy.

Figure A.2: Gap Distribution



Note: The figure presents the kernel density (standardized) of the gap for labor for two periods defined by the labor reform. It omits top and bottom 1% of the distribution.

Finally, we study the effect of 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. Table A.4 presents the results. And, consistent with the baseline specification, on average the labor gap will be higher for firms that decide to increase their share of blue-collar workers compared to white-collar workers. From Model 2, one standard deviation increase in the share of blue-collar workers increases the labor gap by 1 137 euros per year after the policy.

Table A.3: The Absolute Value of the Gap

	Labor gap
Change in gap, 2014-2016	6.928***
	(1.653)
Base period, 1996-2013	21.055***
	(0.649)
year	yes
year ×section	yes
N	496411
R^2	0.133

Note: The sample is restricted to firms that operate at least one year prior and after the reform. Gap estimates are in thousand euros. The reported values are the estimated coefficients from a firm fixed-effects regression. Standard errors in parentheses are estimated after 499 bootstraps.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Overall, the results suggest that the potential gain from labor reallocation was increasing over the sampling period, and it increased even more after the harmonization of labor contracts.

Table A.4: Estimation Results

	Model 1	Model 2	Model 3	Model 4	Model 5
s	-9.560***	-9.748***	-2.516***	-	-
	(0.216)	(0.219)	(0.295)		
s × policy	0.131	1.137***	0.779***	0.759***	0.002
	(0.104)	(0.192)	(0.186)	(0.166)	(0.233)
year	-	yes	yes	yes	yes
nace	-	-	yes	-	-
year × nace	-	-	-	-	yes
firm	-	-	-	yes	yes
N	533822	533822	533822	533822	533822
R^2	0.038	0.047	0.200	0.029	0.128

Note: Coefficients are in thousand euros. Standard errors in parentheses are estimated after 499 bootstraps.

A.2 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 ignores whether or not employee is active. The FTE measure 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 amount of labor 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. Therefore, this section uses effective hours worked as an alternative measure for employment. So that the value of the gap is in euros per hour worked.

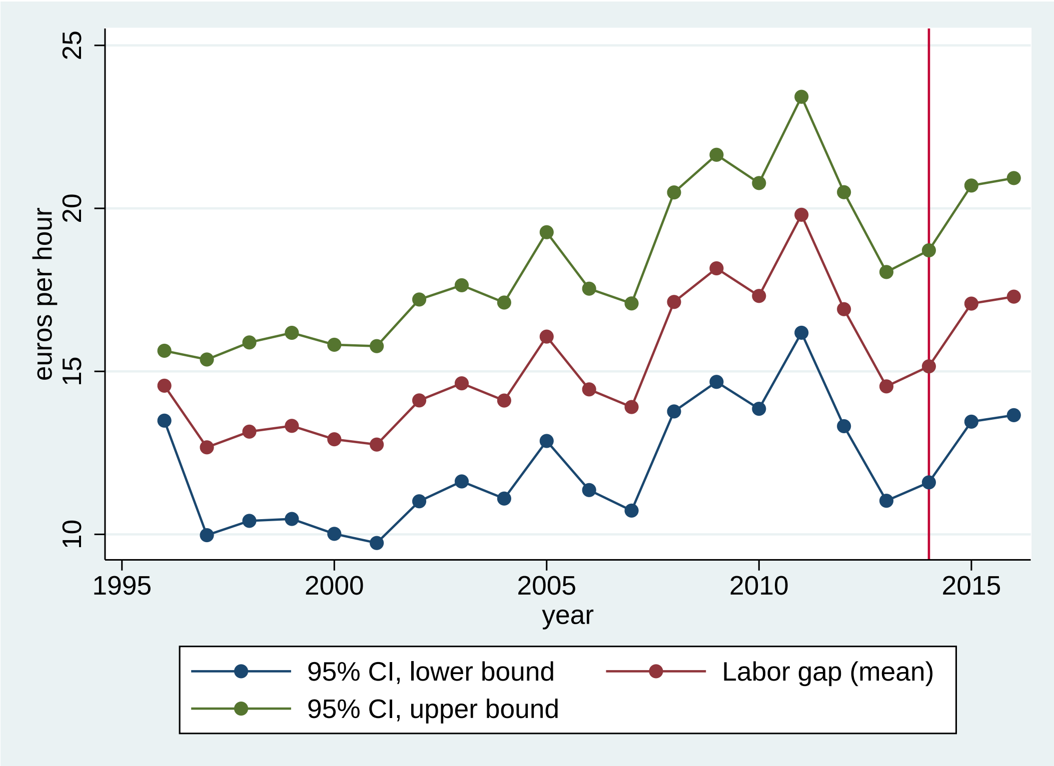
According to the table A.1, the average gain from reallocating a labor in an optimal direction on average is 14.75 euros per hour worked. As in the baseline case, the variation within and across sectors is high and majority of the firms are characterized by positive labor wedge. Table A.2 presents the unconditional mean and median values for the gap estimates. Mean (median) gap for Belgium firms in the 1996-2014 period is 14.75 (9.14) euros per hour worked. Figure A.2 plots the distribution of the hourly labor gap for the periods before and after the changes in labor law. The plot is indicative of increasing positive gaps after the reform. For an alternative measure of employment, we document an increasing trend in absolute value of the gap and the evolution along the sample period is the same as in the baseline specification (figure A.1). In table A.3 we present the results of the fixed-effects regression of the absolute value of the labor gap against period indicators for firms that were operating at least one year before and after the policy introduction. According to the table, in the base period the potential gain from a unit adjustment in labor was 16 euros per hour. After the the reform the potential gain has increased by 3.36 euros per hour. Consistent with the baseline model, the results suggest that gains from adjusting the labor input increased after the policy. Finally, table A.4 present the results from estimating equation (11). Robust to the baseline case, the results suggest that on average, adjustment costs for blue-collar workers have increased compared to white-collar worker. From model 2, one standard deviation increase in the share of blue-collar workers increases the labor gap by 72 euro cents per hour after the harmonization of labor contracts was introduced.

Table A.1: Absolute Gap, by industry

NACE	Description	Mean	CV	Pos %	Obs
1-3	Agriculture, forestry, and fishing	13.19	1.16	60.39	8805
5-9	Mining and Quarrying	14.44	0.98	68.44	1109
10-12	Manufacturing Food products; Beverages; Tobacco products	10.51	1.09	61.07	25268
13-15	Manufacturing Textiles; Wearing apparel; Leather and related products	8.31	1.13	48.69	9386
16	Manufacturing Wood, products of wood and cork, except furniture; ...	9.53	1.18	52.99	5656
17	Manufacturing Paper and paper products	13.09	0.88	44.46	2690
18	Manufacturing Printing and reproduction of recorded media	10.66	1.02	52.47	10513
19-21	Manufacturing Coke and refined petroleum products; Chemicals and chemical products; Basic pharmaceutical products and preparations	19.76	0.97	79.17	6952
22	Manufacturing Rubber and plastic products	10.21	1.03	53.55	5952
23	Manufacturing Other non-metallic mineral products	11.93	0.98	79.33	9010
24	Manufacturing Basic metals	18.68	1.24	67.98	1846
25	Manufacturing Fabricated metal products, except machinery and equipment	9.53	1.04	65.06	24233
26	Manufacturing Computer, electronic and optical products	11.98	0.94	41.13	2808
27	Manufacturing Electrical equipment	10.18	1.06	57.93	3014
28	Manufacturing Machinery and equipment	10.22	1.08	65.25	8745
29	Manufacturing Motor vehicles, trailers and semi-trailers	12.24	1.23	60.94	1641
30	Manufacturing Other transport equipment	13.77	0.91	62.18	661
31-32	Manufacturing Furniture and Other manufacturing	9.13	1.18	72.33	10912
33	Manufacturing Repair and installation of machinery and equipment	12.74	0.99	77.02	2507
36-39	Water supply, sewerage, waste management and remediation activities	27.95	0.85	85.97	5829
45	Wholesale and retail trade; repair of motor vehicles and motorcycles	11.23	1.12	73.94	50357
46	Wholesale trade, except motor vehicles and motorcycles	18.82	1.05	69.47	139281
47	Retail trade, except motor vehicles and motorcycles	10.04	1.28	60.20	120581
49	Land transport and via pipelines	8.57	1.26	55.35	37075
50-53	Water and air transport; Warehousing and support activities for transportation; Postal and courier activities	21.17	1.01	68.14	15649
55-56	Accommodation; Food and beverage services activities	8.68	1.44	50.88	64393
58	Publishing activities	15.32	1.00	68.00	3569
59-60	Motion picture, video and television, ...; Programming and broadcasting activities	22.58	0.97	77.07	3402
61	Telecommunications	31.47	1.00	53.81	1429
62-63	Computer programming, consultancy and related activities; Information service activities	15.47	1.00	63.04	17959
64-66	Financial and Insurance activities	28.24	0.82	85.17	39392
68	Real estate activities	28.32	1.03	67.31	21574
69-75	Professional, scientific, and technical activities	18.04	0.99	68.48	70426
77	Rental and leasing activities	26.97	1.19	66.07	6505
78	Employment activities	11.47	1.37	45.60	2919
79	Travel agency, tour operator reservation service and related activities	14.94	1.02	62.97	5037
80-82	Security and investigation activities; Services to buildings and landscape activities; Office administrative, office support and other business support activities	13.02	1.11	62.80	24308
	Total	14.75	1.19	65.02	771393

Note: Average absolute labor gap was calculated by $\overline{RG^l_s} = \frac{\sum_{i\in s} RG^l_{it}}{N_s}$, reported in thousands euros. Coefficient of variation is $CV_s = \frac{sd_s}{\overline{RG^l_s}}$. Percent of positive labor gap is defined as $Pos = \frac{N^+_s}{N_s} \times 100$.
Estimates are in euros per hour worked.

Figure A.1: Absolute Gap: 95% Confidence Interval for Change in Gap



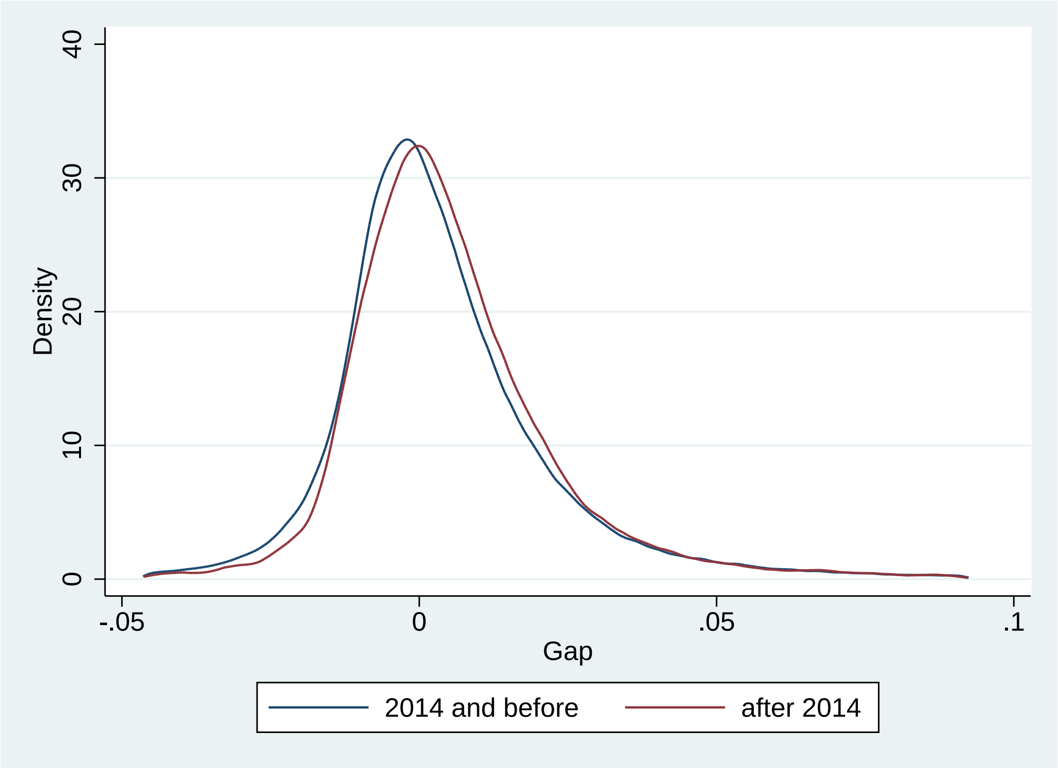
Note: Gap estimates are in euros per hour worked. The figure plots the coefficients from the regression of the absolute value of the labor gap on yearly and year × industry indicator variables, and firm-fixed-effects. Standard errors are clustered at the firm level.

Table A.2: Summary of the labor gap

	RG^l_{it}			RG^+_{it}			RG^-_{it}		
	mean	median	obs.	mean	median	obs.	mean	median	obs.
Total	14.753	9.139	771393	17.294	11.476	501528	10.030	6.224	269865
	(17.581)			(19.013)			(13.320)		
year $\leq$ 2013	14.791	9.149	670270	17.364	11.482	432919	10.098	6.275	23735
	(17.607)			(19.091)			(13.286)		
year $>$ 2013	14.496	9.067	101123	16.849	11.429	68609	9.530	5.889	32514
	(17.409)			(18.504)			(13.555)		

Standard errors in parentheses. Estimates are in euros per hour worked.

Figure A.2: Gap Distribution



Note: The figure presents the kernel density (standardized) of the gap for labor for two periods defined by the labor reform. It omits top and bottom 1% of the distribution.

Table A.3: The Absolute Value of the Gap

	Labor gap
Change in gap, 2014-2016	3.360**
	(1.502)
Base period, 1996-2013	15.990***
	(0.477)
year	yes
year ×section	yes
N	554624
R^2	0.068

Note: The sample is restricted to firms that operate at least one year prior and after the reform. Gap estimates are in euros per effective hour. The reported values are the estimated coefficients from a firm fixed-effects regression. Standard errors in parentheses are estimated after 499 bootstraps. Estimates are in euros per hour worked.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Estimation Results

	Model 1	Model 2	Model 3	Model 4	Model 5
s	-7.31***	-7.41***	-2.40***	-	-
	(0.184)	(0.186)	(0.266)		
s × policy	0.05	0.72***	0.76***	0.62***	-0.21
	(0.087)	(0.150)	(0.149)	(0.138)	(0.204)
year	-	yes	yes	yes	yes
nace	-	-	yes	-	-
year × nace	-	-	-	-	yes
firm	-	-	-	yes	yes
N	601288	601288	601288	601288	601288
R^2	0.030	0.033	0.139	0.007	0.065

Note: Coefficients are in euros per hour worked. Standard errors in parentheses are estimated after 499 bootstraps.

B Production Function Estimation

The aim of this section is to provide an overview on different methods of the production function estimation.[27] As it was discussed in Section 3, our measure of aggregate productivity growth calculation is obtained using the value-added records. Therefore, we will discuss the estimation procedure on value added production function.

As common in the productivity estimation literature we will rely on the Cobb-Douglas production function to describe the transformation of inputs into outputs, given by:

$$Y_{ist} = A_{ist} L_{ist}^{\beta_s^l} K_{ist}^{\beta_s^k},$$

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. To be able to estimate the production function, take the natural logarithms transformation:

$$y_{ist} = \beta_s^l l_{ist} + \beta_s^k k_{ist} + \varepsilon_{ist}$$

where small letters represent log variables.[28]

To estimate productivity, we need to estimate elasticities of capital and labor inputs consistently. OLS estimation procedure requires zero conditional mean and zero correlation assumptions to hold. [29] However, a firm's capital and labor decisions are influenced by some factors known to the firm, but not to econometrician, problem known as endogeneity. Hence, OLS will result in biased and inconsistent estimates.

Lets split ε_{it} (full error) into two components:

$$\varepsilon_{it} = \omega_{it} + \eta_{it}$$

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).

[27] Please see Van Beveren (2012) and Van Biesebroeck (2007) for a more comprehensive overview.
[28] For notational simplicity we will ignore s subscript for all variables.
[29] formally $E(\varepsilon_i) = 0$ and $Cov(k_i, \varepsilon_i) = 0$ and $Cov(l_i, \varepsilon_i) = 0$

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

$$\omega_{it} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} - \eta_{it} \tag{14}$$

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. Firm with a larger capital stock is less likely to exit the market, even if it has low productivity shock than a firm with a 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) addresses 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. Assumption here is that it takes a whole time period to order, deliver and install the capital. So, firms decide on its 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. 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[30] and given that productivity is the only scalar unobservable in the investment equation, investment function is invertable:

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

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

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + f_t^{-1}(k_{it}, i_{it}) + \eta_{it} \tag{15}$$

and collect industry specific labor elasticities.

Since capital is decided one period before $E(\xi_{it} k_{it}) = 0$. Given that $\hat{\omega}_{it} = g(P; \hat{\phi}(k_{it}, i_{it}) - \beta_k k_{it})$ and $\hat{\omega}_{it} = \hat{\omega}_{it-1} + \hat{\omega}_{it-1}^2 + \hat{\omega}_{it-1}^3 + \xi_{it}$, 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.[31]

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

[31] 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).

Levinsohn and Petrin (2003) (hereinafter, LP) criticized the choice of control variable of the OP procedure. They 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. The LP estimation procedure is the same[32] as the OP, but requires additional assumption on the level of adjustment for inputs and additional moment condition, $E[(\xi_{it} + \epsilon_{it})m_{it-1}] = 0$. Moreover, they advise to rely on bootstrapping in obtaining the standard errors of the estimated coefficients.

Ackerberg et al. (2015) (hereinafter, ACF) questions the flexible input assumption of the OP/LP methods. They propose to rely on the same assumptions used by OP/LP in identifying the capital coefficients to obtain labor elasticities. Hence, their model allows there to be exogenous, serially correlated, unobserved firm-specific shocks to the price of labor, or firm-specific unobserved adjustment costs to labor input. It also allows labor input to have dynamic effects (hiring or firing costs). Recall that productivity evolves according to the first order Markov process:

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

assumption implying that a firm's expectations on future productivity depend only on its current productivity. So, by construction 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, these generate the following moment conditions:

$$\begin{aligned} E[\xi_{it}\beta_k \cdot k_{it}] &= 0 \\ E[\xi_{it}\beta_l \cdot l_{it-1}] &= 0. \end{aligned} \tag{16}$$

ACF use the sample analogue of these moment conditions to obtain consistent estimates for input elasticities. Practically this can be done using two-stage estimation

[32]Now assumption on invertability applies to intermediate inputs demand function:

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

procedure. Estimate equation (15) to obtain η_{it} and initial values of β_l and β_k, which allows to construct initial values for ω_{it} from equation (14). Non-parametric regression of ω_{it} on ω_{it-1} gives estimates for $\xi_{it}(\beta_k, \beta_l)$. These estimates are used to bring the sample analogue of equation (16) as close to zero as possible and allows to 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 this set of assumptions allows to obtain coefficient estimates in one-step procedure using the GMM estimator. It is more efficient because does not require bootstrapping to obtain standard errors. Using the Cobb-Douglas production function (in logs) and when applying the Markov-process assumption on the evolution of the productivity we obtain:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + f_t^{-1}(k_{it-1}, m_{it-1}) + \xi_{it} + \eta_{it}.$$

In this equation there is no simultaneity bias since the proxy function contains a non-parametric function (third-order polynomial) of lag values of capital and material costs. Even though labor is uncorrelated with η_{it}, if it has dynamic implications then it will be correlated with ξ_{it}. Hence, by instrumenting labor, l_{it}, with its first lag, l_{it-1} Wooldridge (2009) procedure allows to obtain consistent estimates. Bootstrapping is not required for the Wooldridge estimation procedure, which makes it more attractive compared to the ACF technique. However, there is a cost of searching over a larger parameter space.

We proceed with the ACF methodology, because it deals with the issues originally addressed by OP and LP, in addition extending their model to allow for adjustment costs to labor input. Table B.1 shows the coefficients of the Cobb-Douglas production function estimated with the ACF methodology. Standard errors are estimated after 399 block-bootstraps. We observe that on average coefficient on labor input is increasing over the sampling period, while it decreases for capital coefficient. Figure B.1 illustrate this evolution.

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 B.2 and

Table B.1: **Cobb-Douglas production function coefficient estimates**

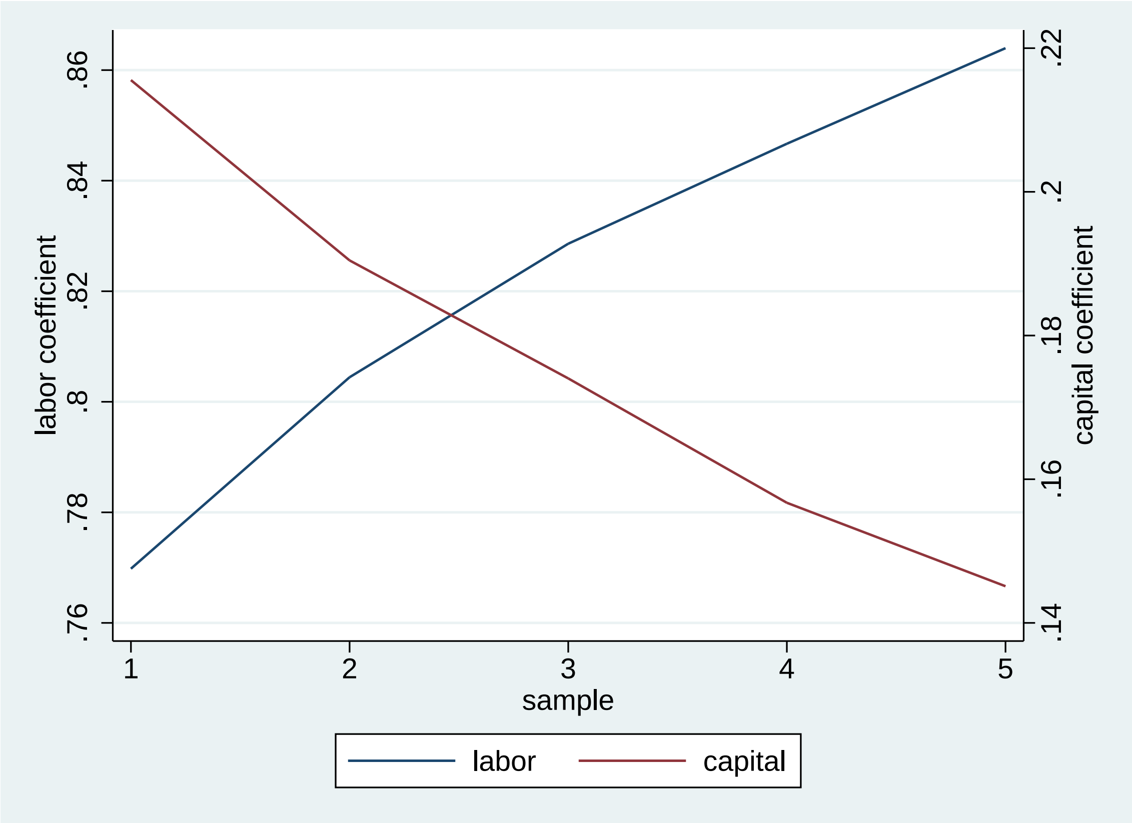
NACE /	Labor					Capital				
sample	*1*	*2*	*3*	*4*	*5*	*1*	*2*	*3*	*4*	*5*
1-3	0.607	0.618	0.628	0.666	0.688	0.227	0.216	0.217	0.204	0.181
5-9	0.894	0.943	0.878	0.851	0.791	0.357	0.241	0.238	0.272	0.268
10-12	0.763	0.804	0.834	0.872	0.875	0.231	0.212	0.207	0.184	0.186
13-15	0.771	0.754	0.822	0.816	0.865	0.236	0.223	0.167	0.145	0.135
16	0.671	0.772	0.775	0.799	0.782	0.221	0.185	0.176	0.149	0.152
17	1.021	0.988	1.029	1.015	1.010	0.102	0.120	0.102	0.087	0.091
18	0.702	0.778	0.828	0.843	0.852	0.258	0.232	0.200	0.190	0.176
19-21	0.791	0.914	0.961	0.970	0.981	0.226	0.136	0.110	0.112	0.117
22	0.851	0.796	0.843	0.857	0.898	0.158	0.182	0.144	0.111	0.110
23	0.933	0.805	0.824	0.807	0.819	0.164	0.220	0.193	0.196	0.177
24	0.692	0.802	0.787	0.837	0.883	0.214	0.247	0.273	0.206	0.169
25	0.826	0.820	0.814	0.827	0.840	0.155	0.176	0.155	0.146	0.144
26	0.785	0.852	0.872	0.896	0.930	0.198	0.182	0.168	0.130	0.121
27	0.647	0.822	0.890	0.897	0.928	0.241	0.195	0.152	0.137	0.132
28	0.830	0.819	0.872	0.880	0.903	0.204	0.203	0.169	0.146	0.125
29	0.767	0.827	0.808	0.833	0.839	0.288	0.202	0.191	0.141	0.124
30	0.997	1.010	1.002	1.012	1.033	0.137	0.089	0.089	0.083	0.074
31-32	0.843	0.846	0.826	0.855	0.865	0.176	0.169	0.185	0.168	0.158
33	0.880	0.938	0.946	0.944	0.936	0.127	0.071	0.079	0.082	0.085
36-39	0.688	0.674	0.693	0.705	0.730	0.321	0.268	0.249	0.231	0.222
45	0.790	0.787	0.822	0.846	0.861	0.182	0.197	0.182	0.164	0.151
46	0.784	0.812	0.845	0.877	0.904	0.140	0.127	0.105	0.086	0.073
47	0.677	0.689	0.702	0.727	0.746	0.199	0.203	0.198	0.184	0.177
49	0.738	0.752	0.772	0.781	0.796	0.254	0.232	0.209	0.194	0.179
50-53	0.719	0.727	0.776	0.780	0.786	0.197	0.177	0.152	0.151	0.151
55-56	0.609	0.677	0.711	0.726	0.740	0.244	0.223	0.210	0.197	0.184
58	0.814	0.905	0.925	0.972	0.948	0.191	0.150	0.099	0.058	0.001
59-60	0.829	0.894	0.884	0.905	0.920	0.148	0.112	0.118	0.113	0.102
61	0.662	0.886	0.926	0.966	1.209	0.408	0.210	0.240	0.216	0.193
62-63	0.818	0.900	0.959	0.984	0.996	0.166	0.140	0.096	0.077	0.065
64-66	0.786	0.865	0.909	0.942	0.942	0.167	0.140	0.127	0.114	0.106
68	0.546	0.566	0.618	0.638	0.653	0.286	0.281	0.256	0.244	0.237
69-75	0.861	0.865	0.887	0.904	0.915	0.154	0.149	0.127	0.106	0.097
77	0.582	0.486	0.559	0.603	0.640	0.490	0.421	0.388	0.365	0.324
78	0.784	0.832	0.824	0.825	0.821	0.116	0.129	0.133	0.124	0.118
79	0.731	0.801	0.837	0.868	0.828	0.226	0.187	0.151	0.126	0.112
80-82	0.793	0.740	0.771	0.801	0.814	0.165	0.201	0.185	0.162	0.152
Average	0.770	0.804	0.829	0.847	0.864	0.216	0.190	0.174	0.157	0.145

Standard errors in parentheses are estimated after 399 block-bootstraps.

B.3, respectively.[33] From the table we observe different methodologies to result in similar estimates for labor coefficient. The correlation coefficients are quite high (ranging from 0.652 to 0.945). Capital estimates show less similarity (from 0.331 to 0.926), which could be due to the sensitivity of each methodology to measurement

[33]The same industry classification and period sample splits applied.

Figure B.1: Average input elasticities



errors, usually observed in capital.[34] 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 B.2: Correlations Matrix: Labor Estimates

	OLS	LP	Wooldridge	ACF
OLS	1			
LP	0.837***	1		
Wooldridge	0.806***	0.945***	1	
ACF	0.833***	0.682***	0.652***	1

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

Once we calculate elasticities for production inputs, we calculate total factor productivity. Figure B.2 shows the distribution of firm-level TFP over selected years - 1998, 2013 and 2016. From the plot we can observe that along the sample period symmetric distribution in 1998 evolves into distribution with two peaks. The

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

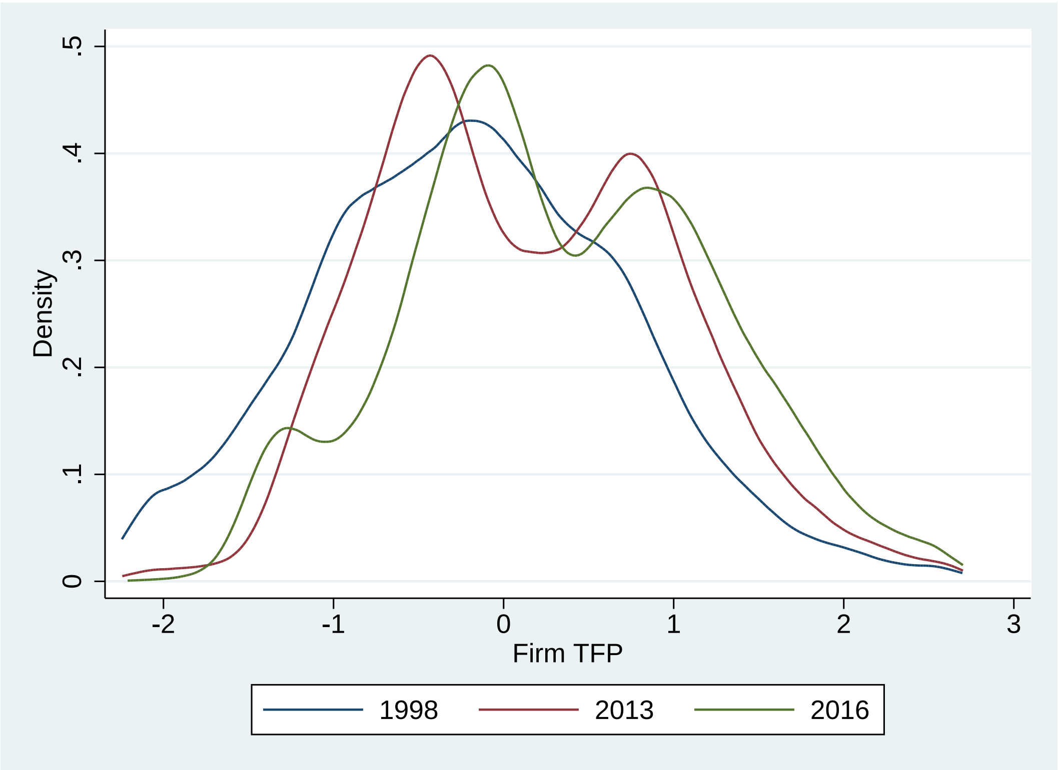
Table B.3: Correlations Matrix: Capital Estimates

	OLS	LP	Wooldridge	ACF
OLS	1			
LP	0.331***	1		
Wooldridge	0.342***	0.655***	1	
ACF	0.926***	0.341***	0.375***	1

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

plot suggests that productivity is increasing over time. Moreover, it is indicative of increase in dispersion of the productivity distribution.

Figure B.2: Firms' productivity distribution, ω_{it}



Note: The figure plots the standardized (zero mean and standard deviation equal to one across pooled sample) distribution of firm TFP for selected years. The plot ignores the top and bottom 1% of the distribution.

C Data construction

C.1 Imputed Data

We impute missing values for key variables in the following cases: (i) if a value is missing in year t but reported in $t-1$ and $t+1$, replace the missing value with the average of the previous and following year; (ii) if a value is missing for the first year, then replace it with the value of the next year; and, (iii) if a value is missing for the last year, then replace it with its lagged value.

Once we impute some part of the missing values, we ignore the rest.

C.2 Deflator

Collect value added at current and constant prices from the National Bank of Belgium Database at NACE two-digit industry level. Then calculate detailed value added deflator by dividing value added at current prices to value added at constant prices. Some NACE codes miss 2016 value added data (1-3, 16-18, 22-25, 29-33, 36-39, 45-47, 49-53, 58-60, 64-66, 69-71, 73-75, 77-82). We filled in the missing values of detailed deflator with PPI data for 2016. Similarly we compute two-digit output deflator.

We use calculated value added deflators to get the real value added measures, while output deflators are used to obtain real values for intermediary inputs (materials) and wages. On the other hand, we use gross capital formation deflator for calculating real values for capital. Yearly gross capital formation deflator is collected from the UNECE Database.

C.3 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) and construction industry (Section F). Due to small number of observations, we also exclude electricity, gas, steam and air conditioning supply industry (Section D) from the analysis. Table C.3.1 presents industry descriptions.

Table C.3.1: 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

C.4 Sample

Originally, we start with around 660 000 (unique VAT numbers) firms in our dataset. Unfortunately, not all observations can be used. First, we ignore all public sectors and construction industry from our analysis. Then, we impute some parts of the missing data. There are about 485 000 firms for the period 1996-2016 left. Second, we drop all firms that have missing values for value added, capital, employment and materials. Moreover, given that production function estimation involves log-transformation of the variables, we ignore all negative and zero values for key variables. After removing all these observations from our sample, we remain with the sample of 118 367 firms for the 1996-2016 period. Table C.4.1 presents summary statistics of key variables used.

Table C.4.1: Summary Statistics

	N	Mean	SD	Min	Max
employment (FTE)	741181	32	322	0.05	47729
tangible fixed assets (1000 euros)	741181	2549	35626	0.5	3680862
value added (1000 euros)	741181	2900	30866	1	4551431
material costs (1000 euros)	741181	10939	185906	0.5	32108477
blue-collar workers (FTE)	616061	18	193	0	60366
white-collar workers (FTE)	664814	19	282	0	70037
wage bill (1000 euros)	741175	1705	15950	0	1640402

D Additional Tables and Figures

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

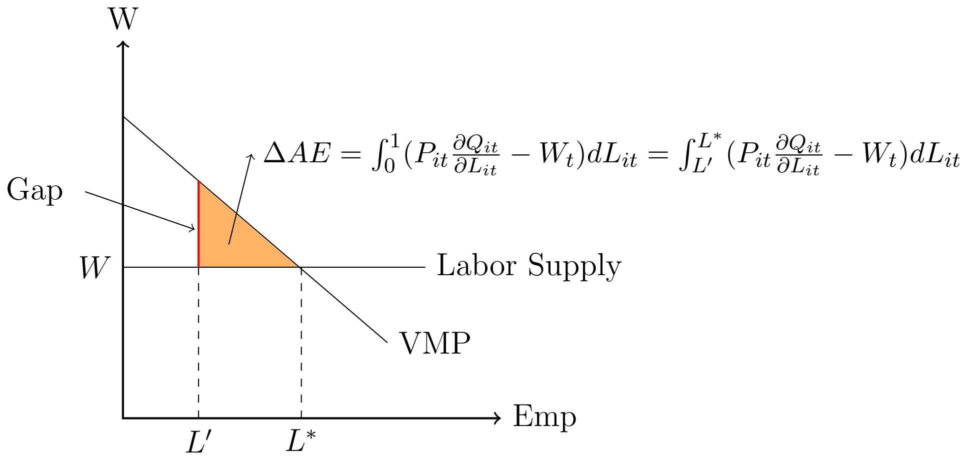


Figure D.2: Average Annual Wages