

- Supplemental Appendix -

This Supplemental Appendix accompanies the paper “**Heterogeneous Firing Costs, Worker Types, and Productivity: Evidence from a Natural Experiment**”, by Andrea Caggese, Ozan Güler, Mike Mariathasan, and Klaas Mulier.

This Supplemental Appendix provides additional details on various aspects:

- Appendix [A](#) provides variable definitions.
- Appendix [B](#) compares the pre-reform working conditions of blue- and white-collar workers.
- Appendix [C](#) explains additional changes introduced by the reform.
- Appendix [D](#) presents a stylized model on firing costs, selection, training, and TFP.
- Appendix [E](#) illustrates additional figures.
 - Evolution of the aggregate share of blue-collar employment ([E.1](#))
 - Comparing pre-period and post-period elasticities ([E.2](#))
- Appendix [F](#) demonstrates additional tables.
 - NACE 2-digit industry-level elasticities ([F.1](#))
 - Alternative dependent variables for separations and entering emp. ([F.2](#))
 - Dynamic estimates (not shown in the main text) of the outcomes in Tables 3, 4, and 5 ([F.3](#))
 - Using different productivity measures ([F.4](#))
 - Placebo test: assuming the reform was announced in 2008 ([F.5](#))
 - Defining treatment based on 2008 ([F.6](#))
 - The effect on profits ([F.7](#))
 - Less versus more affected industries ([F.8](#))

- Results across less versus more R&D intensive industries (F.9)
- Treating outsourced labor as a production input (F.10)
- Adding firms that operate with only blue- or only white-collar workers and firms that do not report intermediate inputs (F.11)
- Results with controls (F.12)
- Results with the matched samples (F.13)
- Results with treatment intensity (F.14)
- Linear effects of firing costs (F.15)
- Results across industries with larger declines in blue-collar employment share (F.16)
- Accounting for industry heterogeneity at a more granular level (F.17)
- Additional tests (F.18)
- Results across firms with low average cost per employee (F.19)
- Results within initially exempt industries (F.20)
- Firing costs, input choices, and bias in estimating TFP when using a pooled-workers production function (F.21)
- The effect on firm exit & entry (F.22)
- The role of credit access (F.23)
- Cross-country analysis: Belgian versus German and French firms (F.24)

Appendix A. Variable definitions

Variable	Definition
<i>Firm level</i>	
(%) Blue-collar	Pre-period (2009-2012) average share of blue-collar employees
Blue-collar	Dummy variable equal to 1 if the firm's pre-period (2009-2012) average share of blue-collar employees was above the sample median, and to 0 otherwise
Post	Dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012
TFP	Residual from the estimation of a Cobb-Douglas production function, defined in natural log
ln(Value added)	Natural log of value added
ln(Blue-collar emp.)	Natural log of the number of blue-collar employees
ln(White-collar emp.)	Natural log of the number of white-collar employees
ln(Separations)	Natural log of the number of employees that left the firm
ln(1+Separations)	Natural log of one plus the number of employees that left the firm
Separations/2012 emp.	Number of employees that left the firm, divided by the firm's total number of employees in 2012
ln(Entering emp.)	Natural log of the number of new hires
ln(1+Entering emp.)	Natural log of one plus the number of new hires
Entering emp./2012 emp.	Number of new hires, divided by the firm's total number of employees in 2012
ln(Total emp.)	Natural log of the total number of employees
ln(Cost per emp.)	Natural log of the average yearly cost per employee
ln(Hours per emp.)	Natural log of the average yearly number of hours worked per employee
ln(Outsourced emp.)	Natural log of the number of outsourced employees through agencies
ln(Permanent emp.)	Natural log of the number of employees with permanent contracts
ln(Temporary emp.)	Natural log of the number of employees with fixed-term contracts
ln(Permanent separations)	Natural log of the number of employees with permanent contracts that left the firm
ln(Temporary separations)	Natural log of the number of employees with fixed-term contracts that left the firm
ln(Permanent entering emp.)	Natural log of the number of new hires with permanent contracts
ln(Temporary entering emp.)	Natural log of the number of new hires with fixed-term contracts
ln(Tangible fix.)	Natural log of tangible fixed assets
ln(Mac., Equip.)	Natural log of the sum of machinery and equipment
ln(Land, Build., Furn., Other)	Natural log of the sum of land, building, furniture, and other tangible fixed capital
ln(Intangible fix.)	Natural log of intangible fixed assets
Train. emp.	Number of employees who participated in training activities, scaled by the total number of employees
Train. costs	Total training costs scaled by the total employee costs
Train. hours	Total training hours scaled by the total number of employment hours
Size	Natural log of total assets
Age	Number of years since the firm's incorporation date
Leverage	Sum of long- and short-term debt, divided by total assets
ln(EBITDA)	Natural log of EBITDA
EBITDA-to-assets	Ratio of EBITDA to total assets
EBITDA-to-sales	Ratio of EBITDA to total sales
Cash holdings	Ratio of cash holdings to total assets
Capital-to-labor	Natural log of the ratio of tangible fixed assets to the total number of employees
<i>Industry level</i>	
Exit share	Ratio of the total number of firm exits (defined through firms' legal status) to the total number of firms in the industry in a given year.
Entry share	Ratio of the total number of firm entries (defined through the firm's year of incorporation) to the total number of firms in the industry in a given year.
<i>Country level</i>	
GDP growth	Annual growth rate of gross domestic product (in %)
GDP per capita	Gross domestic product, divided by midyear population (in thous. \$)

Appendix B. Pre-reform working conditions

Table B1: Pre-reform working conditions of blue- and white-collar workers

	Blue-collar workers	White-collar workers
Notice Periods	-Fixed within each industry, and calculated based only on seniority.	-Irrespective of the worker's industry, calculated based mainly on seniority and wage.
Trial Period	-Maximum 2 weeks. The trial period can end prematurely for serious reasons between the 1st and the 7th days. After that, the trial period can finish without notice or compensation.	-Maximum 12 months. The trial period can finish only if the worker has used 7 days of sickness leave. If the trial period is terminated from the first month onward, a notice period of 7 days is required.
Sickness Leave	-The first day of the sickness leave is not paid if the duration of sickness leave is less than 14 days. - The workers get paid at the regular wage rate for 7 days.	-The first day of the sickness leave is not paid if the duration of sickness leave is less than 14 days, only for those who are with temporary contracts or well-defined job contracts for less than three months, as well as for those who are on trial periods. - The workers get paid at the regular wage rate for 30 days.
Unfair dismissal	-The employer has to justify the reason for the dismissal under the work contract law (art. 63). In case of proof of unfair dismissal, the worker will be compensated with a fixed sum.	-The worker has to prove, under the common law, that the dismissal was unfair. In case of proof of unfair dismissal, the worker will be compensated in accordance with the level of the breach.
Temporary Unemployment	-The worker can be placed on temporary unemployment (relatively easily) in a number of circumstances: e.g., economic reasons, bad weather conditions, technical reasons,...	-The worker can be placed on temporary unemployment (under strict conditions) in a few circumstances: e.g., economic reasons (only if the firm is officially recognized as an enterprise in distress),...
Wages	-Contract stipulates an hourly wage. -Weekly payday (or twice per month).	-Contract stipulates a monthly wage. -Monthly payday.
Holiday Bonus	-Paid by a government institution, namely the National Office of Annual Vacation.	-Paid by the employer. There is a chance of a double holiday bonus.
Contributions	-Employers' contribution is fixed within industries, usually at 38.38% of 108% of the worker's gross wage (the extra 8% adds up for holiday bonus). Social security contribution is 13.07% of 108% of the worker's gross wage.	-Employers' contribution is not fixed within industries, usually at 32.38% of the worker's gross wage. Social security contribution is 13.07% of the worker's gross wage.

This table demonstrates the main similarities and differences in the working conditions of blue- and white-collar workers prior to 1 January 2014, the effective date of the new Belgian labor legislation (the Act of 26 December 2013). Source: [Ajzen and Vermandere \(2014\)](#).

Appendix C. Act of 26 December 2013: Further changes

Other elements of the reform suggest that the Act has primarily increased labor adjustment costs for blue-collar workers. First, it is only possible for employers to specify a different notice period than the one stated under the new law if the specified period benefits the employee. While it is unlikely that employers would extend notice periods for blue-collar workers beyond the already substantial increase mandated by the reform, one can imagine that white-collar workers—especially those in higher pay grades—might be able to mitigate the effect of the legal reform by negotiating longer notice periods.

Second, the Act has also introduced changes that benefited both blue- and white-collar workers. Importantly, it has improved the protection against unfair dismissals. Previously, for blue-collar workers, the arbitrary “dismissal regime” applied; and for white-collar workers, there was no legal regulation, but the “concept of abuse of rights” was used in practice. The new law, however, has created uniform protection against unfair dismissals. Particularly, the new law has allowed a dismissed employee to know the exact reasons for the dismissal and to obtain compensation from the employer in the case of a manifestly unfair dismissal. In addition, the new law has improved outplacement rights for all worker types. Specifically, it now requires employers to provide outplacement support to all dismissed employees with at least 30 weeks of notice. Lastly, the new legislation has abolished the rule of no pay for the first day of sick leave (the so-called “carenz” day). All these elements have increased labor costs for both worker types: for white-collar workers, employers need to weigh these costs against (somewhat) reduced notice periods, while they add to the cost of (significantly) increased notice periods for blue-collar workers.

Appendix D. Firing costs, selection, training, and TFP: A stylized model

In this section, we provide a stylized model to explain how firing costs might affect TFP in Equation (2). We consider many firms that operate for two periods and assume a real interest rate of zero. The firms are identical, except for their productivity z and the cost of training workers m . For simplicity but without loss of generality, we further assume that all workers are blue-collar workers ($\gamma = 0$) and that capital is irrelevant for production ($\alpha = 0$). It follows that value added VA is linear in blue-collar employment B (henceforth “workers”):

$$VA = TFP \cdot B \quad (1)$$

The total number of workers B comprises L_0 workers already employed in period 0 and L_1 workers hired in period 1. Workers’ productivity is initially normalized to 1 but can change through training and depreciation. In period 1, firms can fire existing workers by paying a per-worker cost $F > 0$ or hire new workers with a normalized productivity of 1. In period 0, firms decide on worker training and skills randomly depreciate.

Timing

At the beginning of period 0, firms decide whether to train existing workers at cost m to increase their skills to $\lambda > 1$. Since productivity is linear in labor, firms either train all workers, or none. After the training decision, a skill depreciation shock occurs. With probability $\mu \in (0, 1)$, workers’ skills depreciate by a factor $\delta \in (0, 1)$; with probability $1 - \mu$, no depreciation occurs. At the end of the period the original workers’ skills h_0 can thus have four values: δ (no training and depreciation), $\delta\lambda$ (training and depreciation), 1 (no training and no depreciation), or λ (training and no depreciation). We assume $\delta\lambda < 1$, so that depreciation causes even trained workers to be less productive than new workers.¹

$$\delta < \delta\lambda < 1 < \lambda$$

In period 1, firms can hire an exogenously fixed number L_1 of new workers, each with skills equal to 1.² TFP in Equation (1) thus becomes:

¹As we explain below, we focus on firms with $z > w$, which always find it optimal to hire in period 1. For these firms, $\delta\lambda \geq 1$ implies that trained workers are never fired and that firing costs do not affect firms’ training decisions. With $\delta\lambda < 1$, instead, firing costs interact with the training decision. For firms with $z < w$, on the other hand, firing costs might also increase training if $\delta\lambda \geq 1$.

²We assume L_1 to be fixed because our framework is a partial equilibrium model and because technology is linear in labor. Firms would thus optimally hire infinitely many workers in period 1. Below, we show that our results also hold in a model with concave technology, in which the optimal value of L_1 is derived endogenously.

$$TFP = z\theta^B,$$

where z is neutral productivity and θ^B is the weighted average labor productivity of the remaining original workers $L_0^k \in \{0, L_0\}$ and new workers L_1 :

$$\theta^B = \frac{h_0 L_0^k + L_1}{L_0^k + L_1},$$

Period 1 decisions

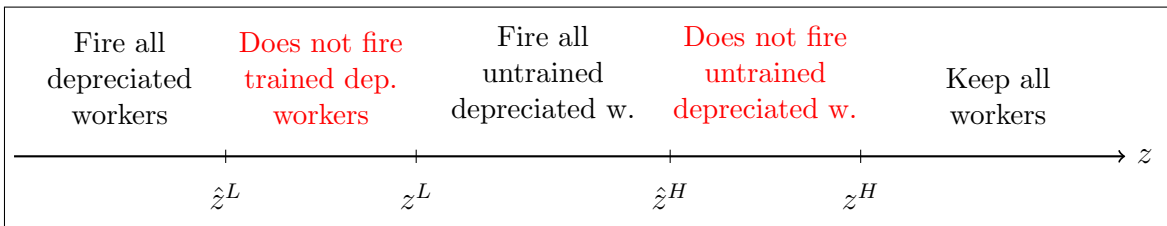
For simplicity, we assume that all workers are paid the same exogenous wage w and focus on firms with $z > w$, i.e., on firms that find it optimal to hire new workers in period 1. The fact that older workers are unprofitable if $w > zh_0$ and get fired if $w - zh_0 > F$ then implies:

Proposition 1. *Higher firing costs reduce measured TFP by inducing firms to retain more unproductive workers.*

Proof. Consider $F = 0$ and define two productivity thresholds $z^H \equiv \frac{w}{\delta}$ and $z^L \equiv \frac{w}{\lambda\delta}$. Because $\delta < \lambda\delta$ and $\lambda\delta < 1$, it follows that $w < z^L < z^H$. For firms with $z \geq z^H$, old workers, even untrained and with depreciated skills, are always profitable and firing costs are irrelevant. For firms with $z^L \leq z < z^H$, untrained depreciated workers are unprofitable, while trained workers remain profitable if their skills depreciate. For $z < z^L$, even trained workers become unprofitable if their skills depreciate. Without firing costs, firms fire all unprofitable workers. Next, consider $F > 0$. With firing costs, firms with $\hat{z}^L < z < z^L$ (where $\hat{z}^L \equiv \frac{w-F}{\lambda\delta}$) no longer fire trained depreciated workers and firms with $\hat{z}^H < z < z^H$ (where $\hat{z}^H \equiv \frac{w-F}{\delta}$) no longer fire untrained depreciated workers. Since these—now remaining—workers are less productive than new workers, θ^B and measured TFP drop. For higher F , the intervals $(\hat{z}^L, z^L)$ and $(\hat{z}^H, z^H)$ widen, firing costs affect more firms, and TFP drops further. $\square$

To illustrate the effect of firing costs, we summarize firms' firing decisions as a function of productivity z in the graph below and highlight the inefficient worker retentions in red.

Firing decisions as a function of firms' productivity z .



Period 0 decisions

In period 0, firms decide whether or not to invest in training their original workforce. We show that firing costs can increase training, but that the effect on TFP is ambiguous.

Proposition 2. *Firing costs induce some firms to train their existing workforce, but the productivity effect of such training is ambiguous.*

Proof. Assume that firms are uniformly and independently distributed over productivity z and training costs m . From Proposition 1, we know that firing costs change firms' firing behavior only in the intervals $z \in (\hat{z}^L, z^L)$ and $z \in (\hat{z}^H, z^H)$. This changing behavior implies that the returns of training are higher in the presence of firing costs in both these regions.

Consider first the region $z \in (\hat{z}^L, z^L)$. In the absence of firing costs, firms fire trained depreciated workers, and the returns from training are the difference between the profits generated by trained $(\lambda z - w)$ and untrained $(z - w)$ workers, multiplied by the probability of no depreciation: $(1 - \mu) \cdot z(\lambda - 1)$. In the presence of firing costs, firms in this region keep trained depreciated workers. In other words, with probability μ they keep workers that generate (negative) profits equal to $\lambda \delta z - w$, rather than pay the firing cost $-F$. Hence their additional profits are $\lambda \delta z - w - (-F) = F + \lambda \delta z - w > 0$.

Now consider the region $z \in (\hat{z}^H, z^H)$. In this region, in the absence of firing costs, the firm fires untrained workers with depreciated skills. Thus without training, profits are $(1 - \mu) \cdot (z - w)$, while with training, they are: $(1 - \mu) \cdot (\lambda z - w) + \mu \cdot (\lambda \delta z - w)$. Taking the difference between these two values yields:

$$T^0 = (1 - \mu) \cdot z(\lambda - 1) + \mu \cdot (\lambda \delta z - w)$$

Instead, in the presence of firing costs, the firm does not fire untrained depreciated workers. Returns without training are: $(1 - \mu) \cdot (z - w) + \mu \cdot (\delta z - w)$; with training they are $(1 - \mu) \cdot (\lambda z - w) + \mu \cdot (\lambda \delta z - w)$. Taking the difference yields:

$$T^F = (1 - \mu) \cdot z(\lambda - 1) + \mu \cdot \delta z(\lambda - 1)$$

Thus, firing costs increase the returns from training by $T^F - T^0 = \mu \cdot (w - \delta z) > 0$. This difference is positive because we are in the region in which untrained depreciated workers are loss-making, so $\delta z < w$.

Finally, firing costs also increase the returns from training for $z \in [z^L, \hat{z}^H]$. Firms in this region always fire untrained workers with depreciated skills, and the return to training, absent firing costs, is T^0 . Firing costs add the return of not having to pay $-F$ with probability μ .

To sum up, define Φ as the increase in returns from training induced by firing costs:

$$\Phi = \mu(F + \lambda\delta z - w) > 0 \text{ if } z \in (\hat{z}^L, z^L) \quad (2)$$

$$\Phi = \mu F > 0 \text{ if } z \in [z^L, \hat{z}^H] \quad (3)$$

$$\Phi = \mu(w - \delta z) > 0 \text{ if } z \in (\hat{z}^H, z^H) \quad (4)$$

Recall that firms are uniformly distributed over training costs m . Assume some training happens in equilibrium, so that for each productivity level z , some firms have values of m just above the threshold that would make training profitable. To prove that firing costs increase training, it is then sufficient to show that they increase the value of Ω for some firms. This follows immediately from Equations (2) to (4). They imply $\Omega = 0$ for all firms if $F = 0$, while the range of firms with $\Omega > 0$ expands as F increases.

Although training increases workers' productivity, the overall effect of firing costs on TFP is in principle ambiguous. On the one hand, higher firing costs induce more firms to invest in training, which positively contributes to TFP if skills do not depreciate. On the other hand, firing costs and training also prevent the firing of inefficient workers, which negatively contributes to TFP. This potentially happens in the region $z \in (\hat{z}^L, z^L)$. In this region, trained depreciated workers are fired without firing costs, because they generate losses. Firing costs instead imply that the firm keeps these workers. Even though training unambiguously increases productivity in all the other regions, which effect dominates is ultimately a question of how firing costs and productivity are distributed across the firm population, and thus ex-ante ambiguous. $\square$

Extension: ex-ante selection

One important way in which firing costs can affect worker quality is ex-ante selection (Pries and Rogerson, 2005). To view this effect in our simple model, consider a modification in which there is no training, but in which the firm has to hire the L_0 workers in period 0. Before hiring them, the firm receives a signal ξ_i about worker quality. The signal is equal to the probability that the worker will be highly productive ($h_0 = 1$), while with probability $1 - \xi_i$ the worker has lower productivity ($h_0 = \delta < 1$).

In other words, while in the previous model workers exogenously depreciated with the same probability $1 - \gamma$, in this version workers are ex-ante heterogeneous with respect to that probability. After observing ξ_i , the firm then decides whether to pay $\kappa > 0$ in hiring costs and hire the worker. After hiring, all workers reveal their quality (that is, they depreciate with their individual probability $1 - \xi_i$).

Firing costs matter for ex-ante selection when low-quality workers are loss-making, so we

focus on $\delta z < w$, i.e., on the case in which depreciated workers are always fired in the absence of firing costs. If ξ_i is independently and identically distributed across workers between 0 and 1, and there are no firing costs, firms hire all workers with a signal $\xi_i \geq \underline{\xi}$, where $\underline{\xi}(z - w) = \kappa$. Intuitively, since the worker is fired in period 1 if her productivity turns out to be low, the expected value of the marginal worker is $\underline{\xi}(z - w)$, which implies $\underline{\xi} = \frac{\kappa}{z-w}$. Naturally, we focus on the case in which $\frac{\kappa}{z-w} < 1$ so that some workers are always hired in period 0.

If firing costs rise above zero, but it remains optimal to fire low-productivity workers, the overall cost of a worker increases by the expected firing costs $(1 - \xi_i)F$. The marginal worker quality with firing costs $\underline{\xi}$ is thus given by $\underline{\xi}(z - w) - (1 - \underline{\xi})F = \kappa$, which implies $\underline{\xi} = \frac{\kappa+F}{z-w+F}$. If firing costs are even higher and low-productivity workers are not fired, the hiring threshold becomes: $\underline{\xi} = \frac{\kappa+(w-\delta)}{z-w+(w-\delta)}$. We can thus summarize the effect of firing costs on the hiring threshold $\underline{\xi}$ as follows:

No firing costs ($F = 0$)	$\underline{\xi} = \frac{\kappa}{z-w}$
Low firing costs ($w - \delta z > F > 0$)	$\underline{\xi} = \frac{\kappa+F}{z-w+F}$
High firing costs ($F > w - \delta z > 0$)	$\underline{\xi} = \frac{\kappa+(w-\delta)}{z-w+(w-\delta)}$

In other words, for firms with $\delta z < w$, firing costs unambiguously increase the minimum threshold $\underline{\xi}$. By being more selective, the firm obtains the additional benefit of reducing expected firing costs (or losses if it is too costly to fire the worker). For more productive firms with $\delta z > w$, firing costs are irrelevant (period 0 workers are never fired) and do not affect ex-ante selection. It follows that higher firing costs increase the average threshold $\underline{\xi}$ across firms and thus average labor productivity θ^B .

Other Extensions

Our results assume that wages cannot be contingent on training or skill depreciation. For skill depreciation, this assumption is supported by ample evidence that wages are downward rigid, especially for heavily unionized employees such as Belgian blue-collar workers.

With respect to the training results, if wages are upward flexible, the training surplus could in part accrue to the worker. While this would generally reduce training incentives for the firm, higher firing costs would continue to make ex-ante training more likely.

Likewise, adding other production inputs would quantitatively change the optimality conditions but not the qualitative results: rising firing costs would still imply that some firms find it optimal to keep some unproductive workers, which, in turn, would cause a drop in measured TFP.

Finally, our results also hold for production functions with decreasing marginal returns. We only show this explicitly for the firing decisions in period 1, but similar results can be

obtained for the training and selection decisions in period 0. The production function is:

$$Y = z[h_0 L_0^k + L_1]^\alpha,$$

with $0 < \alpha < 1$. A generic firm chooses new hiring L_1 and the retained number of old workers L_0^k , to maximize profits:

$$\pi = \max_{L_1, L_0^k} Y - w(L_0^k + L_1) - F(L_0 - L_0^k),$$

subject to $L_1 \geq 0$ and $L_0^k \leq L_0$, with $L_0 - L_0^k$ being the number of old workers that are fired. Taking the first-order conditions with respect to L_1 and L_0^k , we can show that the optimal number of new hires, given L_0^k , is:

$$L_1^* = \left(\frac{z\alpha}{w} \right)^{\frac{1}{1-\alpha}} - h_0 L_0^k.$$

If $L_1^* > 0$, older workers are fired if $F < w(1 - h_0)$ and kept if $F \geq w(1 - h_0)$. Intuitively, the loss of keeping old workers is their lower return $w(1 - h_0)$ relative to new workers, which is a positive quantity if they depreciated and hence $h_0 \in \{\delta, \delta\lambda\} < 1$. Old workers are fired if this loss is larger than the firing cost F . Thus, an increase in firing costs would prevent the firing of these workers and reduce TFP, as in the benchmark model illustrated above.

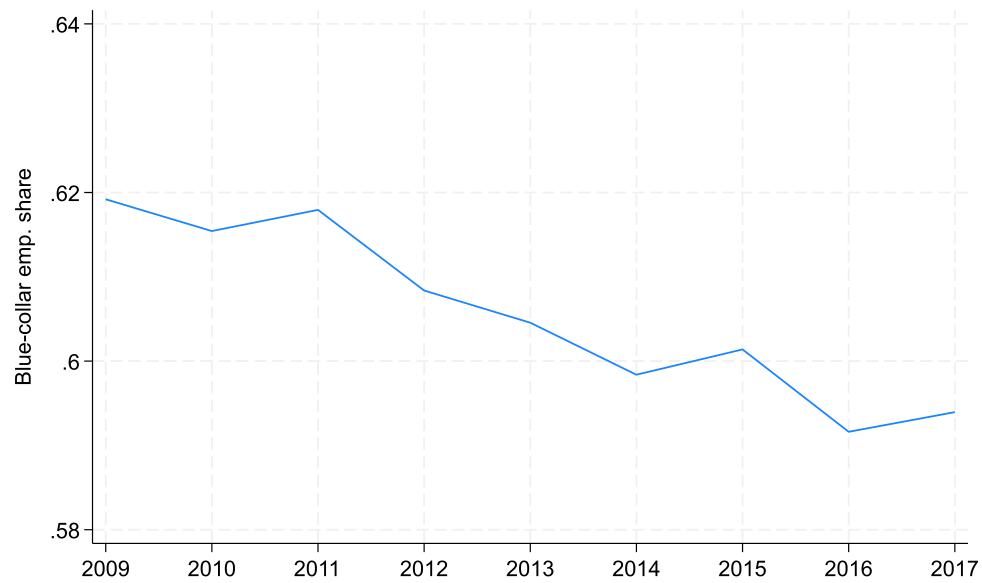
If $L_1^* \leq 0$, the constraint $L_1 \geq 0$ holds with equality. Substituting $L_1 = 0$ and taking the first-order condition for L_0^k yields:

$$L_0^k = \left(\frac{\alpha z h_0^\alpha}{w - F} \right)^{\frac{1}{1-\alpha}}$$

If $L_0^k > L_0$, the constraint $L_0^k \leq L_0$ holds with equality and the firm sets $L_0^k = L_0$. The firm neither hires nor fires and remains with the current old workers. If $L_0^k \leq L_0$, the first-order condition above determines L_0^k .

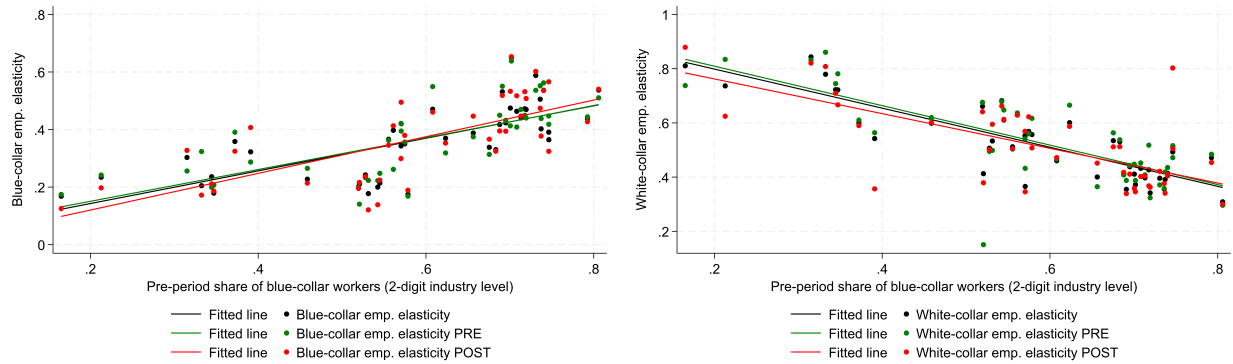
Appendix E. Additional figures

Figure E.1. Evolution of the aggregate share of blue-collar employment



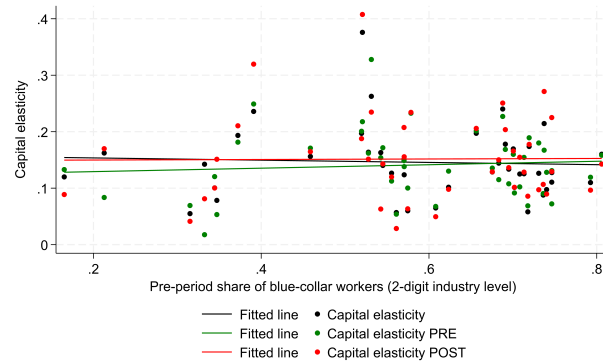
This figure presents the aggregate share of blue-collar workers in our regression sample. The share is calculated as the total number of blue-collar workers in a given year divided by the total number of workers in that year.

Figure E.2: Comparing pre-period and post-period elasticities



(a) Elasticities for blue-collar workers

(b) Elasticities for white-collar workers



(c) Elasticities for capital

This figure shows the pre-period (2009-2012) and post-period (2013-2017) industry-level elasticities for blue-collar workers (Panel (a)), white-collar workers (Panel (b)), and capital (Panel (c)). The x-axis shows the industry's average share of blue-collar workers over the pre-period. The y-axis illustrates the elasticity of substitution.

Appendix F. Additional tables

F.1. NACE 2-digit industry-level elasticities

Table F.1: NACE 2-digit industry-level elasticities

NACE 2-digit industry	N	Blue-collar emp. el.		White-collar emp. el.		Capital el.	
1	196	0.33	(0.16)	0.53	(0.26)	0.14	(0.09)
8	261	0.40	(0.19)	0.39	(0.18)	0.21	(0.10)
10	3247	0.42	(0.00)	0.41	(0.00)	0.24	(0.00)
11	345	0.17	(0.04)	0.56	(0.12)	0.23	(0.05)
13	940	0.39	(0.17)	0.49	(0.22)	0.11	(0.05)
14	210	0.34	(0.30)	0.55	(0.46)	0.15	(0.15)
16	622	0.51	(0.00)	0.36	(0.00)	0.09	(0.00)
17	572	0.47	(0.08)	0.41	(0.07)	0.17	(0.04)
18	708	0.44	(0.03)	0.35	(0.02)	0.18	(0.00)
20	1480	0.20	(0.00)	0.66	(0.00)	0.20	(0.00)
21	208	0.16	(0.10)	0.75	(0.44)	0.12	(0.07)
22	1211	0.34	(0.00)	0.53	(0.00)	0.13	(0.00)
23	1438	0.47	(0.00)	0.34	(0.00)	0.17	(0.00)
24	758	0.46	(0.02)	0.43	(0.02)	0.13	(0.01)
25	2890	0.44	(0.00)	0.40	(0.00)	0.13	(0.00)
26	406	0.18	(0.01)	0.72	(0.06)	0.08	(0.02)
27	536	0.35	(0.07)	0.61	(0.10)	0.12	(0.09)
28	1532	0.35	(0.00)	0.57	(0.00)	0.06	(0.00)
29	406	0.47	(0.05)	0.43	(0.08)	0.06	(0.05)
30	130	0.40	(0.99)	0.63	(1.56)	0.06	(0.14)
31	647	0.42	(0.00)	0.44	(0.00)	0.13	(0.00)
32	278	0.21	(0.03)	0.61	(0.07)	0.14	(0.02)
33	422	0.37	(0.06)	0.60	(0.08)	0.10	(0.03)
37	65	0.68	(0.24)	0.34	(0.17)	0.16	(0.10)
38	688	0.39	(0.02)	0.40	(0.01)	0.20	(0.02)
41	2399	0.36	(0.03)	0.51	(0.04)	0.13	(0.01)
42	1292	0.44	(0.04)	0.47	(0.04)	0.11	(0.01)
43	3988	0.54	(0.00)	0.41	(0.00)	0.10	(0.00)
45	5680	0.37	(0.00)	0.51	(0.00)	0.13	(0.00)
46	10598	0.23	(0.00)	0.60	(0.00)	0.16	(0.00)
47	2443	0.36	(0.00)	0.60	(0.00)	0.19	(0.00)
49	2983	0.54	(0.02)	0.31	(0.01)	0.16	(0.03)
52	1550	0.24	(0.01)	0.51	(0.02)	0.16	(0.03)
55	289	0.42	(0.13)	0.37	(0.11)	0.12	(0.04)
56	332	0.65	(0.01)	0.37	(0.01)	0.10	(0.01)
58	105	0.17	(0.07)	0.81	(0.25)	0.12	(0.05)
59	103	0.20	(0.10)	0.68	(0.25)	0.16	(0.10)
62	114	0.23	(0.20)	0.74	(0.29)	0.16	(0.13)
68	235	0.32	(0.07)	0.54	(0.06)	0.24	(0.08)
69	34	0.20	(0.16)	0.78	(0.47)	0.14	(0.13)
70	229	0.29	(0.09)	0.67	(0.19)	0.13	(0.06)
71	301	0.24	(0.04)	0.72	(0.09)	0.10	(0.02)
73	161	0.30	(0.11)	0.84	(0.29)	0.05	(0.03)
77	464	0.18	(0.06)	0.53	(0.02)	0.26	(0.08)
78	46	0.33	(0.29)	0.54	(0.47)	0.02	(0.05)
80	102	0.45	(0.09)	0.46	(0.06)	0.08	(0.06)
81	492	0.59	(0.03)	0.40	(0.02)	0.13	(0.02)
92	32	0.21	(0.12)	0.41	(0.21)	0.38	(0.20)
95	61	0.47	(0.28)	0.46	(0.28)	0.06	(0.08)
96	223	0.53	(0.08)	0.35	(0.11)	0.18	(0.04)

This table reports estimates of industry-level elasticities. Standard errors (in parentheses) are computed using the bootstrap with 200 replications.

F.2. Alternative dependent variables for separations and entering emp.

Table F.2: Analysis of employment turnover with alternative dependent variables

A. Main estimates

	ln(Separations)	ln(Entering emp.)	ln(1+Separations)	ln(1+Entering emp.)	Separations/2012 emp.	Entering emp./2012 emp.
	(benchmark)	(benchmark)				
	(1)	(2)	(3)	(4)	(5)	(6)
Blue-collar x Post	-0.057*** (0.017)	-0.058*** (0.018)	-0.047*** (0.015)	-0.062*** (0.017)	-0.010** (0.005)	-0.015*** (0.005)
Observations	50,528	49,371	54,452	54,452	54,452	54,452
R-squared	0.769	0.736	0.781	0.750	0.640	0.639
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes

(Continued)

B. Dynamic estimates

	$\ln(\text{Separations})$	$\ln(\text{Entering emp.})$	$\ln(1+\text{Separations})$	$\ln(1+\text{Entering emp.})$	$\text{Separations}/2012 \text{ emp.}$	$\text{Entering emp.}/2012 \text{ emp.}$
	(benchmark)	(benchmark)				
	(1)	(2)	(3)	(4)	(5)	(6)
Blue-collar x 2009 dummy	-0.007 (0.027)	-0.002 (0.031)	0.011 (0.024)	0.010 (0.028)	0.004 (0.008)	0.010 (0.008)
Blue-collar x 2010 dummy	-0.006 (0.025)	0.024 (0.028)	0.009 (0.022)	0.014 (0.025)	0.005 (0.008)	0.011 (0.008)
Blue-collar x 2011 dummy	-0.004 (0.023)	0.021 (0.025)	0.002 (0.020)	0.011 (0.022)	-0.000 (0.007)	0.006 (0.007)
Blue-collar x 2013 dummy	-0.040* (0.021)	-0.050** (0.025)	-0.019 (0.019)	-0.041* (0.021)	-0.007 (0.006)	-0.013** (0.007)
Blue-collar x 2014 dummy	-0.063*** (0.024)	-0.082*** (0.026)	-0.059*** (0.021)	-0.098*** (0.023)	-0.014** (0.007)	-0.017** (0.007)
Blue-collar x 2015 dummy	-0.090*** (0.025)	-0.031 (0.028)	-0.053** (0.022)	-0.034 (0.025)	-0.011 (0.007)	-0.001 (0.008)
Blue-collar x 2016 dummy	-0.061** (0.028)	-0.024 (0.030)	-0.041* (0.025)	-0.043 (0.027)	-0.005 (0.008)	-0.003 (0.009)
Blue-collar x 2017 dummy	-0.051* (0.030)	-0.036 (0.032)	-0.036 (0.026)	-0.042 (0.029)	-0.001 (0.009)	-0.003 (0.010)
Observations	50,528	49,371	54,452	54,452	54,452	54,452
R-squared	0.769	0.736	0.781	0.751	0.640	0.639
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of employment turnover over the period of 2009 to 2017. The dependent variables: (1) $\ln(\text{Separations})$, the natural log of the number of employees that left the firm; (2) $\ln(\text{Entering emp.})$, the natural log of the number of new hires; (3) $\ln(1+\text{Separations})$, the natural log of one plus the number of employees that left the firm; (4) $\ln(1+\text{Entering emp.})$, the natural log of one plus the number of new hires; (5) $\text{Separations} / 2012 \text{ emp.}$, the number of employees that left the firm, divided by the firm's total number of employees in 2012; (6) $\text{Entering emp.} / 2012 \text{ emp.}$, the number of new hires, divided by the firm's total number of employees in 2012. *Blue-collar* is a dummy variable equal to 1 if the firm's pre-period (2009-2012) average share of blue-collar workers was above its sample median, and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. Year dummies are equal to 1 for observations in the given year, and to 0 otherwise. E.g., *2009 dummy* is equal to 1 for observations in the year of 2009, and to 0 for other years. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.3. Dynamic estimates (not shown in the main text) of the outcomes in Tables 3, 4, and 5

Table F.3: The effect of firing costs: Supplementary dynamic estimates

	ln(Cost per emp.)	ln(Hours per emp.)	ln(Permanent separations)	ln(Temporary separations)
	(1)	(2)	(3)	(4)
Blue-collar x 2009 dummy	-0.000 (0.006)	-0.013** (0.005)	0.002 (0.030)	-0.011 (0.057)
Blue-collar x 2010 dummy	0.001 (0.005)	-0.005 (0.005)	-0.009 (0.028)	-0.020 (0.052)
Blue-collar x 2011 dummy	-0.004 (0.005)	-0.004 (0.005)	-0.022 (0.026)	0.022 (0.046)
Blue-collar x 2013 dummy	0.003 (0.005)	-0.004 (0.004)	-0.029 (0.025)	-0.023 (0.043)
Blue-collar x 2014 dummy	0.007 (0.005)	0.001 (0.005)	-0.055** (0.026)	-0.035 (0.048)
Blue-collar x 2015 dummy	-0.006 (0.006)	-0.010** (0.005)	-0.101*** (0.027)	-0.026 (0.051)
Blue-collar x 2016 dummy	0.003 (0.006)	0.001 (0.005)	-0.079*** (0.030)	-0.074 (0.057)
Blue-collar x 2017 dummy	-0.000 (0.006)	-0.001 (0.005)	-0.096*** (0.031)	-0.008 (0.060)
Observations	54,452	54,452	43,650	21,804
R-squared	0.837	0.539	0.729	0.691
Firm FE	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes

(Continued)

	ln(Permanent entering emp.)	ln(Temporary entering emp.)	Train. costs	Train. hours
	(5)	(6)	(7)	(8)
Blue-collar x 2009 dummy	0.024 (0.034)	-0.049 (0.058)	0.001 (0.000)	0.003* (0.001)
Blue-collar x 2010 dummy	0.007 (0.032)	0.021 (0.052)	0.000 (0.000)	0.001 (0.001)
Blue-collar x 2011 dummy	0.014 (0.028)	0.002 (0.045)	-0.000 (0.000)	-0.001 (0.001)
Blue-collar x 2013 dummy	-0.048* (0.029)	-0.034 (0.043)	-0.000 (0.000)	0.001 (0.001)
Blue-collar x 2014 dummy	-0.069** (0.030)	-0.075 (0.047)	-0.000 (0.000)	-0.006 (0.005)
Blue-collar x 2015 dummy	-0.072** (0.031)	0.005 (0.050)	-0.000 (0.000)	0.000 (0.001)
Blue-collar x 2016 dummy	-0.067** (0.034)	-0.009 (0.056)	-0.001 (0.000)	-0.001 (0.002)
Blue-collar x 2017 dummy	-0.096*** (0.036)	0.055 (0.058)	-0.001 (0.001)	-0.002 (0.002)
Observations	41,780	22,879	54,452	54,452
R-squared	0.679	0.692	0.559	0.151
Firm FE	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes

This table reports dynamic estimates of main outcomes (those that are not shown in the main text) over the period of 2009 to 2017. The dependent variables: (1) $\ln(\text{Cost per emp.})$, the natural log of the average yearly cost per employee; (2) $\ln(\text{Hours per emp.})$, the natural log of the average yearly number of hours worked per employee; (3) $\ln(\text{Permanent separations})$, the natural log of the number of employees with permanent contracts that left the firm; (4) $\ln(\text{Temporary separations})$, the natural log of the number of employees with fixed-term contracts that left the firm; (5) $\ln(\text{Permanent entering emp.})$, the natural log of the number of new hires with permanent contracts; (6) $\ln(\text{Temporary entering emp.})$, the natural log of the number of new hires with fixed-term contracts; (7) *Train. costs*, total training costs scaled by total employee costs; (8) *Train. hours*, total training hours scaled by the total number of employment hours. *Blue-collar* is a dummy variable equal to 1 if the firm's pre-period (2009-2012) average share of blue-collar employees was above its sample median, and to 0 otherwise. Year dummies are equal to 1 for observations in the given year, and to 0 otherwise. E.g., *2009 dummy* is equal to 1 for observations in the year of 2009, and to 0 for other years. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.4. Using different productivity measures

Table F.4 illustrates the results from estimating Equation (3) using alternative productivity measures.³ In column (1), we construct TFP by accounting for firms' survival probabilities, motivated by the finding that increased firing costs are associated with higher firm exit rates (as shown in Table F.22). In column (2), TFP is recovered through the one-step estimation procedure suggested by Wooldridge (2009), where we use intermediate inputs as a proxy for unobserved productivity.

We also consider specifications that are more flexible and consistent with possible differences across the production functions of blue- and white-collar firms, as well as between the pre- and post-reform periods. In column (3), we estimate a translog production function which is a more general functional form that includes the Cobb-Douglas as a special case, and also allows that the elasticity of substitution between inputs can vary with the levels of inputs. Therefore, it is potentially consistent with different types of firms employing different shares of blue- and white-collar workers. In column (4), we recover TFP using our baseline approach (i.e., the approach of Akerberg et al. (2015)), but instead of constant elasticities, we estimate elasticities separately for the pre- and post-period for each NACE 2-digit industry. We do so to account for the possibility that the increase in firing costs could incentivize firms to adopt new technologies that are less dependent on blue-collar workers, even though we do not find evidence of such behavior. In column (5), we additionally estimate a Cobb-Douglas production function separately for blue- and white-collar firms.

In column (6), to further address the concern about time-varying elasticities, we estimate the production function separately for each NACE 2-digit industry $\times$ year, using OLS because the production function cannot be estimated for each year with the estimators of Wooldridge (2009) or Akerberg et al. (2015). For reference, in column (7), we estimate the production function for each NACE 2-digit industry with constant elasticities through OLS. In column (8), we estimate the production function using revenues as output and materials as inputs to relax the assumption that the output elasticity of materials is equal to one.⁴

Lastly, in column (9), we construct TFP using our baseline approach but use labor hours (instead of the number of employees) as the measure of labor input to account for potential substitutions between job positions and hours. Note that hours are not disaggregated by worker type in our dataset. To approximate hours by worker category, we assume that firms are likely to report the contractually binding 38 hours per week for their white-collar workers, but the number of hours worked per week by a blue-collar worker can easily vary.

³In Table F.4, after estimating each production function, as in our benchmark analysis, we drop observations with resulting negative elasticities, which leads to some variation in sample size across columns. Nevertheless, our results remain unchanged if we retain them.

⁴The sample size decreases by 15% for this analysis. This is because revenue data, unlike value-added data, is only available for large firms.

This is because blue-collar workers (i) are paid on a weekly basis for the actual number of hours worked, based on an hourly wage, and (ii) can more readily be placed on temporary unemployment due to, for example, economic reasons such as declining demand or technical reasons such as adverse weather conditions. In contrast, white-collar workers receive a fixed monthly salary, so variations in their hours worked are likely to average out over the year. Then, we assume that each full-time white-collar worker works 42 weeks because, in Belgium, we first deduct paid leave (24 days or 4.8 weeks) and public holidays (10 days or 2 weeks) from the 52 weeks. Additionally, we deduct another 3.2 weeks to account for other potential unworked time, such as sick leave, personal leave, or seniority-based vacation. Taken together, we assume that each full-time white-collar worker works 1,596 hours annually ($= 38 \text{ hours} \times 42 \text{ weeks}$), and allocate the remaining firm-level hours to blue-collar workers. Nevertheless, our results remain robust when we assign different numbers of working weeks to white-collar workers, ranging from 40 weeks (further extending time not worked) to 46 weeks (assuming fewer holidays/more days worked).

Regardless of the TFP measure, as illustrated in Panel A, the estimated effect is always negative and significant.⁵ Furthermore, the dynamic estimates in Panel B show that all different specifications support the ex-ante parallel trends assumption, and exhibit similar dynamics ex-post, with an estimated drop in TFP (relative to 2012) that often peaks around the year 2017. The magnitude of the peak depends on the specification, ranging between 1.4% and 6.3%, but most of the specifications show a significant drop of around 5%.

⁵The estimated coefficient is particularly large in column (5). However, this specification is very demanding for the data, since we estimate four different sets of elasticities for each 2-digit sector, resulting in around 200 different production function estimations in total. Therefore, these results are likely to be less reliable than those in the other specifications.

Table F.4: Firing costs and productivity: Different productivity measures

A. Main Estimates

	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP
	Akerberg et al. (with firm survival)	Wooldridge	Akerberg et al. (translog)	Akerberg et al.	Akerberg et al.	OLS	OLS	OLS	Akerberg et al.
	Value-added	Value-added	Value-added	Value-added	Value-added	Value-added	Value-added	Revenue	Value-added
	constant el.	constant el.	constant el.	pre & post el.	blue- & whitecollar firm, pre & post el.	yearly-varying el.	constant el.	constant el.	constant el. with imputed labor hours
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Blue-collar x Post	-0.047*** (0.008)	-0.040*** (0.008)	-0.018* (0.010)	-0.042*** (0.009)	-0.243*** (0.067)	-0.035*** (0.008)	-0.047*** (0.008)	-0.011*** (0.003)	-0.039*** (0.008)
Observations	54,246	51,440	54,452	53,556	52,122	54,221	54,452	46,297	52,597
R-squared	0.839	0.888	0.903	0.864	0.837	0.838	0.817	0.987	0.906
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(Continued)
B. Dynamic Estimates

	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP
	Akerberg et al. (with firm survival)	Wooldridge	Akerberg et al. (translog)	Akerberg et al.	Akerberg et al.	OLS	OLS	OLS	Akerberg et al.
	Value-added	Value-added	Value-added	Value-added	Value-added	Value-added	Value-added	Revenue	Value-added
	constant el.	constant el.	constant el.	pre & post el.	blue- & white-collar firm, pre & post el.	yearly-varying el.	constant el.	constant el.	constant el. with imputed labor hours
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Blue-collar x 2009 dummy	0.015 (0.013)	0.016 (0.012)	-0.014 (0.016)	0.012 (0.013)	-0.060 (0.042)	0.004 (0.013)	0.015 (0.013)	0.009** (0.005)	0.023* (0.013)
Blue-collar x 2010 dummy	-0.006 (0.011)	-0.006 (0.011)	-0.023* (0.014)	-0.007 (0.011)	-0.053 (0.037)	-0.009 (0.011)	-0.006 (0.011)	0.002 (0.004)	-0.007 (0.011)
Blue-collar x 2011 dummy	-0.007 (0.010)	-0.007 (0.009)	-0.009 (0.009)	-0.008 (0.009)	-0.031 (0.024)	-0.011 (0.009)	-0.006 (0.009)	-0.001 (0.003)	-0.011 (0.009)
Blue-collar x 2013 dummy	-0.039*** (0.009)	-0.037*** (0.009)	-0.024** (0.011)	-0.035*** (0.010)	-0.205** (0.080)	-0.016* (0.009)	-0.039*** (0.009)	-0.004 (0.003)	-0.031*** (0.009)
Blue-collar x 2014 dummy	-0.039*** (0.010)	-0.038*** (0.010)	-0.016 (0.012)	-0.035*** (0.011)	-0.192** (0.079)	-0.026** (0.010)	-0.039*** (0.010)	-0.007* (0.004)	-0.034*** (0.010)
Blue-collar x 2015 dummy	-0.044*** (0.012)	-0.033*** (0.012)	-0.035** (0.014)	-0.039*** (0.013)	-0.393*** (0.081)	-0.050*** (0.012)	-0.043*** (0.012)	-0.009** (0.004)	-0.023* (0.012)
Blue-collar x 2016 dummy	-0.061*** (0.013)	-0.050*** (0.013)	-0.039*** (0.015)	-0.056*** (0.014)	-0.312*** (0.094)	-0.056*** (0.014)	-0.060*** (0.013)	-0.011*** (0.004)	-0.054*** (0.014)
Blue-collar x 2017 dummy	-0.063*** (0.014)	-0.042*** (0.013)	-0.039*** (0.015)	-0.058*** (0.015)	-0.314*** (0.097)	-0.059*** (0.014)	-0.063*** (0.014)	-0.014*** (0.005)	-0.063*** (0.014)
Observations	54,246	51,440	54,452	53,556	52,122	54,221	54,452	46,297	52,597
R-squared	0.839	0.888	0.903	0.864	0.837	0.838	0.817	0.987	0.906
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of total factor productivity over the period of 2009 to 2017. Panels A and B show the main and dynamic estimates, respectively. The dependent variable, *TFP*, is the residual from the estimation of a production function, defined in the natural log. A Cobb-Douglas production function is estimated, using blue- and white-collar workers as separate inputs, through the methodology of [Akerberg et al. \(2015\)](#) and controlling for the firm's survival probability ((column (1)), through the methodology of [Wooldridge \(2009\)](#) (column (2)), through the methodology of [Akerberg et al. \(2015\)](#) separately for the pre- and post-periods (column (4)), through the methodology of [Akerberg et al. \(2015\)](#) separately for the pre- and post-periods across blue- and white-collar firms (column (5)), through OLS separately for each year (column (6)), through OLS (column (7)), through OLS and using revenues as output (column (8)), through the methodology of [Akerberg et al. \(2015\)](#) and using imputed labor hours (instead of the number of employees) as inputs (column (9)). In column (3), *TFP* is instead constructed from the estimation of a translog production function, defined in the natural log. *Blue-collar* is a dummy variable equal to 1 if the firm's pre-period (2009-2012) average share of blue-collar employees was above its sample median, and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. Year dummies are equal to 1 for observations in the given year, and to 0 otherwise. E.g., *2009 dummy* is equal to 1 for observations in the year of 2009, and to 0 for other years. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.5. Placebo test: assuming the reform was announced in 2008

Table F.5: The effect of firing costs: A placebo test

	TFP	ln(Separations)	ln(Entering emp.)	ln(Blue-collar emp.)	ln(White-collar emp.)
	(1)	(2)	(3)	(4)	(5)
Blue-collar ('05-'07) x Post ('08-'12)	0.003 (0.007)	-0.008 (0.016)	-0.023 (0.018)	-0.009 (0.009)	0.010 (0.008)
Observations	52,065	48,192	47,278	52,065	52,065
R-squared	0.834	0.783	0.748	0.972	0.973
Firm FE	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of total factor productivity, employment, and capital over the period of 2005 to 2012. The dependent variables: (1) *TFP*, the residual from the estimation of a Cobb-Douglas production function through the methodology of [Akerberg et al. \(2015\)](#), using blue- and white-collar worker categories as separate inputs, defined in the natural log; (2) *ln(Separations)*, the natural log of the number of employees that left the firm; (3) *ln(Entering emp.)*, the natural log of the number of new hires; (4) *ln(Blue-collar emp.)*, the natural log of the number of blue-collar employees; (5) *ln(White-collar emp.)*, the natural log of the number of white-collar employees. *Blue-collar* is a dummy variable equal to 1 if the firm's average share of blue-collar employees over 2005-2007 was above its sample median, and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2008 to 2012, and to 0 for observations in the period of 2005 to 2007. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period and at least one observation in the post-period. Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.6. Defining treatment based on 2008

Table F.6: The effect of firing costs: Defining treatment based on 2008

	TFP	ln(Separations)	ln(Entering emp.)	ln(Blue- collar emp.)	ln(White- collar emp.)
	(1)	(2)	(3)	(4)	(5)
Blue-collar ('08) x Post	-0.032*** (0.009)	-0.067*** (0.019)	-0.054** (0.021)	-0.020* (0.011)	0.047*** (0.011)
Observations	41,555	38,837	37,786	41,555	41,555
R-squared	0.844	0.763	0.728	0.964	0.967
Firm FE	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of total factor productivity, employment, and capital over the period of 2009 to 2017. The dependent variables: (1) *TFP*, the residual from the estimation of a Cobb-Douglas production function through the methodology of [Akerberg et al. \(2015\)](#), using blue- and white-collar worker categories as separate inputs, defined in the natural log; (2) *ln(Separations)*, the natural log of the number of employees that left the firm; (3) *ln(Entering emp.)*, the natural log of the number of new hires; (4) *ln(Blue-collar emp.)*, the natural log of the number of blue-collar employees; (5) *ln(White-collar emp.)*, the natural log of the number of white-collar employees. *Blue-collar* is a dummy variable equal to 1 if the firm's share of blue-collar employees in 2008 was above its sample median, and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period and at least one observation in the post-period. Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.7. The effect on profits

Table F.7: The effect of firing costs on profits

	ln(EBITDA)		EBITDA-to-assets		EBITDA-to-sales	
	(1)	(2)	(3)	(4)	(5)	(6)
Blue-collar x Post	-0.021 (0.018)		-0.001 (0.002)		-0.001 (0.001)	
Blue-collar x 2009 dummy		0.029 (0.029)		0.006* (0.003)		0.004** (0.002)
Blue-collar x 2010 dummy		-0.009 (0.026)		0.001 (0.003)		0.002 (0.002)
Blue-collar x 2011 dummy		-0.018 (0.023)		-0.000 (0.002)		0.000 (0.001)
Blue-collar x 2013 dummy		-0.008 (0.023)		-0.001 (0.002)		-0.000 (0.001)
Blue-collar x 2014 dummy		-0.015 (0.025)		0.003 (0.002)		0.001 (0.002)
Blue-collar x 2015 dummy		-0.006 (0.027)		0.004 (0.003)		0.002 (0.002)
Blue-collar x 2016 dummy		-0.071** (0.031)		-0.003 (0.003)		-0.001 (0.002)
Blue-collar x 2017 dummy		-0.023 (0.033)		-0.004 (0.003)		-0.002 (0.002)
Observations	49,923	49,923	54,452	54,452	54,452	54,452
R-squared	0.860	0.860	0.649	0.649	0.784	0.784
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of profits over the period of 2009 to 2017. The dependent variables: (1)-(2) $\ln(EBITDA)$, the natural log of EBITDA; (3)-(4) *EBITDA-to-assets*, the ratio of EBITDA to total assets; (5)-(6) *EBITDA-to-sales*, the ratio of EBITDA to sales. *Blue-collar* is a dummy variable equal to 1 if the firm's share of blue-collar employees in 2008 was above its sample median, and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. Year dummies are equal to 1 for observations in the given year, and to 0 otherwise. E.g., *2009 dummy* is equal to 1 for observations in the year of 2009, and to 0 for other years. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period and at least one observation in the post-period. Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.8. Less versus more affected industries

Table F.8: The effect of firing costs: Less versus more affected industries

	less affec.	more affec.	less affec.	more affec.	less affec.	more affec.	less affec.	more affec.
	TFP		ln(Separations)		ln(Entering emp.)		ln(Blue-collar emp.)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Blue-collar x Post	-0.034** (0.015)	-0.048*** (0.010)	-0.027 (0.030)	-0.066*** (0.020)	-0.063* (0.034)	-0.052** (0.022)	-0.012 (0.017)	-0.021* (0.013)
Observations	13,840	40,450	13,003	37,333	12,620	36,549	13,840	40,450
R-squared	0.887	0.792	0.771	0.774	0.734	0.743	0.973	0.962
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(Continued)

	less affec.	more affec.	less affec.	more affec.	less affec.	more affec.	less affec.	more affec.
	ln(White-collar emp.)		ln(Tangible fix.)		ln(Mac. Equip.)		ln(Land. Build. Furn. Other)	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Blue-collar x Post	0.016 (0.016)	0.063*** (0.012)	0.025 (0.037)	0.021 (0.023)	-0.036 (0.045)	0.019 (0.034)	-0.007 (0.046)	0.035 (0.027)
Observations	13,840	40,450	13,840	40,450	13,524	38,249	13,726	40,261
R-squared	0.976	0.962	0.941	0.921	0.920	0.891	0.915	0.898
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of total factor productivity, employment, and capital over the period of 2009 to 2017. The dependent variables: (1)-(2) *TFP*, the residual from the estimation of a Cobb-Douglas production function through the methodology of [Akerberg et al. \(2015\)](#), using blue- and white-collar worker categories as separate inputs, defined in the natural log; (3)-(4) *ln(Separations)*, the natural log of the number of employees that left the firm; (5)-(6) *ln(Entering emp.)*, the natural log of the number of new hires; (7)-(8) *ln(Blue-collar emp.)*, the natural log of the number of blue-collar employees; (9)-(10) *ln(White-collar emp.)*, the natural log of the number of white-collar employees; (11)-(12) *ln(Tangible fix.)*, the natural log of total tangible fixed assets; (13)-(14) *ln(Mac., Equip.)*, the natural log of the sum of machinery and equipment; (15)-(16) *ln(Land, Build., Furn., Other)*, the natural log of the sum of land, building, furniture, and other tangible fixed capital. *Blue-collar* is a dummy variable equal to 1 if the firm's pre-period average share of blue-collar employees was above its sample median, and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. *Less affected industries* (*More affected industries*) are those where the notice period for a blue-collar worker with a 10-year tenure increased by less than 168 days (by 168 days or more). Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.9. Results across less versus more R&D intensive industries

Table F.9: The effect of firing costs: Heterogeneity across less versus more R&D intensive industries

	TFP	Ln(Separations)	Ln(Entering emp.)	Ln(Blue-collar emp.)	Ln(White-collar emp.)	Ln(Tangible fix.)	Ln(Mac. Equip.)	Ln(Land Build. Furn. Other)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Blue-collar x Post	-0.049*** (0.011)	-0.045** (0.022)	-0.038 (0.023)	-0.023* (0.014)	0.072*** (0.013)	0.042 (0.026)	0.026 (0.038)	0.051* (0.031)
Blue-collar x Post x High R&D	0.006 (0.016)	-0.031 (0.033)	-0.052 (0.037)	0.014 (0.020)	-0.049*** (0.018)	-0.056 (0.038)	-0.063 (0.053)	-0.071 (0.046)
Observations	54,452	50,528	49,371	54,452	54,452	54,452	51,939	54,150
R-squared	0.826	0.769	0.736	0.965	0.966	0.926	0.903	0.901
Blue-collar x High R&D (accounting for firms changing industries)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of total factor productivity, employment, and capital over the period of 2009 to 2017. The dependent variables: (1) *TFP*, the residual from the estimation of a Cobb-Douglas production function through the methodology of [Akerberg et al. \(2015\)](#), using blue- and white-collar worker categories as separate inputs, defined in the natural log; (2) *ln(Separations)*, the natural log of the number of employees that left the firm; (3) *ln(Entering emp.)*, the natural log of the number of new hires; (4) *ln(Blue-collar emp.)*, the natural log of the number of blue-collar employees; (5) *ln(White-collar emp.)*, the natural log of the number of white-collar employees; (6) *ln(Tangible fix.)*, the natural log of total tangible fixed assets; (7) *ln(Mac., Equip.)*, the natural log of the sum of machinery and equipment; (8) *ln(Land, Build., Furn., Other)*, the natural log of the sum of land, building, furniture, and other tangible fixed capital. *Blue-collar* is a dummy variable equal to 1 if the firm's pre-period (2009-2012) average share of blue-collar employees was above its sample median, and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. *High R&D intensive* is equal to 1 if the industry's R&D intensity score, based on the 2011 OECD taxonomy ([Galindo-Rueda and Verger, 2016](#)), is above its sample median, and to 0 otherwise. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.10. Treating outsourced labor as a production input

Table F.10: Firing costs and productivity: Incorporating outsourced workers as an input

	Incorporating outsourced emp. in line with blue/white emp. ratio		Incorporating outsourced emp. as blue emp.		Incorporating outsourced emp. as a separate category using $\ln(1 + Outsourced\ emp.)$	
	TFP	TFP	TFP	TFP	TFP	TFP
	(1)	(2)	(3)	(4)	(5)	(6)
Blue-collar x Post	-0.048*** (0.008)		-0.038*** (0.008)		-0.045*** (0.008)	
Blue-collar x 2009 dummy		0.013 (0.013)		0.007 (0.013)		0.014 (0.013)
Blue-collar x 2010 dummy		-0.007 (0.011)		-0.008 (0.011)		-0.005 (0.011)
Blue-collar x 2011 dummy		-0.008 (0.009)		-0.007 (0.009)		-0.005 (0.009)
Blue-collar x 2013 dummy		-0.040*** (0.009)		-0.035*** (0.008)		-0.036*** (0.008)
Blue-collar x 2014 dummy		-0.042*** (0.010)		-0.033*** (0.010)		-0.037*** (0.010)
Blue-collar x 2015 dummy		-0.043*** (0.012)		-0.034*** (0.011)		-0.041*** (0.011)
Blue-collar x 2016 dummy		-0.062*** (0.013)		-0.050*** (0.013)		-0.058*** (0.013)
Blue-collar x 2017 dummy		-0.067*** (0.014)		-0.056*** (0.013)		-0.062*** (0.013)
Observations	54,348	54,348	54,451	54,451	54,176	54,176
R-squared	0.842	0.842	0.845	0.845	0.847	0.847
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of total factor productivity over the period of 2009 to 2017. The dependent variable, *TFP*, is the residual from the estimation of a Cobb-Douglas production function, defined in the natural log. When estimating the production function, blue- and white-collar worker categories are used as separate inputs, and outsourced workers are incorporated into the employment input as follows: In columns (1) and (2), outsourced workers are allocated between blue- and white-collar categories according to the firm's blue-/white-collar employment ratio in a given year. In columns (3) and (4), all outsourced workers are assumed to be blue-collar. In columns (5) and (6), outsourced workers are included as a separate input using $\ln(1 + Outsourced\ emp.)$. *Blue-collar* is a dummy variable equal to 1 if the firm's pre-period (2009-2012) average share of blue-collar workers was above its sample median, and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. Year dummies are equal to 1 for observations in the given year, and to 0 otherwise. E.g., *2009 dummy* is equal to 1 for observations in the year of 2009, and to 0 for other years. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.11. Adding firms that operate with only blue- or only white-collar workers and firms that do not report intermediate inputs

In our main analysis, we restrict the sample to firms that employ at least one blue-collar worker, at least one white-collar worker, and for which data on intermediate inputs are available. To ensure that our results are not sensitive to this selection, Table F.11 conducts our main analysis using three alternative samples.

Incorporating firms with only one worker type. In columns (1) and (2), we allow firms operating with only one worker type to be included in the sample. For this sample, we recover TFP through estimating the production function using $\ln(1+\text{blue-collar workers})$ and $\ln(1+\text{white-collar workers})$ as labor inputs.

Incorporating firms with missing intermediate inputs. In columns (3) and (4), while still focusing on firms operating with at least one blue-collar worker and at least one white-collar worker, we incorporate firms with missing intermediate inputs into our sample. Because intermediate inputs are typically reported by larger firms in Belgium, this inclusion allows us to incorporate smaller firms into the analysis. For this sample, we construct TFP by estimating our baseline production function through OLS (rather than following the approach of Akerberg et al. (2015) and using intermediate inputs as a proxy).

Incorporating both firms with only one worker type and those with missing intermediate inputs. In columns (5) and (6), we run our analysis using a sample that includes both firms employing only one type of worker and firms with missing intermediate inputs. For this sample, we use TFP from an OLS estimation of the production function with $\ln(1+\text{blue-collar emp.})$ and $\ln(1+\text{white-collar emp.})$.

The results indicate that our main effects are robust across all sample specifications. In fact, the estimated effects on blue- and white-collar workers are even stronger when smaller firms are included. This may reflect the greater internal flexibility of smaller firms, which could enable them to adjust their employment composition more aggressively in response to increased firing costs.

Table F.11: The effect of firing costs: Incorporating firms with only one worker type as well as firms with missing intermediate inputs

	TFP	ln(Separations)	ln(Entering emp.)	ln(Blue-collar emp.)	ln(White-collar emp.)	ln(Tangible fix.)	ln(Mac., Equip.)	ln(Land, Build., Furn., Other)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Incorporating firms with only one worker type								
Blue-collar x Post	-0.047*** (0.009)	-0.057*** (0.016)	-0.057*** (0.017)	-0.016 (0.011)	0.039*** (0.009)	0.014 (0.020)	-0.008 (0.026)	0.015 (0.023)
Observations	72,736	65,601	63,983	58,064	67,548	72,736	65,609	72,043
R-squared	0.849	0.764	0.735	0.960	0.961	0.926	0.903	0.903
B. Incorporating firms with missing intermediate inputs								
Blue-collar x Post	-0.044*** (0.005)	-0.040*** (0.010)	-0.046*** (0.011)	-0.044*** (0.006)	0.086*** (0.006)	0.002 (0.012)	0.002 (0.017)	0.001 (0.014)
Observations	161,858	139,152	136,058	161,858	161,858	161,858	153,445	160,782
R-squared	0.773	0.712	0.689	0.950	0.949	0.903	0.869	0.879
C. Incorporating both firms with only one worker type and firms with missing intermediate inputs								
Blue-collar x Post	-0.038*** (0.005)	-0.027*** (0.009)	-0.033*** (0.010)	-0.043*** (0.006)	0.089*** (0.006)	0.004 (0.011)	-0.020 (0.015)	0.008 (0.013)
Observations	268,285	225,199	220,278	222,994	215,601	268,285	246,123	265,332
R-squared	0.796	0.698	0.681	0.931	0.947	0.893	0.860	0.869
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of total factor productivity, employment, and capital over the period of 2009 to 2017. The dependent variables: (1) *TFP*, the residual from the estimation of a Cobb-Douglas production function, using the levels of blue- and white-collar workers as separate inputs, defined in the natural log; (2) *ln(Separations)*, the natural log of the number of employees that left the firm; (3) *ln(Entering emp.)*, the natural log of the number of new hires; (4) *ln(Blue-collar emp.)*, the natural log of the number of blue-collar employees; (5) *ln(White-collar emp.)*, the natural log of the number of white-collar employees; (6) *ln(Tangible fix.)*, the natural log of total tangible fixed assets; (7) *ln(Mac., Equip.)*, the natural log of the sum of machinery and equipment; (8) *ln(Land, Build., Furn., Other)*, the natural log of the sum of land, building, furniture, and other tangible fixed capital. TFP is constructed as follows. In columns (1) and (2), the production function is estimated through the methodology of [Akerberg et al. \(2015\)](#) and using *ln(1+blue-collar emp.)* and *ln(1+white-collar emp.)* as labor inputs. In columns (3) and (4), the production function is estimated through OLS with the baseline production inputs. In columns (5) and (6), the production function is estimated through OLS and using *ln(1+blue-collar emp.)* and *ln(1+white-collar emp.)* as labor inputs. *Blue-collar* is a dummy variable equal to 1 if the firm's pre-period (2009-2012) average share of blue-collar workers was above its sample median, and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.12. Results with controls

Table F.12: The effect of firing costs: Results with controls

	ln(Separations)	ln(Entering emp.)	ln(Blue-collar emp.)	ln(White-collar emp.)	ln(Tangible fix.)	ln(Mac., Equip.)	ln(Land, Build., Furn., Other)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Blue-collar x Post	-0.055*** (0.017)	-0.056*** (0.018)	-0.015 (0.010)	0.054*** (0.009)	0.015 (0.012)	-0.002 (0.025)	0.017 (0.017)
Observations	50,528	49,371	54,452	54,452	54,452	51,939	54,150
R-squared	0.775	0.738	0.967	0.969	0.953	0.912	0.925
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of employment and capital over the period of 2009 to 2017, with control variables. The dependent variables: (1) $\ln(\text{Separations})$, the natural log of the number of employees that left the firm; (2) $\ln(\text{Entering emp.})$, the natural log of the number of new hires; (3) $\ln(\text{Blue-collar emp.})$, the natural log of the number of blue-collar employees; (4) $\ln(\text{White-collar emp.})$, the natural log of the number of white-collar employees; (5) $\ln(\text{Tangible fix.})$, the natural log of total tangible fixed assets; (6) $\ln(\text{Mac., Equip.})$, the natural log of the sum of machinery and equipment; (7) $\ln(\text{Land, Build., Furn., Other})$, the natural log of the sum of land, building, furniture, and other tangible fixed capital. *Blue-collar* is a dummy variable equal to 1 if the firm's pre-period (2009-2012) average share of blue-collar employees was above its sample median, and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. Firm controls are Size_{t-1} , Age_t , Leverage_{t-1} , $\text{EBITDA-to-assets}_{t-1}$, $\text{Cash holdings}_{t-1}$, and $\text{Capital-to-labor}_{t-1}$. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.13. Results with the matched samples

We create two matched samples with the aim of making blue- and white-collar firms as comparable as possible in terms of their observed pre-period characteristics.

F.13.1. Matching strategy 1

Matching strategy. To create the first matched sample, we carry out a nearest neighbor matching of propensity scores to select a sub-sample of white-collar firms that are similar to blue-collar firms in their observable characteristics. To do so, we first estimate a logit regression using the 2012 values of covariates, with a dependent variable that is a dummy equal to 1 for blue-collar firms, and to 0 for white-collar firms. As explanatory variables, we include (*size*, *age*, *leverage*, *cash holdings*, *capital-to-labor*) among our baseline firm controls. Additionally, we include the log of the total number of workers, the log growth rate of the number of blue-collar workers, the log growth rate of the number of white-collar workers, and the log growth rate of tangible fixed assets to ensure that our matched samples have similar pre-period trends in labor and capital growth. We then perform a nearest neighbor matching of propensity scores (i.e., the predicted probabilities of the logit model) with exact matches in NACE 2-digit industries. We retain one white-collar firm for each blue-collar firm, and allow that a white-collar firm can be used as a match for multiple blue-collar firms.⁶ Although matching with replacement increases the variance of the estimator, it enhances the average quality of matches and ensures that the estimated effect is not sensitive to the order in which blue-collar firms are matched to white-collar firms (Rosenbaum, 1995; Smith and Todd, 2005; Roberts and Whited, 2013).

Summary statistics. In total, we are able to successfully match 3,375 (around 98%) of the 3,451 blue-collar firms to white-collar firms. Table F.13.1 compares the pre-period sample means for blue- and white-collar firms before- and after the matching procedure. We assess the quality of matching by performing t-tests as well as by looking at standardized differences in means of the control variables. An absolute value of standardized mean difference that is less than 0.1 is considered to imply a negligible imbalance between samples. According to the t-tests, the two groups of firms significantly differ in covariates before the matching procedure. The standardized mean differences indicate a non-negligible imbalance for *size*, *EBITDA-to-assets*, and *capital-to-labor* between the non-matched blue- and white-collar samples. After the matching procedure, according to both the t-tests and standardized mean differences, there are no meaningful differences in any covariate between blue-collar and white-collar firms, on average. Thus, our matching procedure yields blue-collar and white-collar samples which are more similar in their characteristics, in comparison with the

⁶Here, as well for matching strategy 2 below, our results hold when we retain two or three white-collar firms for each blue-collar firm.

non-matched sample.

Results. Using the matched sample, Panels A and B of Table F.13.2 present the main and dynamic estimates, respectively, for our main outcomes based on the baseline regression. The estimated effects on TFP and employment are qualitatively similar to our baseline results. The coefficient for tangible fixed capital, however, is noticeably larger in magnitude than our baseline estimate. Importantly, this increase in capital appears to be driven by land, buildings, furniture, and other non-machinery assets, rather than by machines and equipment. This finding is consistent with our main results based on the non-matched sample and suggests that the rise in firing costs did not lead to capital deepening.

F.13.2. Matching strategy 2

Matching strategy. We construct the second matched sample using the same strategy as for the first (i.e., nearest neighbor matching of propensity scores). The only difference is that, in this case, we match firms based only on their pre-period TFP average to more directly account for potential systematic differences in productivity between blue- and white-collar firms. As before, we require exact matches within NACE 2-digit industries, retain one white-collar firm for each blue-collar firm, and allow that a white-collar firm can be used as a match for multiple blue-collar firms.

Summary statistics & results. Using the second strategy, we successfully match nearly all blue-collar firms to white-collar counterparts (3,438 out of 3,451). Table F.13.3 demonstrates that this matching approach leads to an overall improvement in covariate balance between the two groups. Panels A and B of Table F.13.4 illustrate the main and dynamic estimates, respectively, for our key outcomes. The results from this matched sample are broadly consistent with those from the non-matched sample and reveal even larger effects on the reduction in worker turnover and shifts in employment composition.

Table F.13.1: Comparing pre-period sample means for blue-collar and white-collar firms: Matched versus Non-Matched Sample (1)

	Non-matched sample						Matched sample					
	Blue-collar firms		White-collar firms				Blue-collar firms		White-collar firms			
	N	Mean	N	Mean	Diff.	SMD	N	Mean	N	Mean	Diff.	SMD
Dependent variables												
TFP	12,173	6.562	12,230	6.524	0.038***	0.065	12,036	6.563	12,129	6.456	0.107***	0.193
ln(Separations)	11,411	2.125	11,298	1.928	0.197***	0.175	11,296	2.128	11,371	2.126	0.002	0.002
ln(Entering emp.)	11,141	2.122	11,233	1.952	0.170***	0.148	11,017	2.125	11,364	2.104	0.021	0.018
ln(Blue-collar emp.)	12,173	3.506	12,230	2.392	1.115***	0.934	12,036	3.516	12,129	2.914	0.602***	0.494
ln(White-collar emp.)	12,173	1.949	12,230	2.881	-0.932***	-0.795	12,036	1.962	12,129	3.033	-1.071***	-0.884
ln(Total emp.)	12,173	3.737	12,230	3.483	0.254***	0.235	12,036	3.747	12,129	3.775	-0.029	-0.026
ln(Tangible fix.)	12,173	13.894	12,230	13.832	0.062	0.037	12,036	13.904	12,129	13.857	0.047	0.028
ln(Mac., Equip.)	11,696	12.197	11,678	11.823	0.375***	0.170	11,570	12.207	11,632	12.130	0.078	0.035
ln(Land, Build., Furn., Other)	12,107	13.404	12,178	13.431	-0.027	-0.015	11,970	13.414	12,095	13.367	0.047	0.026
Treatment												
(%) Blue-collar	12,173	0.799	12,230	0.405	0.394***	2.843	12,036	0.799	12,129	0.474	0.325***	2.584
Controls												
Size	12,173	15.654	12,230	15.979	-0.325***	-0.232	12,036	15.666	12,129	15.753	-0.088	-0.061
Age	12,173	27.676	12,230	29.136	-1.460***	-0.084	12,036	27.762	12,129	26.617	1.145	0.069
Leverage	12,173	0.592	12,230	0.607	-0.015**	-0.059	12,036	0.592	12,129	0.601	-0.009	-0.038
EBITDA-to-assets	12,173	0.119	12,230	0.106	0.013***	0.128	12,036	0.119	12,129	0.116	0.003	0.027
Cash holdings	12,173	0.090	12,230	0.095	-0.005*	-0.042	12,036	0.089	12,129	0.089	0.001	0.005
Capital-to-labour	12,173	10.157	12,230	10.349	-0.192***	-0.141	12,036	10.157	12,129	10.082	0.075	0.057

This table compares the sample means for blue-collar and white-collar firms over the pre-period (2009-2012). *Blue-collar firms* (*White-collar firms*) are those whose pre-period average share of blue-collar workers was above (below) its sample median. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, for *t*-test of whether the treatment and control groups have equal means for a given variable. In our *t*-tests, we cluster standard errors at the firm level to account for that some white-collar firms are matched to blue-collar firms more than once. Standardized mean difference (SMD) for a variable is calculated as $(Mean_{blue-collar} - Mean_{white-collar}) / \sqrt{(sd_{blue-collar}^2 + sd_{white-collar}^2) / 2}$. Supplemental Appendix A defines all variables.

Table F.13.2: The effect of firing costs: Results with the matched sample (1)

A. Main estimates

	TFP	ln(Separations)	ln(Entering emp.)	ln(Blue- collar emp.)	ln(White- collar emp.)	ln(Tangible fix.)	ln(Mac., Equip.)	ln(Land, Build., Furn., Other)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Blue-collar x Post	-0.058*** (0.013)	-0.056* (0.031)	-0.052* (0.028)	-0.025 (0.016)	0.087*** (0.016)	0.096*** (0.033)	0.047 (0.051)	0.087** (0.043)
Observations	53,461	49,904	48,817	53,461	53,461	53,461	51,109	53,147
R-squared	0.824	0.784	0.752	0.963	0.969	0.928	0.907	0.903
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(Continued)

B. Dynamic estimates

	TFP	ln(Separations)	ln(Entering emp.)	ln(Blue-collar emp.)	ln(White-collar emp.)	ln(Tangible fix.)	ln(Mac., Equip.)	ln(Land, Build., Furn., Other)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Blue-collar x 2009 dummy	0.016 (0.017)	-0.006 (0.047)	-0.076 (0.048)	-0.042 (0.033)	0.001 (0.017)	-0.064 (0.055)	-0.076 (0.060)	-0.053 (0.065)
Blue-collar x 2010 dummy	-0.004 (0.016)	-0.059 (0.045)	-0.032 (0.046)	-0.036 (0.024)	-0.019 (0.015)	-0.050 (0.039)	-0.033 (0.057)	-0.045 (0.046)
Blue-collar x 2011 dummy	-0.006 (0.013)	0.010 (0.052)	-0.002 (0.040)	-0.016* (0.009)	-0.005 (0.012)	-0.020 (0.019)	-0.017 (0.040)	-0.022 (0.026)
Blue-collar x 2013 dummy	-0.038*** (0.013)	-0.043 (0.029)	-0.064 (0.043)	-0.034*** (0.011)	0.041*** (0.011)	0.027 (0.019)	0.001 (0.038)	0.037 (0.027)
Blue-collar x 2014 dummy	-0.046*** (0.016)	-0.017 (0.038)	-0.131*** (0.038)	-0.046*** (0.014)	0.050*** (0.017)	0.024 (0.038)	-0.022 (0.052)	0.031 (0.053)
Blue-collar x 2015 dummy	-0.060*** (0.018)	-0.103** (0.044)	-0.045 (0.044)	-0.040** (0.019)	0.097*** (0.020)	0.049 (0.046)	0.067 (0.094)	0.017 (0.048)
Blue-collar x 2016 dummy	-0.083*** (0.021)	-0.128*** (0.048)	-0.082* (0.046)	-0.047** (0.020)	0.117*** (0.020)	0.119*** (0.041)	0.048 (0.076)	0.098** (0.048)
Blue-collar x 2017 dummy	-0.070*** (0.021)	-0.074 (0.051)	-0.042 (0.056)	-0.072*** (0.024)	0.134*** (0.024)	0.156*** (0.051)	0.009 (0.086)	0.156*** (0.060)
Observations	53,461	49,904	48,817	53,461	53,461	53,461	51,109	53,147
R-squared	0.824	0.784	0.752	0.963	0.969	0.928	0.907	0.903
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of total factor productivity, employment, and capital over the period of 2009 to 2017, using a matched sample. In the matched sample, we retain one white-collar firm for each blue-collar firm. The dependent variables: (1) *TFP*, the residual from the estimation of a Cobb-Douglas production function through the methodology of [Akerberg et al. \(2015\)](#), using blue- and white-collar worker categories as separate inputs, defined in the natural log; (2) *ln(Separations)*, the natural log of the number of employees that left the firm; (3) *ln(Entering emp.)*, the natural log of the number of new hires; (4) *ln(Blue-collar emp.)*, the natural log of the number of blue-collar employees; (5) *ln(White-collar emp.)*, the natural log of the number of white-collar employees; (6) *ln(Tangible fix.)*, the natural log of total tangible fixed assets; (7) *ln(Mac., Equip.)*, the natural log of the sum of machinery and equipment; (8) *ln(Land, Build., Furn., Other)*, the natural log of the sum of land, building, furniture, and other tangible fixed capital. *Blue-collar* is a dummy variable equal to 1 if the firm's pre-period (2009-2012) average share of blue-collar workers was above its sample median, and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. Year dummies are equal to 1 for observations in the given year, and to 0 otherwise. E.g., *2009 dummy* is equal to 1 for observations in the year of 2009, and to 0 for other years. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table F.13.3: Comparing pre-period sample means for blue-collar and white-collar firms: Matched versus Non-Matched Sample (2)

	Non-matched sample						Matched sample					
	Blue-collar firms			White-collar firms			Blue-collar firms			White-collar firms		
	N	Mean	N	Mean	Diff.	SMD	N	Mean	N	Mean	Diff.	SMD
Dependent variables												
TFP	12,173	6.562	12,230	6.524	0.038***	0.065	12,128	6.563	12,183	6.562	0.001	0.001
ln(Separations)	11,411	2.125	11,298	1.928	0.197***	0.175	11,376	2.125	11,161	1.962	0.162***	0.142
ln(Entering emp.)	11,141	2.122	11,233	1.952	0.170***	0.148	11,103	2.122	11,166	1.959	0.162***	0.141
ln(Blue-collar emp.)	12,173	3.506	12,230	2.392	1.115***	0.934	12,128	3.508	12,183	2.698	0.810***	0.679
ln(White-collar emp.)	12,173	1.949	12,230	2.881	-0.932***	-0.795	12,128	1.952	12,183	2.856	-0.904***	-0.756
ln(Total emp.)	12,173	3.737	12,230	3.483	0.254***	0.235	12,128	3.738	12,183	3.573	0.165***	0.149
ln(Tangible fix.)	12,173	13.894	12,230	13.832	0.062	0.037	12,128	13.898	12,183	13.852	0.046	0.027
ln(Mac., Equip.)	11,696	12.197	11,678	11.823	0.375***	0.170	11,655	12.201	11,729	11.970	0.231**	0.105
ln(Land, Build., Furn., Other)	12,107	13.404	12,178	13.431	-0.027	-0.015	12,061	13.409	12,116	13.385	0.024	0.013
Treatment												
(%) Blue-collar	12,173	0.799	12,230	0.405	0.394***	2.843	12,128	0.799	12,183	0.467	0.332***	2.642
Controls												
Size	12,173	15.654	12,230	15.979	-0.325***	-0.232	12,128	15.657	12,183	15.996	-0.339***	-0.238
Age	12,173	27.676	12,230	29.136	-1.460***	-0.084	12,128	27.700	12,183	29.918	-2.218**	-0.127
Leverage	12,173	0.592	12,230	0.607	-0.015**	-0.059	12,128	0.592	12,183	0.610	-0.018	-0.072
EBITDA-to-assets	12,173	0.119	12,230	0.106	0.013***	0.128	12,128	0.119	12,183	0.112	0.007	0.062
Cash holdings	12,173	0.090	12,230	0.095	-0.005*	-0.042	12,128	0.089	12,183	0.096	-0.007	-0.060
Capital-to-labour	12,173	10.157	12,230	10.349	-0.192***	-0.141	12,128	10.160	12,183	10.279	-0.119**	-0.086

This table compares the sample means for blue-collar and white-collar firms over the pre-period (2009-2012). *Blue-collar firms* (*White-collar firms*) are those whose pre-period average share of blue-collar workers was above (below) its sample median. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, for *t*-test of whether the treatment and control groups have equal means for a given variable. In our *t*-tests, we cluster standard errors at the firm level to account for that some white-collar firms are matched to blue-collar firms more than once. Standardized mean difference (SMD) for a variable is calculated as $(Mean_{blue-collar} - Mean_{white-collar}) / \sqrt{(sd_{blue-collar}^2 + sd_{white-collar}^2) / 2}$. Supplemental Appendix A defines all variables.

Table F.13.4: The effect of firing costs: Results with the matched sample (2)

A. Main estimates

	TFP	ln(Separations)	ln(Entering emp.)	ln(Blue- collar emp.)	ln(White- collar emp.)	ln(Tangible fix.)	ln(Mac., Equip.)	ln(Land, Build., Furn., Other)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Blue-collar x Post	-0.048*** (0.012)	-0.069*** (0.026)	-0.098*** (0.027)	-0.035** (0.016)	0.059*** (0.014)	0.066* (0.037)	0.015 (0.044)	0.061 (0.043)
Observations	54,274	50,191	49,148	54,274	54,274	54,274	51,885	53,925
R-squared	0.813	0.773	0.738	0.963	0.965	0.925	0.900	0.904
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(Continued)

B. Dynamic estimates

	TFP	ln(Separations)	ln(Entering emp.)	ln(Blue-collar emp.)	ln(White-collar emp.)	ln(Tangible fix.)	ln(Mac., Equip.)	ln(Land, Build., Furn., Other)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Blue-collar x 2009 dummy	0.025 (0.016)	-0.085** (0.042)	-0.040 (0.049)	0.016 (0.017)	0.018 (0.016)	0.000 (0.043)	-0.043 (0.060)	0.022 (0.051)
Blue-collar x 2010 dummy	-0.007 (0.016)	-0.020 (0.037)	0.011 (0.043)	0.018 (0.014)	0.002 (0.013)	0.005 (0.037)	-0.023 (0.056)	0.030 (0.043)
Blue-collar x 2011 dummy	0.002 (0.014)	-0.025 (0.033)	-0.007 (0.037)	0.012 (0.009)	-0.004 (0.009)	-0.000 (0.026)	-0.048 (0.030)	0.007 (0.033)
Blue-collar x 2013 dummy	-0.037*** (0.012)	-0.065* (0.033)	-0.067* (0.038)	-0.011 (0.013)	0.032*** (0.008)	0.039** (0.018)	-0.017 (0.031)	0.056** (0.022)
Blue-collar x 2014 dummy	-0.041*** (0.014)	-0.092*** (0.033)	-0.163*** (0.043)	-0.025* (0.015)	0.052*** (0.016)	0.064** (0.027)	-0.032 (0.040)	0.085** (0.040)
Blue-collar x 2015 dummy	-0.025 (0.019)	-0.119*** (0.041)	-0.058 (0.045)	-0.006 (0.018)	0.082*** (0.017)	0.061* (0.035)	0.014 (0.053)	0.044 (0.037)
Blue-collar x 2016 dummy	-0.063*** (0.018)	-0.104** (0.044)	-0.130*** (0.042)	-0.029 (0.019)	0.076*** (0.018)	0.106** (0.042)	-0.003 (0.059)	0.120*** (0.046)
Blue-collar x 2017 dummy	-0.059*** (0.018)	-0.126*** (0.044)	-0.116** (0.047)	-0.062*** (0.023)	0.082*** (0.021)	0.082** (0.039)	-0.015 (0.061)	0.077 (0.051)
Observations	54,274	50,191	49,148	54,274	54,274	54,274	51,885	53,925
R-squared	0.813	0.773	0.738	0.963	0.965	0.926	0.900	0.904
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of total factor productivity, employment, and capital over the period of 2009 to 2017, using a matched sample. In the matched sample, we retain one white-collar firm for each blue-collar firm. The dependent variables: (1) *TFP*, the residual from the estimation of a Cobb-Douglas production function through the methodology of Akerberg et al. (2015), using blue- and white-collar worker categories as separate inputs, defined in the natural log; (2) *ln(Separations)*, the natural log of the number of employees that left the firm; (3) *ln(Entering emp.)*, the natural log of the number of new hires; (4) *ln(Blue-collar emp.)*, the natural log of the number of blue-collar employees; (5) *ln(White-collar emp.)*, the natural log of the number of white-collar employees; (6) *ln(Tangible fix.)*, the natural log of total tangible fixed assets; (7) *ln(Mac., Equip.)*, the natural log of the sum of machinery and equipment; (8) *ln(Land, Build., Furn., Other)*, the natural log of the sum of land, building, furniture, and other tangible fixed capital. *Blue-collar* is a dummy variable equal to 1 if the firm's pre-period (2009-2012) average share of blue-collar workers was above its sample median, and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. Year dummies are equal to 1 for observations in the given year, and to 0 otherwise. E.g., *2009 dummy* is equal to 1 for observations in the year of 2009, and to 0 for other years. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.14. Results with treatment intensity

Table F.14: The effect of firing costs: Results with treatment intensity

	TFP	ln(Separations)	ln(Entering emp.)	ln(Blue-collar emp.)	ln(White-collar emp.)	ln(Tangible fix.)	ln(Mac., Equip.)	ln(Land, Build., Furn., Other)
	(1)	(3)	(2)	(4)	(5)	(6)	(7)	(8)
(%) Blue-collar x Post	-0.114*** (0.020)	-0.094*** (0.036)	-0.128*** (0.039)	-0.016 (0.026)	0.149*** (0.021)	0.040 (0.044)	-0.035 (0.062)	0.061 (0.051)
Observations	54,452	50,528	49,371	54,452	54,452	54,452	51,939	54,150
R-squared	0.826	0.769	0.736	0.965	0.966	0.926	0.903	0.901
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of total factor productivity, employment, and capital over the period of 2009 to 2017. The dependent variables: (1) *TFP*, the residual from the estimation of a Cobb-Douglas production function through the methodology of [Akerberg et al. \(2015\)](#), using blue- and white-collar worker categories as separate inputs, defined in the natural log; (2) *ln(Separations)*, the natural log of the number of employees that left the firm; (3) *ln(Entering emp.)*, the natural log of the number of new hires; (4) *ln(Blue-collar emp.)*, the natural log of the number of blue-collar employees; (5) *ln(White-collar emp.)*, the natural log of the number of white-collar employees; (6) *ln(Tangible fix.)*, the natural log of total tangible fixed assets; (7) *ln(Mac., Equip.)*, the natural log of the sum of machinery and equipment; (8) *ln(Land, Build., Furn., Other)*, the natural log of the sum of land, building, furniture, and other tangible fixed capital. (%) *Blue-collar* is the firm's pre-period (2009-2012) average share of blue-collar workers. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.15. Linear effects of firing costs

Table F.15: The effect of firing costs: Linear effects

	TFP	ln(Separations)	ln(Entering emp.)	ln(Blue-collar emp.)	ln(White-collar emp.)	ln(Tangible fix.)	ln(Mac., Equip.)	ln(Land, Build., Furn., Other)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Q2 (%) Blue-collar x Post	-0.009 (0.011)	-0.001 (0.021)	-0.019 (0.023)	-0.003 (0.014)	0.014 (0.011)	-0.009 (0.025)	-0.041 (0.035)	0.004 (0.029)
Q3 (%) Blue-collar x Post	-0.039*** (0.012)	-0.062*** (0.023)	-0.045* (0.025)	-0.022 (0.015)	0.037*** (0.013)	0.011 (0.027)	-0.020 (0.037)	0.019 (0.032)
Q4 (%) Blue-collar x Post	-0.072*** (0.013)	-0.052** (0.025)	-0.103*** (0.027)	-0.014 (0.016)	0.093*** (0.014)	0.021 (0.029)	-0.028 (0.040)	0.033 (0.034)
Observations	54,452	50,528	49,371	54,452	54,452	54,452	51,939	54,150
R-squared	0.826	0.769	0.736	0.965	0.966	0.926	0.903	0.901
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of total factor productivity, employment and capital over the period of 2009 to 2017. The dependent variables: (1) *TFP*, the residual from the estimation of a Cobb-Douglas production function through the methodology of [Akerberg et al. \(2015\)](#), using blue- and white-collar worker categories as separate inputs, defined in the natural log; (2) *ln(Separations)*, the natural log of the number of employees that left the firm; (3) *ln(Entering emp.)*, the natural log of the number of new hires; (4) *ln(Blue-collar emp.)*, the natural log of the number of blue-collar employees; (5) *ln(White-collar emp.)*, the natural log of the number of white-collar employees; (6) *ln(Tangible fix.)*, the natural log of total tangible fixed assets; (7) *ln(Mac., Equip.)*, the natural log of the sum of machinery and equipment; (8) *ln(Land, Build., Furn., Other)*, the natural log of the sum of land, building, furniture, and other tangible fixed capital. Q_i (%) Blue-collar is a dummy equal to 1 if the firm belongs to the i th quartile of the treatment intensity variable (i.e., the firm's average share of blue-collar workers over 2009-2012). *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.16. Results across industries with larger declines in blue-collar employment share

Table F.16: The effect of firing costs: Results across industries with larger declines in blue-collar employment share

	TFP	ln(Separations)	ln(Entering emp.)	ln(Blue-collar emp.)	ln(White-collar emp.)	ln(Tangible fix.)	ln(Mac., Equip.)	ln(Land, Build., Furn., Other)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Blue-collar x Post	-0.043*** (0.015)	-0.051* (0.028)	-0.093*** (0.031)	0.004 (0.019)	0.071*** (0.016)	0.038 (0.035)	0.010 (0.046)	0.023 (0.042)
Blue-collar x Post x High %blue-collar decline industry	-0.005 (0.018)	-0.010 (0.035)	0.054 (0.038)	-0.033 (0.022)	-0.028 (0.020)	-0.027 (0.042)	-0.014 (0.056)	0.000 (0.050)
Observations	54,452	50,528	49,371	54,452	54,452	54,452	51,939	54,150
R-squared	0.827	0.769	0.736	0.965	0.966	0.926	0.903	0.901
Blue-collar x High %blue-collar decline industry (accounting for firms changing industries)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of total factor productivity, employment, and capital over the period of 2009 to 2017. The dependent variables: (1) *TFP*, the residual from the estimation of a Cobb-Douglas production function through the methodology of [Akerberg et al. \(2015\)](#), using blue- and white-collar worker categories as separate inputs, defined in the natural log; (2) *ln(Separations)*, the natural log of the number of employees that left the firm; (3) *ln(Entering emp.)*, the natural log of the number of new hires; (4) *ln(Blue-collar emp.)*, the natural log of the number of blue-collar employees; (5) *ln(White-collar emp.)*, the natural log of the number of white-collar employees; (6) *ln(Tangible fix.)*, the natural log of total tangible fixed assets; (7) *ln(Mac., Equip.)*, the natural log of the sum of machinery and equipment; (8) *ln(Land, Build., Furn., Other)*, the natural log of the sum of land, building, furniture, and other tangible fixed capital. *Blue-collar* is a dummy variable equal to 1 if the firm's pre-period (2009-2012) average share of blue-collar workers was above its sample median, and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. *High %blue-collar decline industry* is equal to 1 if the industry's average change in the blue-collar worker share (weighted by firms' total number of employees in the industry) from 2009 to 2012 is below its sample median—capturing industries with the largest declines in blue-collar worker share—and to 0 otherwise. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.17. Accounting for industry heterogeneity at a more granular level

Table F.17: The effect of firing costs: Granular industry controls

	TFP	ln(Separations)	ln(Entering emp.)	ln(Blue-collar emp.)	ln(White-collar emp.)	ln(Tangible fix.)	ln(Mac., Equip.)	ln(Land, Build., Furn., Other)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Baseline analysis with 4-digit industry x year fixed effects								
Blue-collar x Post	-0.047*** (0.009)	-0.057*** (0.018)	-0.058*** (0.019)	-0.022** (0.011)	0.060*** (0.010)	0.042** (0.021)	0.029 (0.030)	0.041* (0.025)
R-squared	0.839	0.785	0.755	0.967	0.968	0.931	0.908	0.907
B. Defining Blue-collar within 4-digit industries								
Blue-collar (within 4-digit industry) x Post	-0.038*** (0.007)	-0.033** (0.014)	-0.044*** (0.016)	-0.012 (0.008)	0.053*** (0.008)	0.026 (0.016)	0.013 (0.024)	0.033* (0.019)
R-squared	0.839	0.785	0.755	0.967	0.968	0.931	0.908	0.907
Observations	53,987	50,046	48,872	53,987	53,987	53,987	51,470	53,688
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
4-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of total factor productivity, employment, and capital over the period of 2009 to 2017. The dependent variables: (1) *TFP*, the residual from the estimation of a Cobb-Douglas production function through the methodology of [Akerberg et al. \(2015\)](#), using blue- and white-collar worker categories as separate inputs, defined in the natural log; (2) *ln(Separations)*, the natural log of the number of employees that left the firm; (3) *ln(Entering emp.)*, the natural log of the number of new hires; (4) *ln(Blue-collar emp.)*, the natural log of the number of blue-collar employees; (5) *ln(White-collar emp.)*, the natural log of the number of white-collar employees; (6) *ln(Tangible fix.)*, the natural log of total tangible fixed assets; (7) *ln(Mac., Equip.)*, the natural log of the sum of machinery and equipment; (8) *ln(Land, Build., Furn., Other)*, the natural log of the sum of land, building, furniture, and other tangible fixed capital. In Panel A (Panel B), *Blue-collar* is a dummy variable equal to 1 if the firm's pre-period average share of blue-collar workers was above its sample median (above within 4-digit industry median), and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.18. Additional tests

In Table F.18, we carry out a set of additional robustness checks to confirm the validity of our main estimate in Table 6.

Column (1) further restricts our main model by including NACE 2-digit industry $\times$ province $\times$ year fixed effects that net out any variation that is common to all firms in the same industry and location during the same year.⁷ Column (2) even further includes NACE 4-digit industry $\times$ province $\times$ year fixed effects. Including these additional fixed effects neither alters the sign nor the significance of the main result.

Columns (3) and (4) address the concern that standard errors from panel data models may be subject to autocorrelation. As a solution, Bertrand et al. (2004) suggest collapsing time series data into two periods (a pre- and a post-period) around the event. Accordingly, we conduct the estimation on the collapsed data where we first-difference the dependent variable (and thus take the difference between the post- and pre-period). As such, the blue-collar dummy is the main difference-in-differences indicator here. In column (3), we include NACE 2-digit industry fixed effects and cluster standard errors at the same level; column (4) does the same using the 4-digit industry classification. The coefficients of interest in both columns are negative and significant at the 1% confidence level, with magnitudes comparable to those from the panel data estimations.

Column (5) estimates our baseline specification but clusters standard errors at the NACE 2-digit industry level, instead of at the firm level, to allow for the correlation of shocks within an industry. The estimated effect remains significant at the 1% confidence level.

Column (6) bootstraps our entire procedure, re-estimating TFP and re-running the DiD regression, with 1,000 replications. Given that TFP is an estimated outcome, any potential estimation error is absorbed into the regression error term, making our estimates consistent under our baseline specification. However, because this first-stage uncertainty may lead to understated standard errors, we perform bootstrapping. The resulting effect remains very similar to our baseline estimate.

Column (7) includes the interactions of the time-invariant pre-period control dummies and the post dummy.⁸ This addresses the possible concern that firm-specific factors might be correlated with the firm's workforce composition (i.e., selection into blue- and white-collar firm groups). The inclusion of these controls yields an estimate that is very similar to our main result.

⁷There are 10 provinces in Belgium, namely Antwerp, East Flanders, Flemish Brabant, Limburg, West Flanders, Hainaut, Liège, Luxembourg, Namur, Walloon Brabant. On top of that, we separately treat the Brussels Capital Region as a province and take it out of Flemish Brabant.

⁸For example, for *size*, we define a dummy that is equal to 1 if the firm's pre-period average assets were above its sample median, and to 0 otherwise. We similarly create dummies also for *age*, *leverage*, *EBITDA*, *cash holdings*, and *capital-to-labor*. We then interact these dummies with the post dummy and include them in Equation (3) as explanatory variables.

Column (8) defines the blue-collar dummy based on the firm's share of blue-collar workers at the end of 2012, rather than the average pre-period (2009-2012) share. The estimated effect remains qualitatively similar.

Table F.18: Firing costs and productivity: Additional tests

	2-digit industry x province FEs	4-digit industry x province FEs	Collapsed post minus collapsed pre	Collapsed post minus collapsed pre	Clustering standard errors at the industry-level	Bootstrapping	Pre-period control dummies x Post	Treatment based on 2012
	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Blue-collar x Post	-0.044*** (0.009)	-0.043*** (0.011)			-0.048*** (0.008)	-0.046*** (0.009)	-0.043*** (0.008)	-0.037*** (0.008)
Blue-collar			-0.050*** (0.017)	-0.037*** (0.012)				
Observations	53,641	46,995	6,822	6,053	54,452	54,452	54,452	54,452
R-squared	0.839	0.872	0.098	0.218	0.826	0.919	0.828	0.826
Pre-period control dummies x Post	No	No	No	No	No	No	Yes	No
Firm FE	Yes	Yes	No	No	Yes	Yes	Yes	Yes
2-digit industry x year FE	No	No	No	No	Yes	Yes	Yes	Yes
2-digit industry x province FE	No	No	Yes	No	No	No	No	No
2-digit industry x province x year FE	Yes	No	No	No	No	No	No	No
4-digit industry x province FE	No	No	No	Yes	No	No	No	No
4-digit industry x province x year FE	No	Yes	No	No	No	No	No	No

This table reports difference-in-differences estimates of total factor productivity over the period of 2009 to 2017. The dependent variable, *TFP*, is the residual from the estimation of a Cobb-Douglas production function through the methodology of [Akerberg et al. \(2015\)](#), using blue- and white-collar worker categories as separate inputs, defined in the natural log. In columns (4) and (5), the data is collapsed around the event (as opposed to using annual data), and the dependent variable is first differenced. In columns (1)-(7) (in column (8)), *Blue-collar* is a dummy variable equal to 1 if the firm's average share of blue-collar employees over 2009-2012 (only in 2012) was above its sample median, and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. Column (7) includes the interactions of *Post* and time-invariant pre-period control dummies (*Size*, *Age*, *Leverage*, *EBITDA-to-assets*, *Cash holdings*, and *Capital-to-labor*). E.g., for *Size*, we define a dummy that is equal to 1 if the firm's average assets over the pre-period were above its sample median, and to 0 otherwise. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). Standard errors (in parentheses) are clustered at the firm level in columns (1)-(2) & (6)-(8), 2-digit industry level in columns (3) and (5), and 4-digit industry level in column (4). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.19. Results across firms with low average cost per employee

During our sample period (2009–2017), employers benefited from reductions in social security contributions for low-wage workers. Below, we provide the corresponding salary cutoffs for the reductions, the standard employer contribution rates, and the reduced rates after applying the reductions:

Worker type	Annual gross salary threshold (€)	Employer contribution Rate: standard	Employer contribution rate: effective (after reduction)
Before 1 April 2016			
Blue-collar workers	€22,241.96	≈34%	≈27%
White-collar workers	€22,241.96	≈31%	≈25%
After 1 April 2016			
Blue-collar workers	€27,600.00	≈32%	≈24%
White-collar workers	€27,600.00	≈30%	≈23%

Thanks to the reductions, an employer could save up to around €1,500 (€1,300) per year in contributions for a blue-collar (white-collar) worker before 1 April 2016, and up to around €2,200 (€1,900) per year after 1 April 2016.⁹ While the differences in saving rates across worker types are not substantial, the reductions might benefit blue-collar workers more, as they traditionally have lower salaries (Statbel, 2024). For this reason, this policy may have created a wedge in the demand for the two groups and thus potentially confounded our estimates.

To examine whether reductions in employer contributions for low-wage workers influenced our results, we analyze how the effects vary across low-wage firms. We do so by interacting the coefficients of interest in Equation (3) with a *low wage* firm dummy equal to 1 if the firm’s annual average employee cost in 2012 was below its sample median, and to 0 otherwise. In our sample, both the mean and median employee costs for *low wage* firms are around €43,000, capturing firms that predominantly employ low-wage workers.¹⁰ As presented in Table F.19, new hires declined less for low-wage firms, but we do not find statistically significant evidence that these firms experienced a smaller decline in TFP compared to their high-wage counterparts. Overall, our findings suggest that the benefits for employers related to low-wage workers did not largely drive our results.

⁹In 2018, salary cutoffs increased further, and effective employer contribution rates also declined. We do not discuss these changes in detail for brevity, as they fall outside our sample period.

¹⁰Our results remain unchanged when we instead define *low wage* firms as those with annual average employee costs below the 25th percentile of the distribution as of the end of 2012.

Table F.19: The effect of firing costs: Results across low-wage firms

	TFP	ln(Separations)	ln(Entering emp.)	ln(Blue-collar emp.)	ln(White-collar emp.)	ln(Tangible fix.)	ln(Mac., Equip.)	ln(Land, Build., Furn., Other)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Blue-collar x Post	-0.048*** (0.010)	-0.081*** (0.022)	-0.076*** (0.025)	-0.015 (0.014)	0.039*** (0.013)	0.038 (0.026)	0.019 (0.036)	0.027 (0.030)
Low wage x Post	0.001 (0.011)	0.050** (0.022)	-0.076*** (0.023)	0.038*** (0.014)	-0.013 (0.012)	0.021 (0.025)	0.005 (0.037)	0.025 (0.029)
Blue-collar x Post x Low wage	-0.000 (0.014)	0.016 (0.030)	0.066** (0.033)	-0.021 (0.018)	0.027 (0.017)	-0.038 (0.034)	-0.033 (0.050)	-0.018 (0.041)
Observations	54,452	50,528	49,371	54,452	54,452	54,452	51,939	54,150
R-squared	0.826	0.770	0.736	0.965	0.966	0.926	0.903	0.901
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of total factor productivity, employment, and capital over the period of 2009 to 2017. The dependent variables: (1) *TFP*, the residual from the estimation of a Cobb-Douglas production function through the methodology of [Akerberg et al. \(2015\)](#), using blue- and white-collar worker categories as separate inputs, defined in the natural log; (2) *ln(Separations)*, the natural log of the number of employees that left the firm; (3) *ln(Entering emp.)*, the natural log of the number of new hires; (4) *ln(Blue-collar emp.)*, the natural log of the number of blue-collar employees; (5) *ln(White-collar emp.)*, the natural log of the number of white-collar employees; (6) *ln(Tangible fix.)*, the natural log of total tangible fixed assets; (7) *ln(Mac., Equip.)*, the natural log of the sum of machinery and equipment; (8) *ln(Land, Build., Furn., Other)*, the natural log of the sum of land, building, furniture, and other tangible fixed capital. *Blue-collar* is a dummy variable equal to 1 if the firm's pre-period (2009-2012) average share of blue-collar workers was above its sample median, and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. *Low wage* is equal to 1 if the firm's average wage cost in 2012 was below its sample median, and to 0 otherwise. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.20. Results within initially exempt industries

Table F.20: The effect of firing costs: Results within initially exempt industries

A. Main estimates

	TFP	Ln(Separations)	Ln(Entering emp.)	ln(Blue- collar emp.)	ln(White- collar emp.)	Ln(Tangible fix.)	Ln(Mac., Equip.)	ln(Land, Build., Furn., Other)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Blue-collar x Post	-0.037** (0.015)	-0.059* (0.031)	-0.099*** (0.035)	-0.029 (0.019)	0.074*** (0.019)	-0.031 (0.043)	-0.084 (0.059)	0.007 (0.051)
Observations	8,746	8,239	8,059	8,746	8,746	8,746	8,329	8,726
R-squared	0.713	0.787	0.738	0.963	0.964	0.913	0.883	0.880
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(Continued)

B. Dynamic estimates

	TFP	Ln(Separations)	Ln(Entering emp.)	ln(Blue-collar emp.)	ln(White-collar emp.)	Ln(Tangible fix.)	Ln(Mac., Equip.)	ln(Land, Build., Furn., Other)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Blue-collar x 2009 dummy	0.037 (0.024)	-0.033 (0.054)	-0.004 (0.062)	-0.033 (0.025)	-0.012 (0.025)	0.034 (0.051)	0.042 (0.084)	-0.004 (0.063)
Blue-collar x 2010 dummy	-0.006 (0.018)	-0.062 (0.049)	0.020 (0.055)	-0.022 (0.019)	-0.027 (0.021)	0.013 (0.043)	0.078 (0.069)	0.004 (0.053)
Blue-collar x 2011 dummy	0.011 (0.017)	0.008 (0.045)	0.011 (0.049)	-0.012 (0.013)	-0.022 (0.015)	-0.012 (0.029)	0.025 (0.047)	0.003 (0.044)
Blue-collar x 2013 dummy	-0.013 (0.018)	-0.016 (0.043)	-0.036 (0.050)	-0.034** (0.016)	0.020 (0.014)	-0.033 (0.030)	-0.030 (0.045)	0.008 (0.040)
Blue-collar x 2014 dummy	0.014 (0.020)	-0.085* (0.049)	-0.086 (0.055)	-0.038* (0.021)	0.037* (0.019)	-0.049 (0.043)	-0.042 (0.063)	-0.005 (0.055)
Blue-collar x 2015 dummy	-0.038* (0.023)	-0.069 (0.050)	-0.140** (0.058)	-0.045** (0.022)	0.063*** (0.022)	-0.044 (0.049)	-0.056 (0.074)	-0.013 (0.060)
Blue-collar x 2016 dummy	-0.074*** (0.027)	-0.122** (0.054)	-0.161*** (0.060)	-0.062** (0.025)	0.094*** (0.027)	0.030 (0.059)	-0.095 (0.088)	0.065 (0.070)
Blue-collar x 2017 dummy	-0.051* (0.027)	-0.128** (0.056)	-0.042 (0.059)	-0.046* (0.028)	0.112*** (0.033)	-0.001 (0.062)	-0.039 (0.099)	-0.005 (0.074)
Observations	8,746	8,239	8,059	8,746	8,746	8,746	8,329	8,726
R-squared	0.714	0.787	0.738	0.963	0.964	0.913	0.883	0.880
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of total factor productivity, employment, and capital over the period of 2009 to 2017, only for the construction, upholstery and woodworking industries (NACE codes 41–43, 16, and 31). Panels A and B show the main estimates and dynamic estimates, respectively. The dependent variables: (1) *TFP*, the residual from the estimation of a Cobb-Douglas production function through the methodology of [Akerberg et al. \(2015\)](#), using blue- and white-collar worker categories as separate inputs, defined in the natural log; (2) *ln(Separations)*, the natural log of the number of employees that left the firm; (3) *ln(Entering emp.)*, the natural log of the number of new hires; (4) *ln(Blue-collar emp.)*, the natural log of the number of blue-collar employees; (5) *ln(White-collar emp.)*, the natural log of the number of white-collar employees; (6) *ln(Tangible fix.)*, the natural log of total tangible fixed assets; (7) *ln(Mac., Equip.)*, the natural log of the sum of machinery and equipment; (8) *ln(Land, Build., Furn., Other)*, the natural log of the sum of land, building, furniture, and other tangible fixed capital. *Blue-collar* is a dummy variable equal to 1 if the firm's pre-period (2009–2012) average share of blue-collar workers was above its sample median, and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. Year dummies are equal to 1 for observations in the given year, and to 0 otherwise. E.g., *2009 dummy* is equal to 1 for observations in the year of 2009, and to 0 for other years. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009–2012) and at least one observation in the post-period (2013–2017). Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.21. Firing costs, input choices, and bias in estimating TFP when using a pooled-workers production function

In this section, we consider a measure of TFP obtained after estimating the production function with the natural log of the firm's total number of workers, instead of separately including the natural logs of blue- and white-collar workers. Table F.1 shows that the production elasticities of blue- and white-collar workers are substantially different. Furthermore, it is plausible to assume that blue- and white-collar workers are complementary rather than substitute inputs in the production process. It follows that a production function ignoring this distinction is likely to be misspecified. Below, we first derive analytically the bias in estimating TFP when worker types are pooled in the production function. Then, we compare our benchmark results with those obtained when pooling worker types.

Suppose a researcher only observes total employment $L = W + B$ and assumes that the production function is:

$$VA = TFP^{biased} \cdot K^{\tilde{\alpha}} L^{1-\tilde{\alpha}} \quad (5)$$

where we allow for $\tilde{\alpha}$ to be different from α in Equation (2) due to the misspecification of the production function. Revenue TFP will be measured as:

$$\log TFP^{biased} = \log VA - \tilde{\alpha} \log K - (1 - \tilde{\alpha}) \log L \quad (6)$$

while the true revenue TFP can be obtained from Equation (2):

$$\log TFP^{true} = \log VA - \alpha \log K - \gamma(1 - \alpha) \log W - (1 - \gamma)(1 - \alpha) \log B$$

The bias Ω is the difference between both revenue TFP expressions, $\Omega \equiv \log TFP^{biased} - \log TFP^{true}$, which implies:

$$\Omega = (\alpha - \tilde{\alpha}) \log K + (1 - \alpha) \log W^\gamma B^{1-\gamma} - (1 - \tilde{\alpha}) \log(W + B)$$

If the error in the estimated elasticity $\hat{\alpha} = \alpha - \tilde{\alpha}$ is small, the bias is approximately equal to:

$$\Omega \approx (1 - \alpha) \ln \left[\frac{W^\gamma B^{1-\gamma}}{W + B} \right], \quad (7)$$

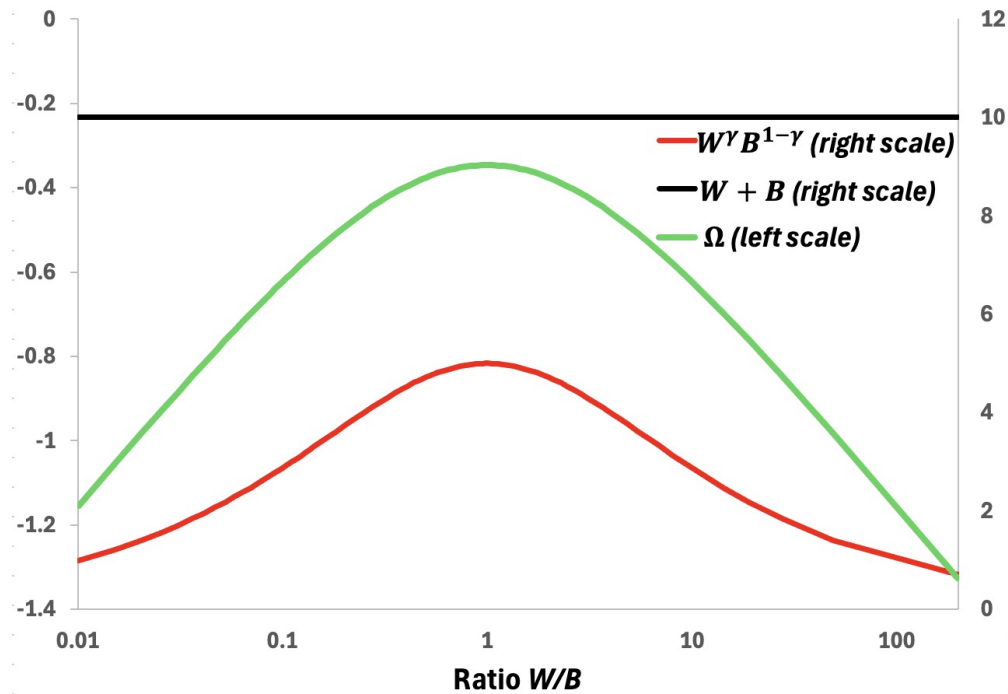
which, using $r = \frac{W}{B}$, can be written as

$$\Omega \approx (1 - \alpha) \ln \left[\frac{r^\gamma}{1 + r^\gamma} \right]$$

It follows that Ω is always negative, since the term $\left[\frac{r^\gamma}{1+r^\gamma}\right]$ is smaller than one. Furthermore, it is easy to see that Ω is smaller in absolute value when $\frac{W}{B} = \frac{\gamma}{1-\gamma}$. In order to understand the intuition, assume for simplicity that γ is equal to 0.5, and therefore that Ω is minimized when $W = B$. In this case, notice that the marginal blue- and white-collar workers have the same marginal return. Therefore, adding these workers in the biased production function (5), which implies that different workers are considered equally productive at the margin because they are assumed to be perfect substitutes, generates a relatively small misspecification error. However, now suppose the number of white-collar workers increases by one. This implies W increases by 1 in Equation (2), while L increases by one in Equation (5). It is easy to see that the misspecified Equation (5) implies output should grow by more than the correct increase implied by (2), and this difference becomes larger as $\frac{W}{B}$ increases further. The same reasoning can be applied to any deviation from $W = B$, implying that the bias increases whenever $\frac{W}{B}$ deviates from 1, or more generally, from $\frac{\gamma}{1-\gamma}$ (when $\gamma \neq 0.5$). In other words, the more the ratio $\frac{W}{B}$ becomes distant from $\frac{\gamma}{1-\gamma}$, the more adding one additional worker in Equation (5) implies a larger error relative to adding one in Equation (2).

This is shown graphically in the figure below, which compares the value of the numerator $W^\gamma B^{1-\gamma}$ and the denominator $W + B$ of the term in square brackets in Equation (7), for different values of W and B , so that the sum is constant and equal to 10, while the ratio $\frac{W}{B}$ goes from 0.1 to 200 (the x-axis scale is logarithmic). The chosen parameter values are $\gamma = 0.5$ and $\alpha = 0.5$. The figure shows how the numerator is largest when $\frac{W}{B} = \frac{\gamma}{1-\gamma} = 1$. When $\frac{W}{B}$ deviates from 1 in either direction, the value of the numerator declines because of the imbalance between the two complementary inputs. Therefore, the ratio $\frac{W^\gamma B^{1-\gamma}}{W+B}$ also declines and, since it is smaller than one, the Bias Ω becomes more negative and larger in absolute value.

Bias Ω , an illustrative example with $\gamma = 0.5$ and $W + B = 10$



Why is this bias relevant for our exercise? Because firing costs alter the optimal ratio between factor inputs, and imply that the ratio $\frac{W}{B}$ changes relative to $\frac{\gamma}{1-\gamma}$, thereby changing the bias. Since we find that firing costs change $\frac{W}{B}$ differentially for blue- and white-collar firms, they also change the bias differentially, and this effect would distort the measured effect of the reform on productivity when using a production function that pools worker types. This can, in part, explain why, when using blue- and white-collar workers pooled in Table F.21, columns (3) and (4), we no longer find a negative effect of the reform.

Table F.21: Firing costs and productivity: Using separate employment inputs versus total employment input

	Separate emp. inputs		Combined emp. input	
	TFP	TFP	TFP	TFP
	(1)	(2)	(3)	(4)
Blue-collar x Post	-0.048*** (0.008)		0.002 (0.008)	
Blue-collar x 2009 dummy		0.015 (0.013)		-0.001 (0.012)
Blue-collar x 2010 dummy		-0.005 (0.011)		-0.020* (0.010)
Blue-collar x 2011 dummy		-0.006 (0.009)		-0.016* (0.009)
Blue-collar x 2013 dummy		-0.039*** (0.009)		-0.009 (0.008)
Blue-collar x 2014 dummy		-0.039*** (0.010)		0.001 (0.009)
Blue-collar x 2015 dummy		-0.043*** (0.012)		-0.006 (0.011)
Blue-collar x 2016 dummy		-0.060*** (0.013)		-0.011 (0.013)
Blue-collar x 2017 dummy		-0.064*** (0.014)		-0.012 (0.013)
Observations	54,452	54,452	54,391	54,391
R-squared	0.826	0.826	0.859	0.859
Firm FE	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of total factor productivity over the period of 2009 to 2017. The dependent variable, *TFP*, is the residual from the estimation of a Cobb-Douglas production function through the methodology of [Akerberg et al. \(2015\)](#), defined in the natural log. When estimating the production function, blue- and white-collar worker categories are used as separate inputs in columns (1) and (2), and these worker categories are pooled into a single employment input in columns (3) and (4). *Blue-collar* is a dummy variable equal to 1 if the firm's pre-period (2009-2012) average share of blue-collar workers was above its sample median, and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. Year dummies are equal to 1 for observations in the given year, and to 0 otherwise. E.g., *2009 dummy* is equal to 1 for observations in the year of 2009, and to 0 for other years. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.22. The effect on firm exit & entry

In addition to examining changes in firms' employment levels from the pre- to the post-period, we also investigate the effect of the reform on firm exit and entry. To do so, we run the following regression at the industry-level:

$$Y_{s,t} = \alpha \text{Blue-collar}_s * \text{Post}_t + \mu_s + \theta_t + \varepsilon_{s,t} \quad (8)$$

where the dependent variable is either *exit share* (defined as the ratio of the total number of firm exits to the total number of firms in industry s and year t), or *entry share* (defined as the ratio of the total number of firm entries to the total number of firms in industry s and year t). We define firm exit based on legal status, identifying firms that ceased activity due to bankruptcy, liquidation or judicial dissolution¹¹, whereas entry is defined by the year of incorporation. *Blue-collar* $_s$ is a dummy variable equal to 1 if the industry's weighted average share of blue-collar workers (where weights correspond to firms' total number of employees) over the pre-period (2009-2012) was above the sample median, and to 0 otherwise.¹² *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. We include industry (μ_s) and time (θ_t) fixed effects. Standard errors are clustered at the industry level.

For this analysis, we focus on the industries used in our baseline analysis (see Table F.1) but include all firms without applying additional firm-level restrictions—that is, we do not require firms to be observed in both 2012 and 2014, to have at least five employees in 2012, or to employ both a blue-collar and a white-collar worker.

Table F.22 presents the results from the estimation of Equation (8) at the 2-digit (columns (1) and (3)) and 3-digit (columns (2) and (4)) industry levels. The evidence indicates that the reform increased the exit share by 0.2 and 0.3 percentage points—corresponding to 12% and 18% increases relative to the sample average of 1.7%—at the 2- and 3-digit industry levels, respectively. However, only the latter effect is significant at the 5% confidence level. In contrast, we do not observe any significant impact on firm entry. Overall, these results provide some evidence that increased firing costs lead to an increase in firm exits.

¹¹Our definition of firm exit does not include voluntary exits, but our results are robust to their inclusion.

¹²Our results are qualitatively similar if we construct the industry-level treatment based on the simple average of firms' blue-collar worker shares within each industry.

Table F.22: The effect of firing costs on firm exit & entry

	2-digit industry	3-digit industry	2-digit industry	3-digit industry
	Exit share		Entry share	
	(1)	(2)	(3)	(4)
Blue-collar (Industry level) x Post	0.002 (0.001)	0.003** (0.002)	-0.000 (0.001)	0.000 (0.002)
Observations	447	1,470	447	1,470
R-squared	0.835	0.484	0.500	0.296
Industry FE	Yes (2-digit)	Yes (3-digit)	Yes (2-digit)	Yes (3-digit)
Year FE	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of firm exit and entry over the period of 2009 to 2017. In columns (1) and (2), the dependent variable, *exit share*, is the ratio of the total number of firm exits (defined through firms' legal status) to the total number of firms in the industry in a given year. In columns (3) and (4), the dependent variable, *entry share*, is the ratio of the total number of firm entries (defined through the firm's year of incorporation) to the total number of firms in the industry in a given year. *Blue-collar* is a dummy variable equal to 1 if the industry's weighted average share of blue-collar workers (where weights correspond to firms' total number of employees) over the pre-period (2009-2012) was above the sample median, and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. Supplemental Appendix A defines all variables. Standard errors (in parentheses) are clustered at the industry level used in the analysis. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.23. The role of credit access

In this section, we investigate how the effect of firing costs on TFP varies with financial constraints. Because financially unconstrained firms are better able to pay larger dismissal costs to replace their inefficient workers, they may experience a smaller decline in productivity when firing costs increase. We capture firms' financial constraints in our sample by estimating the availability of bank credit from loan-level data. Because the firms in our sample are private and relatively small, bank credit is their most important source of external finance. Our measure differs from the existing literature, which has mainly used *cash* as a proxy for financial constraints (e.g., Cingano et al., 2010, 2016). Despite its popularity, however, cash may not truly reflect firms' financial constraints, since it could also reflect the anticipation of future investment or precautionary motives (e.g., Berg, 2018). To address the resulting endogeneity concerns, we therefore use loan-level information from the Belgian credit register and estimate credit supply shocks that firms experience from their lenders by using the approach of Degryse et al. (2019).

Data. To estimate credit supply shocks that firms experience from their lenders, we obtain monthly bank-firm level loan data from the Central Corporate Credit Register in Belgium (National Bank of Belgium, 2012). The availability of such granular data is crucial to disentangle firms' credit demand from banks' credit supply. All financial institutions established in Belgium and licensed by the National Bank of Belgium have to report to the credit register on all debtors whose total borrowing exceeds €25,000. We focus only on banks and retain only those that have at least 30 firms in their lending portfolio. We also take into account bank mergers and acquisitions when measuring loan growth rates. In total, we utilize granted loans from 57 banks, and match them with borrowers' balance sheets.

Estimation of credit supply shocks. We construct firm-level credit shocks using the approach of Degryse et al. (2019). We first run the following regression on a sample of borrowing firms at the bank-firm-month level separately for each pre-period year:

$$\Delta Lending_{bft} = \alpha_{lst} + \beta_{bt} + error\ term \quad (9)$$

where $\Delta Lending_{bft}$ is the annual percentage growth rate of credit at the intensive margin at month t , α_{lst} are location-industry-size-time (LSST) dummies that capture credit demand under the assumption that firms with similar size in the same industry and location in a given time have similar credit demand, and β_{bt} are bank-time dummies that capture time-varying credit supply shocks.¹³ We estimate Equation (9) by omitting one firm dummy, and demean

¹³Since Gan (2007) and Khwaja and Mian (2008), contemporary banking research has mainly relied on firm-time fixed effects to control for credit demand in samples where firms borrow from multiple banks. However, the Belgian economy is comprised vastly of single-bank firms to which the firm-time fixed effects approach is not applicable. Degryse et al. (2019) therefore suggest using LSST fixed effects instead of firm-time fixed effects to control for credit demand. They compare estimations with LSST fixed effects to

the estimated bank credit supply dummies (i.e., $\tilde{\beta}_{bt} = \hat{\beta}_{bt} - \bar{\beta}_t$) to leave out the omitted firm dummy effect. Then, we create yearly firm-level credit supply measures by averaging the demeaned estimated monthly bank credit supply dummies, weighted by each lender's share in the firm's borrowing portfolio.

Results. Using TFP as the dependent variable, we then estimate Equation (3) by splitting the sample at the median of the firms' pre-period credit supply measure. Because credit supply conditions likely matter more for firms with less spare debt capacity, we also split the sample at the median of firms' long-term debt-to-fixed assets ratio, calculated in 2012 end year. Table F.23 illustrates the results. Our sample is now smaller in size as we focus only on firms that borrowed before the legal change. Columns (1)-(3) exhibit the results for firms with a lower long-term debt to fixed assets ratio (i.e., firms with more spare debt capacity). Columns (4)-(6) illustrate the results for firms with a higher long-term debt to fixed assets ratio (i.e., firms with limited spare debt capacity). Within each group, we demonstrate the results for the entire group of firms, firms facing tight credit supply conditions (i.e., those experiencing low credit supply shocks), and firms enjoying lax credit conditions (i.e., those experiencing high credit supply shocks), respectively. The results show that credit supply conditions do not seem to matter for firms with higher spare debt capacity. In contrast, among firms with lower spare debt capacity, firms enjoying lax credit supply conditions on average experienced a smaller decline in TFP than firms facing tight credit supply conditions. Overall, these results suggest that relaxed credit supply conditions may help firms efficiently cope with increases in firing costs.

those with firm-time fixed effects and show that LSST fixed effects are indeed capable of controlling for credit demand. See Güler et al. (2021) for a review of the corresponding literature.

Table F.23: Firing costs and productivity: The role of credit access

	Higher debt capacity			Lower debt capacity		
	Full sample	Low credit supply	High credit supply	Full sample	Low credit supply	High credit supply
	TFP	TFP	TFP	TFP	TFP	TFP
	(1)	(2)	(3)	(4)	(5)	(6)
Blue-collar x Post	-0.026* (0.015)	-0.031 (0.022)	-0.031 (0.020)	-0.041*** (0.012)	-0.049*** (0.015)	-0.027 (0.018)
Observations	16,764	7,849	8,855	22,001	11,554	10,391
R-squared	0.830	0.826	0.843	0.850	0.852	0.855
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
2-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes

This table reports difference-in-differences estimates of total factor productivity across credit constraints over the period of 2009 to 2017. The sample only includes firms that borrowed during the pre-period. A firm is assumed to have *higher debt capacity* (*lower debt capacity*) if its long-term financial debt-to-fixed assets ratio in 2012 end year was below (above) the sample median. *Low credit supply* (*High credit supply*) sample includes firms whose estimated credit supply shock over the pre-period (2009-2012) was below (above) its sample median. The dependent variable, *TFP*, is the residual from the estimation of a Cobb-Douglas production function through the methodology of [Akerberg et al. \(2015\)](#), using blue- and white-collar worker categories as separate inputs, defined in the natural log. *Blue-collar* is a dummy variable equal to 1 if the firm's pre-period (2009-2012) average share of blue-collar workers was above its sample median, and to 0 otherwise. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). Standard errors (in parentheses) are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

F.24. Cross-country analysis: Belgian versus German and French firms

In this section, we compare Belgian firms to German and French firms (i.e., firms in the two largest neighboring countries of Belgium) that are not affected by the Belgian labor legislation and that, to the best of our knowledge, did not experience a significant shock (legal or other) that would affect the composition of their workforce during our sample period. This analysis is interesting for two reasons. First, it helps us to separately assess the effect of the new Belgian labor legislation on blue- and white-collar firms. Second, it helps us to address potential concerns that financial support programs, such as the Outright Monetary Transactions program, implemented in response to the sovereign debt crisis, might have differently affected blue- and white-collar firms.

Data. We collect data on German and French firms' financial accounts and employment from the ORBIS database provided by BvD ([Bureau van Dijk, 2018](#)). As in our main sample, we use historical files and incorporate both surviving and failed firms into our analysis. Unlike the Bel-first database, however, ORBIS does not provide information on German and French firms' workforce composition. For this reason, in this analysis, we compare Belgian firms in blue-collar industries to German and French firms in the same industries, assuming that workforce composition in Belgium, Germany, and France is similar within the same industries. We also conduct the same comparison for firms in white-collar industries.

Methodology. We estimate the following difference-in-differences model separately for blue-collar industries (i.e., NACE 4-digit industries whose pre-period aggregate share of blue-collar workers, measured as the ratio of total blue-collar workers to total workers in the industry, was above the sample median) and white-collar industries (i.e., NACE 4-digit industries whose corresponding share was below the sample median):

$$\ln(\text{Value added})_{i,s,c,t} = \beta \text{Belgian}_c * \text{Post}_t + \Pi \text{Controls}_{c,t} + \theta_i + \mu_{st} + \varepsilon_{i,s,c,t} \quad (10)$$

where the dependent variable is the natural log of value-added for firm i , in industry s , country c , and year t . Belgian_c is a dummy variable equal to 1 if the firm is located in Belgium, and to 0 if the firm is located in Germany or France. Post_t is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. $\text{Controls}_{c,t}$ include *GDP growth* and *GDP per capita* to account for time-varying macroeconomic conditions across countries.¹⁴ This is because we cannot include country-time fixed effects in our model, as they would subsume the interaction term (i.e., our main variable of interest). We saturate our model with firm fixed effects (θ_i) and 4-digit industry $\times$ year

¹⁴We obtain data on *GDP growth* and *GDP per capita* from the World Bank ([World Bank, 2017](#)).

(μ_{st}) fixed effects. Lastly, standard errors are clustered at the country $\times$ 4-digit industry level.¹⁵

Note that we do not use TFP as the dependent variable because we are not able to estimate elasticities separately for blue- and white-collar workers due to data limitations for German and French firms, which is crucial in our setting (see Sections 5.6 and F.21 for a detailed discussion).

Our intensive set of fixed effects considerably accounts for the heterogeneity between Belgian firms (i.e., treated firms) and German and French firms (i.e., control firms). Additionally, since the treated and control firms are drawn from different countries, we implement a propensity score matching procedure to improve comparability between these two groups. To obtain propensity scores, we consider 2012 as a baseline year and estimate a logit regression using *Belgian* as the dependent variable. As explanatory variables, we include *size*, *age*, *leverage*, *cash holdings*, and *capital-to-labor* among baseline firm controls. To further ensure that our matched samples exhibit similar pre-treatment trends in labor and capital, we also include the log growth of tangible fixed assets, the log growth of the total number of employees, as well as both the lagged and contemporaneous values of the natural log of the total number of employees. Finally, we include NACE 4-digit industry dummies to control for industry-level differences. Then, we carry out a nearest neighbor matching of propensity scores with exact matches in NACE 4-digit industries. We match each Belgian firm with a non-Belgian firm, and allow that a non-Belgian firm can be used as a match for multiple Belgian firms.¹⁶ Table F.24.1, in Panel A, demonstrates the summary statistics for the full baseline (i.e., unmatched) sample. Panel B compares the pre-treatment sample means of Belgian and non-Belgian firms in both the unmatched and matched samples. As evidenced by the t-tests and the standardized mean differences, the matching procedure improves the balance in pre-period covariates between the Belgian and non-Belgian groups, relative to the unmatched sample.

Results. Panel A of Table F.24.2 illustrates the results from the estimation of Equation (10). Columns (1) and (2) use the unmatched sample and report the results for blue-collar and white-collar industries, respectively. Columns (3) and (4) use the matched sample and repeat the same estimations. The point estimates for blue-collar industries are negative and statistically significant, with magnitudes that are consistent across both the unmatched and matched samples. Specifically, the evidence indicates that Belgian firms in blue-collar industries (i.e., those facing an increase in firing costs) on average experienced a 2% decline in value-added relative to their German and French counterparts. This result is consistent with the estimated effect from the within-Belgium analysis (see Column (8) of Table 5).

At the same time, the point estimates for firms in white-collar industries are not significant,

¹⁵We obtain nearly similar results when we cluster standard errors at the firm level.

¹⁶Our results are also robust when two non-Belgian firms are retained for each Belgian firm.

suggesting that the reduction in the notice periods for white-collar workers did not lead to an increase in output. This is consistent with the possibility that the reduction in notice periods might have been offset by increased protection through other channels, including the abolition of trial periods, improved outplacement rights, and enhanced safeguards against unfair dismissals.

Using the full sample of firms, we also conduct a triple difference-in-difference approach by interacting the Belgian and post dummy variables in Equation (10) with an indicator variable that is equal to 1 if the firm operates in a blue-collar industry, and to 0 if the firm operates in a white-collar industry. For this analysis, we are able to use country $\times$ year fixed effects, as the coefficient of interest now varies at the country-industry-year level. These results are shown in Panel B of Table F.24.2. Columns (1) and (2) demonstrate the estimates from the unmatched sample, without and with the inclusion of the triple interaction terms, respectively. Although the average estimated effect is not significant in the former, the point estimate on the triple interaction term is negative and significant at the 1% confidence level in the latter. This indicates that, after the implementation of the new notice periods, the value-added of Belgian firms relative to non-Belgian firms in blue-collar industries was significantly lower than the value-added of Belgian firms relative to non-Belgian firms in white-collar industries. Column (3) exhibits the dynamic version of the estimation in column (2). These estimates show that the triple interaction terms are significant after, but not before, the introduction of the new notice periods. Finally, columns (4)-(6) repeat the first three estimations using the matched sample, and the results remain consistent.

Overall, we find that Belgian firms in blue-collar industries on average experienced a decrease in output relative to their non-Belgian counterparts, whereas we do not observe any significant effect for firms in white-collar industries. These results corroborate the negative effect of higher firing costs on output identified in the within-Belgium analysis. Moreover, by comparing equally affected European firms within the same industries, our cross-country estimates mitigate the concern that financial programs implemented during the sovereign debt crisis may have confounded our results by differently affecting blue- and white-collar firms.

Table F.24.1: Cross-country analysis of firing costs: Summary statistics

A. Full sample						
	N	Mean	SD	p(25)	p(50)	p(75)
<i>Firm level</i>						
Ln(Value added)	248,139	15.127	1.692	13.739	15.028	16.291
Size	248,139	15.241	1.920	13.701	15.247	16.549
Age	248,139	26.905	21.933	13.000	22.000	35.000
Leverage	248,139	0.630	0.265	0.450	0.631	0.794
EBITDA-to-assets	248,139	0.109	0.122	0.045	0.099	0.168
Cash holdings	248,139	0.149	0.170	0.020	0.083	0.224
Capital-to-labour	248,139	9.392	1.583	8.410	9.427	10.444
<i>Country level</i>						
GDP growth (%)	248,139	0.853	1.763	0.420	0.956	1.949
GDP per capita (in thous. \$)	248,139	39.765	3.639	37.441	39.524	42.291

B. Comparing pre-period sample means for treatment and control firms								
	Non-matched sample				Matched sample			
	Belgian N=20,972	non-Belgian N=94,014	Diff.	SMD	Belgian N=19,835	non-Belgian N=18,666	Diff.	SMD
<i>Firm level</i>								
Ln(Value added)	15.612	14.925	0.687***	0.469	15.612	15.824	-0.212***	-0.151
Size	16.097	14.964	1.133***	0.680	16.098	16.165	-0.067	-0.042
Age	29.326	24.143	5.182***	0.256	29.459	30.171	-0.711	-0.030
Leverage	0.593	0.641	-0.048***	-0.185	0.593	0.615	-0.022***	-0.089
EBITDA-to-assets	0.109	0.113	-0.004***	-0.032	0.110	0.111	-0.001	-0.012
Cash holdings	0.087	0.168	-0.081***	-0.541	0.087	0.095	-0.009***	-0.073
Capital-to-labour	10.295	9.178	1.116***	0.770	10.301	10.294	0.007	0.005
<i>Country level</i>								
GDP growth (%)	0.878	0.666	0.212***	0.099	0.889	0.798	0.091***	0.038
GDP per capita (in thous. \$)	40.363	37.765	2.599***	1.246	40.332	38.423	1.909***	0.840

This table presents summary statistics for the main variables used in the cross-country analysis over the period of 2009 to 2017. Panel A shows the summary statistics for the entire sample. Panel B compares the sample means of Belgian and non-Belgian (German or French) firms in the unmatched and matched samples over the pre-period (2009-2012). *Belgian* is a dummy variable equal to 1 if the firm is located in Belgium, and to 0 if the firm is located in Germany or France. Supplemental Appendix A defines all variables. The sample only contains firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, for *t*-test of whether the Belgian and non-Belgian groups have equal means for a given variable. In our *t*-tests, we cluster standard errors at the firm level to account for that some non-Belgian firms are matched to Belgian firms more than once. The standardized mean difference (SMD) for a variable is calculated as $(Mean_{Belgian} - Mean_{non-Belgian}) / \sqrt{(sd_{Belgian}^2 + sd_{non-Belgian}^2) / 2}$.

Table F.24.2: Cross-country analysis of firing costs: Results

A. Split sample analysis

	Non-matched sample		Matched sample	
	Blue-collar industries	White-collar industries	Blue-collar industries	White-collar industries
	ln(Value added)			
	(1)	(2)	(3)	(4)
Belgian x Post	-0.020*** (0.007)	0.005 (0.006)	-0.027*** (0.009)	0.005 (0.008)
Observations	119,125	129,014	40,973	40,890
R-squared	0.988	0.988	0.981	0.983
Macro controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
4-digit industry x year FE	Yes	Yes	Yes	Yes

(Continued)

B. Triple-difference

	Non-matched sample			Matched sample		
	ln(Value added)					
	(1)	(2)	(3)	(4)	(5)	(6)
Belgian x Post	0.001 (0.006)			-0.009 (0.007)		
Blue-collar industries x Belgian x Post		-0.024** (0.010)			-0.031*** (0.012)	
Blue-collar industries x Belgian x 2009 dummy			0.017 (0.011)			0.019 (0.015)
Blue-collar industries x Belgian x 2010 dummy			0.001 (0.008)			0.000 (0.012)
Blue-collar industries x Belgian x 2011 dummy			-0.006 (0.006)			-0.011 (0.007)
Blue-collar industries x Belgian x 2013 dummy			-0.017*** (0.005)			-0.021** (0.009)
Blue-collar industries x Belgian x 2014 dummy			-0.026*** (0.008)			-0.034*** (0.011)
Blue-collar industries x Belgian x 2015 dummy			-0.024** (0.011)			-0.029** (0.014)
Blue-collar industries x Belgian x 2016 dummy			-0.029** (0.012)			-0.051** (0.020)
Blue-collar industries x Belgian x 2017 dummy			-0.011 (0.014)			-0.009 (0.022)
Observations	248,139	248,139	248,139	81,863	81,863	81,863
R-squared	0.988	0.988	0.988	0.982	0.982	0.982
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
4-digit industry x year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country x year FE	No	Yes	Yes	No	Yes	Yes

This table reports difference-in-differences (Panel A) and triple-difference (Panel B) estimates of value-added over the period of 2009 to 2017. *Blue-collar industries* (*White-collar industries*) are 4-digit industries whose pre-period aggregate share of blue-collar workers (i.e., the ratio of the total number of blue-collar workers to the total number of workers in the industry) was above (below) the sample median. The dependent variable, $\ln(\text{Value added})$, is the natural log of value added. *Belgian* is a dummy variable equal to 1 if the firm is located in Belgium, and to 0 if the firm is located in Germany or France. *Post* is a dummy variable equal to 1 for observations in the period of 2013 to 2017, and to 0 for observations in the period of 2009 to 2012. Year dummies are equal to 1 for observations in the given year, and to 0 otherwise. E.g., *2009 dummy* is equal to 1 for observations in the year of 2009, and to 0 for other years. Macro controls are $GDP\ growth_{t-1}$ and $GDP\ per\ capita_{t-1}$. Supplemental Appendix A defines all variables. The regressions only contain firms that have at least one observation in the pre-period (2009-2012) and at least one observation in the post-period (2013-2017). Standard errors (in parentheses) are clustered at the country $\times$ 4-digit industry level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

References

- Akerberg, D. A., Caves, K., and Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, 83(6):2411–2451.
- Ajzen, M. and Vermandere, C. (2014). Agreement gives equal status to blue- and white-collar workers. January 6. See [here](#).
- Berg, T. (2018). Got rejected? Real effects of not getting a loan. *Review of Financial Studies*, 31(12):4912–4957.
- Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How much should we trust difference-in-differences estimates? *Quarterly Journal of Economics*, 119(1):249–275.
- Bureau van Dijk (2007–2018). Orbis database. <https://orbis.bvdinfo.com/>. Accessed via Moody’s DataHub through KU Leuven institutional subscription on March 19, 2022.
- Cingano, F., Leonardi, M., Messina, J., and Pica, G. (2010). The effects of employment protection legislation and financial market imperfections on investment: Evidence from a firm-level panel of EU countries. *Economic Policy*, 25(61):117–163.
- Cingano, F., Leonardi, M., Messina, J., and Pica, G. (2016). Employment protection legislation, capital investment and access to credit: Evidence from Italy. *Economic Journal*, 126(595):1798–1822.
- Degryse, H., De Jonghe, O., Jakovljević, S., Mulier, K., and Schepens, G. (2019). Identifying credit supply shocks with bank-firm data: Methods and applications. *Journal of Financial Intermediation*, 40:100813.
- Galindo-Rueda, F. and Verger, F. (2016). OECD taxonomy of economic activities based on R&D intensity. https://www.oecd.org/en/publications/oecd-taxonomy-of-economic-activities-based-on-r-d-intensity_5j1v73sqqp8r-en.html. OECD Science, Technology and Industry Working Papers, No. 2016/04.
- Gan, J. (2007). The real effects of asset market bubbles: Loan-and firm-level evidence of a lending channel. *Review of Financial Studies*, 20(6):1941–1973.
- Güler, O., Mariathasan, M., Mulier, K., and Okatan, N. (2021). The real effects of banks’ corporate credit supply: A lit. review. *Economic Inquiry*, 59(3):1252–1285.
- Khwaja, A. I. and Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, 98(4):1413–1442.

- National Bank of Belgium (2009–2012). Belgian corporate credit register. <https://www.nbb.be/en/central-credit-registers/corporate-credit-register-ccr>. Accessed on February 2, 2020.
- Pries, M. and Rogerson, R. (2005). Hiring policies, labor market institutions, and labor market flows. *Journal of Political Economy*, 113(4):811–839.
- Roberts, M. R. and Whited, T. M. (2013). Endogeneity in empirical corporate finance. In *Handbook of the Economics of Finance*, volume 2, pages 493–572. Elsevier.
- Rosenbaum, P. (1995). *Observational Studies*. Applied Mathematical Sciences. Springer.
- Smith, J. A. and Todd, P. E. (2005). Does matching overcome LaLonde’s critique of nonexperimental estimators? *Journal of Econometrics*, 125(1-2):305–353.
- Statbel (2024). Overview of belgian wages and salaries. <https://statbel.fgov.be/en/themes/work-training/wages-and-labourcost/overview-belgian-wages-and-salaries>. Accessed May 7, 2025.
- Wooldridge, J. M. (2009). On estimating firm-level production functions using proxy variables to control for unobservables. *Economics Letters*, 104(3):112–114.
- World Bank (2007–2017). World development indicators. <https://data.worldbank.org/>. Accessed on December 14, 2020.