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// EFFROSYNI ADAMOPOULOU, FRANCESCO MANARESI, OMAR RACHEDI, AND EMIRCAN YURDAGUL

Minimum Wages and Insurance within the Firm

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Effrosyni Adamopoulou Francesco Manaresi

Omar Rachedi Emircan Yurdagul

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Abstract

Minimum wages generate an asymmetric pass-through of firm shocks across workers. We establish this result leveraging employer-employee data on Italian metal-manufacturing firms, which face different wage floors that vary within occupations. In response to negative firm productivity shocks, workers close to the wage floors experience higher job separations but no wage loss. However, the wage of high-paid workers decreases, and more so in firms with higher incidence of minimum wages. A neoclassical model with complementarities across workers with different skills rationalizes these findings. Our results uncover a novel channel that tilts the welfare gains of minimum wages toward low-paid workers.

JEL Codes: E24, E25, E64, J31, J38, J52.
Keywords: Firm productivity shocks, pass-through, employer-employee data, skill complementarities, incomplete-market model.

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*Adamopoulou: University of Mannheim, ZEW, IZA (adamopoulou@uni-mannheim.de); Manaresi: Banca d'Italia (francesco.manaresi@bancaditalia.it); Omar Rachedi: ESADE Business School, Universitat Ramon Llull (omar.rachedi@esade.edu); Emircan Yurdagul: Universidad Carlos III de Madrid, CEPR (eyurdagu@eco.uc3m.es).
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1 Introduction

Firm heterogeneity accounts for a sizable fraction of log-earnings variance (Abowd et al., 1999; Sorkin, 2018; Song et al., 2019), which implies that the pass-through of firm shocks into wages is a key source of variation for workers' labor earnings (Kline et al., 2019; Chan et al., 2023). However, little is known on how this pass-through could be affected by the presence of minimum wages, which by construction reduce the room for wage cuts among low-paid workers. This paper argues that minimum wages generate an asymmetric pass-through of firm productivity shocks such that the burden of the wage adjustment is tilted towards high-paid workers employed by minimum-wage-intensive firms.

We first provide a simple conceptual framework to clarify how minimum wages alter the pass-through of firm shocks across workers. We consider a neoclassical model in which a firm hires workers with low and high skills, subject to a minimum wage. Importantly, the firm's labor demand is characterized by complementarities across low- and high-skill workers (Krusell et al., 2000; Caselli and Coleman, 2006; Shao et al., 2023). The minimum wage implies the rationing of low-skill workers whose marginal product of labor (MPL) is below the wage floor.

In this setting, a drop in productivity reduces the MPL—and thus the wage—of all workers. However, the pass-through is asymmetric insofar there is a degree of skill complementarities. This effect hinges on the fact that the drop in productivity exacerbates the rationing of low-skill workers. The higher rationing of low-skill employees reduces the MPL of high-skill workers due to the labor-demand complementarities, hence amplifying the wage drop at the high end of the skill distribution. Instead, since low-skill workers become scarcer, their MPL rises, which mutes the wage drop at the low end of the skill distribution.

To test these mechanisms in the data, we focus on the Italian metal-manufacturing sector, which is an ideal laboratory for four main reasons. First, we can leverage employer-employee data from 1995 to 2015 matched to firm balance sheets. Second, metal-manufacturing firms hire workers subject to different wage floors, which are set by collective contracts and act as *de-facto* minimum wages.[1] Crucially, the wage floors vary within occupations. For instance, in 2015 blue-collar metalworkers faced six distinct levels, whose wage floors ranged from €1,297.81 up to €1,744.89. This variation is critical to test empirically the asymmetric pass-through within occupations (i.e., within blue and white collars). Third, wage floors are quantitatively relevant: on average they account for more than 50% of the mean wage within each floor. Fourth, the metal manufacturing sector has been declining over time—as in most advanced economies—with a contribution to total employment shrinking from 7.5% to 6.2% between 2000 and 2015. This yields a large variation in productivity shocks across firms.

We start by showing prima-facie evidence on the presence of skill complementarities in two ways. First, we build on the approach of Battisti et al. (2024), who derive a measure of

[1] While in Italy there is no statutory universal minimum wage, firms face distinct wage floors depending on their industry. Throughout the paper, we use the terms minimum wages and wages floors interchangeably.

skill complementarities using employer-employee data from the northern Italian region of Veneto. Their measure leverages variation in employees' working time adjustments relative to their earnings growth. Importantly, this measure correlates with O*NET indicators of teamwork activities across sectors. We replicate their measurement with our data, confirming the evidence in support of complementarities. This is not surprising since Battisti et al. (2024) document that the metal-manufacturing sector is among the industries with the highest degree of complementarities. Second, we estimate a value-added production function as in De Loecker and Warzynski (2012), and find strong complementarities between low-skill and high-skill workers, especially for blue collars. Thus, the role of complementarities in generating the asymmetric pass-through should be more relevant when looking into blue collars' wages.

We next move into the analysis of the pass-through. Our main shock measure is a firm TFP shock, which we identify using firm balance sheet data and the control method of De Loecker and Warzynski (2012). However, we also ascertain the robustness of our results by considering firm-specific labor-productivity shocks as well as a firm-specific export shock, which is derived using confidential custom-level export information, as in Garin and Silvério (2024). Then, we plug-in the estimated TFP shocks into a worker-level regression and evaluate how a drop in firm productivity affects workers' wages, as well as to what extent this pass-through depends on firms' share of minimum-wage workers. In the spirit of Abowd et al. (1999), we saturate the regression with worker-firm and time fixed effects to absorb any unobserved variation in labor earnings as well as in firms' long-run efficiency levels.

When focusing on blue collars, we uncover considerable heterogeneity in the effects of negative firm productivity shocks on wages. On the one hand, the wages of the workers that are close to the minima are unresponsive, confirming that the wage floors act *de facto* as minima. This lack of wage adjustment among minimum-wage workers is accompanied by changes at the extensive margin: negative productivity shocks raise job separations. On the other hand, negative TFP shocks reduce wages—with no effect on employment outcomes—of high-paid workers. Crucially, the magnitude of this channel increases with the share of minimum-wage employees at the firm level. Thus, the pass-through of productivity shocks into wages is concentrated among high-wage workers employed in minimum-wage-intensive firm. We refer to the relatively larger sensitivity of the wage of high-paid workers in minimum-wage-intensive firms to productivity shocks as the *asymmetric pass-through*. Instead, for white collars the asymmetric pass-through emerges only when looking into firms with high incidence of minimum wages.

To dig deeper into the asymmetric pass-through, we show that the relatively larger response of wages to TFP shocks for high-paid blue collars in minimum-wage-intensive firms holds independently of some key worker and firm characteristics. More specifically, the asymmetric pass-through holds also above and beyond the role of workers' risk aversion and firms' markups, profit ratios, bankruptcy risk, uncertainty, and local labor-market employment shares. These results suggest that the asymmetric pass-through cannot be fully explained by worker-firm risk sharing (e.g., Ellul et al., 2018; Lamadon et al., 2022), rent sharing (e.g., Card et al., 2014), or firm monopsony power (e.g., Berger et al., 2022a; Chan et al., 2023).

We then evaluate the welfare implications of these novel facts by extending our simple conceptual framework into a fully-fledged incomplete-market economy with heterogeneous households and heterogeneous firms. We calibrate the model to the Italian metal-manufacturing industry, and leverage the model equilibrium wage equation to derive a tight condition that allows to identify the degree of skill complementarities. We back out an elasticity of substitution of 1.43, which is in line with the estimate of the aggregate long-run elasticity of Ciccone and Peri (2005). The calibrated model replicates not only qualitatively but also *quantitatively* the way in which the incidence of minimum wages at the worker and firm level shapes the pass-through of firm productivity shocks into labor earnings.

We use the model as a laboratory to study the welfare implications of removing minimum wages. We find substantial heterogeneity across the labor earnings distribution. The elimination of wage floors tilts the welfare gains toward high-skill white collars at the expense of low-skill blue collars, with welfare gains and losses that are highly economically relevant. Blue collars are mostly worse off, with consumption equivalent welfare losses up to -1% for those low-skill workers employed in minimum-wage-intensive firms. Conversely, white collars benefit from the absence of wage floors, with welfare gains up to 0.8% for high-skill workers employed in firms intensive in minimum wage employees. Our analysis, thus, uncovers a novel channel through which minimum wages benefit relatively more low-wage workers at the cost of high-paid employees.

Our results offer a novel view on the insurance within the firm studied by Guiso et al. (2005), Lagakos and Ordoñez (2011), Ellul et al. (2018), Juhn et al. (2018), and Balke and Lamadon (2022), as we uncover a relatively lower amount of insurance provision toward high wage workers employed in firms with high incidence of minimum wages. The presence of wage floors raises the insurance of low-wage workers, at cost of a greater volatility in the earnings of high-paid workers. From this perspective, we provide direct evidence on the hypothesis of Friedrich et al. (2021), who argue that the lower pass-through of productivity shocks into low-skilled workers' wages could be due to minimum wage constraints. We also connect to Chan et al. (2023), who use employer-employee data to study the heterogeneous effects of firm productivity shocks by controlling for differences in workers' labor quality. However, the focus— and main contribution—of our paper differs as we show that the pass-through crucially depends on the relevance of minimum wages at both the worker and firm level.

We build on the work that studies the implications of minimum wages across the distribution of firms and workers (e.g., Dube et al., 2010; Sorkin, 2016; Cengiz et al., 2019; Berger et al., 2022b; Engbom and Moser, 2022). These studies derive the pass-through of changes in the minimum wage *per se* into earnings and profits. Instead, we take a complementary approach by considering the minimum wage as given and evaluating how its presence shapes the pass-through of firm-level productivity shocks into wages. In other words, rather than focusing on how changes in wage floors alter the wage *level*, we uncover how a given set of wage floors affects the wage *cyclicality* with respect to firm-idiosyncratic risk.[2]

Minimum wage policies are often analyzed through the lens of frictional-market models (e.g., Flinn and Mullins, 2021; Engbom and Moser, 2022). In this paper, we consider a neoclassical model in which the asymmetric pass-through is due to a technological channel. The rationale of our choice is two-fold. First, we build a model with heterogeneity across both (multi-worker) firms and (risk-averse) households within an incomplete-market setting. These features are key to derive the welfare implications of the uneven pass-through across the wage distribution as well as across individuals employed by firms which differ in the share of minimum wage workers. Second, our approach is consistent with the fact that the asymmetric wage pass-through of firm-specific shocks does not vary with the firms' characteristics that could envisage a scope for worker-firm bargaining over risk/rent sharing.

2 Conceptual Framework

To fix ideas on how the presence of a minimum wage can alter the pass-through of firm productivity shocks into workers' wages, we provide a simple conceptual framework. The aim is to uncover that in an economy in which the workers of different skills are complementary, the presence of a minimum wage constraint gives rise to an asymmetric wage pass-through which is relatively larger for high-skill workers.

Specifically, we consider an economy populated by a perfectly competitive representative firm, a measure λ_L of low-skill workers, and a measure λ_H of high-skill workers. The efficiency units of hours of these workers are such that $x_H > x_L$, which implies that high-skill workers are more productive than low-skill workers.

As in Krusell et al. (2000) and Caselli and Coleman (2006), the firm produces output Y with a technology featuring complementarities between low-skill and high-skill workers:

$$Y = z\left[(\mu_L x_L)^\rho + (\mu_H x_H)^\rho\right]^{\frac{1}{\rho}}, \tag{1}$$

where z is productivity and μ_L and μ_H are the firm's demand of low-skill and high-skill workers, respectively.[3] The parameter ρ is the key factor determining the degree of complementarities in firm labor demand: workers of different skills are perfect substitutes if $\rho = 1$, and imperfect substitutable as long as $\rho < 1$. This labor aggregation follows the specifications in Ciccone and Peri (2005) and Caselli and Coleman (2006) for the aggregate production functions in economies with different skill groups of workers.[4]

The profit-maximization problem of the firm is static: it chooses the measure of workers

[2] Another strand of the literature evaluates how minimum wages alter aggregate business cycles (e.g., Glover, 2019; Faia and Pezone, 2024).

[3] The assumption of constant returns to scale is without loss of generality. The asymmetric pass-through emerges even with decreasing returns to scale.

[4] Our labor aggregation captures the complementarities between skill groups within firms, rather than countries or sectors, in the spirit of Rosen (1978). This feature parsimoniously generates a pattern for labor demand such that the firm hires workers with different skill levels, see Iranzo et al. (2008).

of each skill level and its output, as follows:

$$\pi(z) = \max_{\mu_L, \mu_H, Y} Y - \mu_L w_L(z) - \mu_H w_H(z) \tag{2}$$

$$\text{s.t. } Y = z\left[(\mu_L x_L)^\rho + (\mu_H x_H)^\rho\right]^{\frac{1}{\rho}}, \tag{3}$$

where $w_L(z)$ and $w_H(z)$ denote the wages of low-skill and high-skill workers, respectively, which both depend on the realization of firm productivity z.

The economy features a minimum wage constraint:

$$w_H(z) \geq \underline{w}, \qquad w_L(z) \geq \underline{w}, \tag{4}$$

which imposes that wages have always to be larger than or equal to an exogenous floor $\underline{w}$. For simplicity, we assume that there exists solely one wage floor. Note that in this setting, the firm's maximization problem does not need to explicitly take into account the existence of the minimum wage constraints. Since the firm takes wages as given, the restriction imposed by the minimum wage emerges in equilibrium as $\mu_L = [1 - U(z)]\lambda_L$ and $\mu_H = \lambda_H$, but without appearing explicitly in the firm's optimization problem. However, the presence of a minimum wage generates a probability $U(z)$ that low-skill workers—whose wage is closer to the wage floor—end up not being hired, which happens when their MPL in case of full employment is below the minimum wage. Although the function $U(z)$ is endogenous and depends on productivity, firms and workers take it as given.

The solution to the problem in Equations (2)-(3) yields the following optimal wages:

$$w_H(z) = z x_H^\rho \left\{([1 - U(z)]\lambda_L x_L)^\rho + (\lambda_H x_H)^\rho\right\}^{\frac{1-\rho}{\rho}} \lambda_H^{\rho-1}, \tag{5}$$

$$w_L(z) = z x_L^\rho \left\{([1 - U(z)]\lambda_L x_L)^\rho + (\lambda_H x_H)^\rho\right\}^{\frac{1-\rho}{\rho}} \left\{[1 - U(z)]\lambda_L\right\}^{\rho-1}. \tag{6}$$

The pass-through of firm productivity shocks into wages can be then derived by taking the derivative of log wages with respect to log firm productivity, which yields:

$$\frac{\partial \log w_H(z)}{\partial \log z} = \underbrace{1}_{\substack{\text{direct}\\\text{effect}}} + \underbrace{(1-\rho)\Psi \times \left(-\frac{\partial U(z)}{\partial \log z}\right)}_{\text{amplifying indirect effect}}, \tag{7}$$

$$\frac{\partial \log w_L(z)}{\partial \log z} = \underbrace{1}_{\substack{\text{direct}\\\text{effect}}} + \underbrace{(1-\rho)\Psi \times \left(-\frac{\partial U(z)}{\partial \log z}\right)}_{\text{amplifying indirect effect}} - \underbrace{(1-\rho)\frac{1}{1-U(z)} \times \left(-\frac{\partial U(z)}{\partial \log z}\right)}_{\text{muting indirect effect}}, \tag{8}$$

where $\Psi = \frac{(\lambda_L x_L)^\rho [1-U(z)]^{\rho-1}}{([1-U(z)]\lambda_L x_L)^\rho + (\lambda_H x_H)^\rho}$ is a positive convolution of variables and parameters.

We can characterize the wage pass-through of firm productivity in three cases:

1. Without minimum wages: there is no rationing, so that $\partial U(z) / \partial \log z = 0$. This means that the second and third terms disappear, and the pass-through only features the direct effect of firm productivity on wages. In this case, the pass-through equals 1 and is constant across workers, independently of the degree of skill complementarities.

2. With minimum wages but without skill complementarities ($\rho = 1$): also in this case the second and third terms disappear, and the pass-through only features the direct effect

of firm productivity. Again, the pass-through is constant across workers.

3. With minimum wages and skill complementarities ($\rho < 1$): the wage pass-through features additional terms that depend on the derivative $\partial U(z) / \partial \log z$, which captures how the rationing of low-skill workers varies with productivity. This derivative is negative: higher productivity boosts wages and lowers rationing/unemployment.

   In the high-skill wage pass-through, the second term is positive. This captures the fact that a drop in productivity reduces high-skill wages also through an indirect effect via the rationing of low-skill workers. As a result, imperfect substitutability makes the rationing of low-skill employees amplify the pass-through of productivity into high-skill wages. Thus, the pass-through for high-skill workers is above 1.

   In the low-skill wage pass-through, there is also a third term, which captures the fact that lower productivity exacerbates the rationing of low-skill workers, making them scarcer. This boosts their MPL due to the complementarities. This effect is negative and mutes the wage pass-through for low-skill workers. The muting effect dominates the amplifying one, leading the wage pass-through of low-skill workers to be below 1.

Overall, this analysis has shown that in an economy with minimum wages and complementarities in labor demand across workers of different skills, it emerges an asymmetric wage pass-through of productivity shocks in which the responsiveness of high-skill workers is larger than that of low-skill workers. The existence and the extent of the asymmetric pass-through is modulated by the dynamics of the rationing of low-skill workers.

3 Institutional Setting and Data

3.1 Wage Floors in Italy

To study the effect of minimum wages on the pass-through of firm productivity shocks across workers, we focus on the case of Italy. While there is no statutory minimum wage in Italy, collective bargaining between major trade unions and employer federations set minimum floors which apply on average over a 2-3 year horizon to both unionized and non-unionized workers at the industry level (Adamopoulou and Villanueva, 2022).[5,6] Collective contracts envisage nominal increases of the negotiated wage floors that typically take place every year.

Crucially for our analysis, in the Italian metalworking sector there is close-to-full compliance with the wage floors: in our sample only less than 1% of wage observations are below the minima. Our focus on the wage floors is further supported by the fact that collective bargaining at the firm level is rare, and during the period of our analysis could only envisage top-ups. In other words, negotiated wage floors act as *de facto* minimum wages.

[5] Although there are no legal provisions for mandatory extensions, labor courts identify the "fair wage" level for workers using the wage floors defined by the corresponding sectoral collective contracts.

[6] Sectoral collective contracts apply to most European countries, with the exception of the U.K.

An important feature of wage floors in Italy is that they vary across job titles ("livelli di inquadramento" in Italian) that are explicitly defined by the collective bargaining agreements. These titles are based not only on the specific content of each job task, but may depend also on the seniority and education of the worker. As such, blue-collar workers may face different wage floors, even though they share the same occupation. The same applies for white collars.

To put the variation of the minimum wages within occupations into context, in 2015 a blue-collar metalworker was subject to one out of 6 different wage floors depending on the job title: €1,297.81, €1,432.58, €1,588.63, €1,622.96, €1,657.28, and €1,744.89. Similarly, white-collar metalworkers faced 7 wage floors: €1,432.58, €1,588.63, €1,622.96, €1,657.28, €1,744.89, €1,902.42, and €2,278.56. This implies that a blue-collar metalworker with a job title associated with the highest wage floor faced a minimum wage that is 35% larger than that of a blue-collar metalworker with a job title associated with the lowest wage floor.

This institutional feature of the Italian labor market allows us to compute worker-specific minimum wages by exploiting the fact that different workers may be associated with different job titles, and thus wage floors. This structure stands in contrast with the standard universal minimum wage which applies to all workers independently of their occupation, such as in the U.S., in which the current federal minimum wage is $7.25 per hour. From this perspective, the existence of multiple wage floors allows us to leverage variation in the level of minimum wages across workers, even within the same occupation.

3.2 Data Sources

To carry out our analysis, we build a unique dataset at the worker-firm-year level by bringing together information from a firm-level survey, firm balance sheets, administrative employer-employee social security records, and hand-collected wage floors from collective contracts.

We start with a representative survey of 4,000 Italian firms with at least 20 employees in the manufacturing sector, the "Indagine sugli investimenti delle imprese manifatturiere" (Inquiry into the investments of manufacturing firms; henceforth, Invind). This survey contains detailed information on revenues, capital structure, as well as the usage of production factors.[7] We complement this information with three additional data sources. First, we get a complete picture of firms' sales and production inputs with the detailed balance sheets from the proprietary database CERVED. Second, we merge the firm-level data to a linked employer-employee database from the Italian National Social Security Institute (INPS). In this way, we observe the complete working histories for all workers employed by any establishment associated with each of the Invind firms over the period 1995-2015.[8] Third, we add hand-collected data on negotiated minimum wages by occupation and year using the information on the collective

[7]The survey is conducted by the Bank of Italy through its regional branches, ensuring the high quality of the data collection (D'Aurizio and Papadia, 2016). The survey is regularly used in academic research (Pozzi and Schivardi, 2016; Rodano et al., 2016). The survey is representative insofar the analysis uses the Invind survey weights, as we do throughout the paper.

[8]Our data allow us to track this sample of metalworkers also if they move to non-Invind firms.

contract covering each worker from the Social Security data. We describe in detail the wage floor assignment to each worker in the next section.

3.3 Assignment of Wage Floors

While workers face several wage floors depending on their job title, unfortunately we do not observe the information on the job title in our data. For this reason, we need to impute the job title—and in this way assign the corresponding wage floor—to each worker. We do so following a multi-step procedure, which allows us to validate the accuracy of the assignment. In particular, we corroborate our imputed assignment of wage floors with a survey that reports the distribution of workers across job titles for a set of metal-manufacturing firms. This last validation is critical for guaranteeing that we do not end up biasing the distribution of workers across job titles. This crucial step motivates why throughout the paper we focus exclusively on metal-manufacturing workers: this is the sample which allows us to observe the entire workforce for each firm, and in which we can safely determine the wage floor associated to each worker. Throughout this procedure, we focus on the wage floors associated with the main metalworking collective contract.[9] We provide all the details and additional information on this approach in Appendix A.2. Let us describe the three main steps of our procedure.

First, we access an additional data source provided by INPS, which gives us a random and representative 6.5% sample of the Italian workforce, drawn from the universe of private non-farm employees. The advantage of this dataset is that it includes explicitly the information on the job title up to 2004, which determines which of the 8 wage floors is associated to each metal-manufacturing worker. We take the worker-level information on the job title, age, sex, tenure, type of contract (permanent or temporary), occupation (blue collar or white collar), firm size (number of employees of the firm in which the worker is employed), and province (location of the firm). We focus on these variables because we can also observe them in our main employer-employee dataset, and are key determinants of the job titles. We then regress workers' job titles as of 2004 on this extended set of covariates and collect the estimated coefficient associated to each variable. To assess the goodness of fit of our approach, we find that regressing the actual job titles observed in the INPS representative sample on the imputed ones yields a R^2 of around 92%. Consequently, our imputation approach can explain almost the entire variation in job titles which is reported in the INPS representative sample.

Second, we combine the estimated coefficients with the variables as observed in our Invind-INPS data, and impute the wage floor for each worker for the entire period of analysis (i.e., the workers observed in both Invind-INPS data and the INPS representative sample). In this case, regressing the imputed wage floors on the actual ones yields a R^2 of 93%.

Third, we validate the distribution of job titles across firms using a survey of Federmeccanica, the Italian Federation of Metalworking Industries. The survey reports firm-level infor-

[9] FIAT was covered by the main collective contract but opted out in 2012. FIAT was part of the Invind survey in 2004-2009. In that period, its workforce was part of our benchmark analysis. We exclude FIAT workers in a robustness exercise in Appendix C.2. We provide further details on collective contracts in Appendix A.1.

mation on the total number of workers and the number of workers by job title. In this way, we can compute for each firm the distribution of workers across the different wage floors. The fiscal code which allows us to match this information with that of our employer-employee data is available only starting in 2009. For this reason, we use the data from 2009 to 2013 as validation. This last step guarantees that our imputation yields a distribution of wage floors across firms which matches that reported by this survey.

After having assigned the wage floor to each worker, we compute daily wages by dividing gross annual earnings with the number of days worked during the year.[10] Unfortunately, our wage measure includes only the base wage but not bonuses and top ups. This implies that we likely underestimate any change in actual labor earnings for all those workers whose salary features a relevant component of variable pay. For this reason, we exclude from our analysis all managers, since these are the cases in which bonuses account for a sizable fraction of overall earnings. We focus on workers aged 20-64 with some labor-force attachment, by selecting those who have worked for at least 6 months in a year.[11] We keep workers employed in firms in which at least 95% of their workforce is covered by the main metalworking collective contract. We end up with a final sample that contains around 600,000 person-firm-year observations over the period 1995-2015. Appendix B presents some descriptive statistics.

3.4 Incidence of Wage Floors

The variation in minimum wages allows us to pin down the distance of each worker's salary from its specific floor. Since we observe the entire workforce of each firm, we can derive a measure of minimum wage incidence for each worker and each firm. We use these measures in the worker-level regressions to estimate how the pass-through of firm negative TFP shocks into wages depends on the minimum wage exposure of both workers and firms.

The assignment procedure described above gives us a specific wage floor $\underline{W}_{i,t}$ for each worker i. We then define the distance between workers' wage and its associated floor, which we refer to as the *worker minimum wage cushion*, that is

$$\text{Worker MinW Cushion}_{i,f,t} = \left(\text{Wage}_{i,f,t} - \underline{W}_{i,t}\right) / \underline{W}_{i,t}, \tag{9}$$

which is the distance of the salary of worker i employed by firm f in year t, $\text{Wage}_{i,f,t}$, from the wage floor that corresponds to the worker's job title, $\underline{W}_{i,t}$. A lower cushion implies a relatively higher incidence of minimum wages at the individual level.

We can use the workers' cushion to define the incidence of minimum wages at the firm level, which we refer to as *firm minimum wage bite*, that is

$$\text{Firm MinW Bite}_{f,t} = \frac{\sum_{i \in \mathcal{N}_{f,t}} \mathbb{I}_{\{\text{Worker MinW Cushion}_{i,f,t} < 10\%\}}}{\sum_{i \in \mathcal{N}_{f,t}}} \tag{10}$$

which describes the fraction of workers close to their corresponding wage floors in firm f in

[10]We exclude outliers by winsorizing wages in the top-1% and bottom-1% of the wage distribution.
[11]Individuals who worked less than 6 months in a year are considered non-employed in that year.

year t. We denote the total number of employees in each firm by $\mathcal{N}_{f,t}$, and consider workers to be close to the minimum wage if they feature a cushion up to 10%, that is, if the workers' wage is at most 10% above their relevant wage floor. A higher bite implies a relatively higher incidence of minimum wages at the firm level.

4 Empirical Evidence

4.1 Evidence on Skill Complementarities

The simple conceptual framework of Section 2 highlights the key role of skill complementarities in firm labor demand in explaining the wage pass-through of firm productivity shocks across workers. Therefore, this section provides some prima-facie evidence on the relevance of skill complementarities in the data. We do so in two ways.

First, we build on the approach of Battisti et al. (2024), who derive a measure of skill complementarities using employer-employee data from the northern Italian region of Veneto. Their measure leverages variation in employees' working time adjustments relative to their earnings growth. The basic idea is that—absent complementarities—any idiosyncratic shock that raises a worker's earnings should be accompanied by a rise in working time. However, if a firm features strong skill complementarities, changes in working time would be mitigated as a worker cannot individually work longer if this is not met by a similar effort by the side of the co-workers. From this perspective, the ratio of the variance of the idiosyncratic component of annual earnings growth to the variance of the idiosyncratic component of log working time (days worked) changes measures the strength of skill complementarities. When the ratio is one, there is perfect substitutability across skills, while high values of the ratio indicate a prevalence of skill complementarities. This measure is appealing for two reasons. First, it does not require any parametric restriction on firms' technology. Second, Battisti et al. (2024) show that this measure correlates with O*NET indicators of teamwork activities across sectors.

We measure this ratio in our data by leveraging our employer-employee data. We focus on workers that have been paid for at least 1 day in every month in 2 consecutive years, and estimate the idiosyncratic components of earnings growth and log working days. Denoting the log change in days worked by employee i in firm f between years $t-1$ and t with $\Delta \log h_{i,f,t}$, and its log change in earnings with $\Delta \log W_{i,f,t}$, we estimate the following regressions

$$\Delta \log h_{i,f,t} = \mathbf{X}'_{i,f,t}\theta + \phi_{f,t} + \epsilon^h_{i,f,t} \tag{11}$$

and

$$\Delta \log W_{i,f,t} = \mathbf{X}'_{i,f,t}\theta + \phi_{f,t} + \epsilon^W_{i,f,t}, \tag{12}$$

where $\mathbf{X}_{i,f,t}$ are cubic terms in workers' tenure controls, $\phi_{f,t}$ is a firm-year fixed effect, and $\epsilon^h_{i,f,t}$ and $\epsilon^W_{i,f,t}$ are the residuals. Our object of interest is the ratio of $\text{var}\left(\epsilon^W_{i,f,t}\right)/\text{var}\left(\epsilon^h_{i,f,t}\right)$. When focusing on all workers, we estimate a ratio of 3.4, which ranges from a value of 3.07 for white collars up to 3.57 for blue collars. The fact that these values are substantially larger than

1 indicate a strong evidence in favor of the presence of skill complementarities in our data. This result is not surprising since Battisti et al. (2024) document that the metal-manufacturing sector is among the industries with the highest degree of complementarities in the Veneto region.

Second, we estimate a value-added production function in which we explicitly distinguish between blue collars and white collars with low and high skills. We proxy workers' skills with the estimated workers' fixed effects in a regression featuring firm-time fixed effects, as in Abowd et al. (1999). Low-skill workers are those whose estimated fixed effect is below the median measured in each year within each type of occupation. Those above the median are considered as high-skill workers. We then consider a value-added production function with 6 inputs: capital, low- and high-skill blue collars, low- and high-skill white collars, and the rest of workers (i.e., managers and apprentices). The production function also exploits information on the degree of capacity utilization, provided by the Invind questionnaire. The final sample is composed of 7,078 observations from 1,551 firms, on which we estimate a value added production function following De Loecker and Warzynski (2012).

When considering only the cross-derivative between low- and high-skill workers within blue and white collars, we find a statistically significant complementarity for blue collars, with an estimate of 0.0341 and a p-value below 1%. For white collars, we estimate a value of 0.0002. However, when we estimate the production function by considering also the cross-derivative across skills between workers of different occupations, the estimate of the skill complementarities for blue collars is 0.1180, again with a p-value below 1%, and the analogous coefficient for white collars becomes statistically significant, with a value of 0.0308 and also a p-value below 1%. Consequently, this production-function approach also points towards the existence of complementarities between low-skill and high-skill workers, especially for blue collars.

4.2 Estimation of Firm Productivity Shocks

Our empirical analysis aims at uncovering how the pass-through of firm negative productivity shocks across workers is shaped by the presence of minimum wages. To construct the series of firm productivity shocks, we estimate a firm-level Solow residual by positing a Cobb Douglas revenue production function, and use the control function approach of De Loecker and Warzynski (2012) and Ackerberg et al. (2015).[12] We posit that the Hicks-neutral productivity shocks follow a first-order Markov process, and assume that intermediates are optimally chosen in response to observed productivity to back out this unobserved process. Since the construction of the TFP shocks series is based on inputs' growth rates, it also requires the use of lagged values for the instruments. As a result, the TFP shock cannot be computed for the first two years of the dataset, that is, 1995 and 1996. This approach leads to the estimation of a series of firm-specific TFP shocks spanning from 1997 until 2015. We then generate a dummy variable that equals 1 when the realization of the TFP shock of a given firm is negative.[13]

[12]Capital is set as pre-determined so that it does not correlate with contemporaneous productivity shocks.

[13]While our model considers firms' production function with skill complementarities, the estimation abstracts from this feature, imposing skill perfect substitutability. In this way, we do not plug into the estimated produc-

While our baseline shock measure consists of productivity shocks, we ascertain the validity of our results by considering alternative firm-level shocks. To do so, we perform robustness checks with firm-specific labor-productivity shocks and two different export shocks, which are derived using also confidential custom-level export information, as in Garin and Silvério (2024). We provide further details on these alternative shocks in Appendix C.1.

4.3 Worker-level Analysis

This section documents how minimum wages generate an asymmetric pass-through of firm productivity shocks across workers. To uncover this fact, we leverage our employer-employee data and characterize how the pass-through jointly depends on the incidence of minimum wages at the worker and firm level. Our baseline worker-level regression is the following:

$$\begin{aligned}\Delta \log \text{Wage}_{i,f,t} = \beta_1 \text{Negative TFP Shock}_{f,t} + \beta_2 \text{Firm MinW Bite}_{f,t-1} + \dots \\ \dots + \beta_3 \text{Negative TFP Shock}_{f,t} \times \text{Firm MinW Bite}_{f,t-1} + \alpha_{i,f} + \alpha_t + \epsilon_{i,f,t},\end{aligned} \tag{13}$$

where, as in Guiso et al. (2005), Friedrich et al. (2021), Bianchi et al. (2023), and Chan et al. (2023), the dependent variable $\Delta \log \text{Wage}_{i,f,t}$ is the log-change of the daily wage of worker i employed by firm f between years t and t-1. Then, $\text{Negative TFP Shock}_{f,t}$ is the series of firm negative TFP shocks (which equals 1 if firm f experiences a negative TFP shock in year t and 0 otherwise), and $\text{Firm MinW Bite}_{f,t-1}$ denotes the lagged bite of minimum wages of firm f.[14]

The regression includes workers' age dummies (specified over 5-year age groups), worker-firm fixed effects, $\alpha_{i,f}$, and year fixed effects, α_t, which control for time-invariant unobserved heterogeneity as well as any common time variation across firms. Thus, the variation in the incidence of minimum wages across firms and our set of fixed effects allow us to identify how the pass-through of wages to firm shocks depends on the firms' exposure to minimum wages which holds above and beyond differences in firms' long-run productivity levels.

Our coefficient of interest is β_3, which is associated with the interaction between the negative productivity shock and firms' incidence of minimum wages. A larger coefficient in absolute value implies that the pass-through is relatively larger in those firms with relatively more workers close to the wage floors. To evaluate also the relevance of minimum wages at the individual level, we estimate regression (13) for two samples: one for the workers who are close to the minimum wage, defined as all workers whose minimum wage cushion, $\text{Worker MinW Cushion}_{i,f,t}$, is below 10%, and one for the workers who are way above the wage floors, defined as all workers with a cushion above 10%.

Table 1 estimates the wage pass-through for three group of workers: all employees, blue collars, and white collars. It does so by deriving the effect of a negative TFP shock on workers' wage growth, distinguishing between workers close to the minima, and those far from them. Columns (1) and (2) report the results on all employees, and show that there is no pass-through

tivity shocks the implications that labor-demand complementarities *per se* have on wage elasticities.

[14]Standard errors are derived with Invind survey weights and a two-way clustering by workers and firms.

Table 1: Worker-level wage pass-through of firm negative TFP shocks.

Dependent variable:	Δ log $\text{Wage}_{i,f,t}$					
	All Workers		Blue Collars		White Collars	
Worker MinW $\text{Cushion}_{i,f,t}$:	0-10%	>10%	0-10%	>10%	0-10%	>10%
	(1)	(2)	(3)	(4)	(5)	(6)
Negative TFP $\text{Shock}_{f,t}$	-0.001	-0.001	0.005	0.002	-0.011	-0.006
	(0.005)	(0.003)	(0.006)	(0.003)	(0.009)	(0.004)
Negative TFP $\text{Shock}_{f,t}$ $\times$ Firm MinW $\text{Bite}_{f,t-1}$	0.001	-0.045*	-0.017	-0.077***	0.028	0.014
	(0.019)	(0.027)	(0.020)	(0.030)	(0.064)	(0.041)
Worker-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,473	603,292	13,108	391,410	6,309	210,439

Note: The table reports the estimates of worker-level regressions on annual data from 1997 to 2015. The dependent variable is the daily wage growth of worker i employed in firm f in year t. The variable Negative TFP $\text{Shock}_{f,t}$ is a dummy variable for all the negative realizations of firm TFP shocks. Firm shocks are interacted with the lagged value of the firm minimum wage bite, Firm MinW $\text{Bite}_{f,t-1}$. We also control for the firm bite in isolation. Columns (1) and (2) focus on all workers, Columns (3) and (4) restrict the sample to blue collars, and Columns (5) and (6) restrict the sample to white collars. Columns (1), (3), and (5) estimate the regression for workers whose minimum wage cushion is below 10%, and Columns (2), (4), and (6) focus on workers whose cushion is above 10%. All regressions include year and worker-firm fixed effects. Robust standard errors clustered at the firm and worker level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

whatsoever into the wages of the workers close to the minima. This lack of adjustment confirms that the wage floors act *de facto* as minima. On the contrary, negative TFP shocks do reduce the wage of high-cushion workers: the coefficient associated with the interaction of the negative TFP shocks with Firm MinW $\text{Bite}_{f,t-1}$ is negative and statistically significant. The implications of this result are twofold. First, the direct pass-through of firm productivity into high-cushion workers' wages in a firm with an average minimum wage bite is -0.003, with a p-value of 0.002. Thus, the direct effect of a negative productivity shock reduces wage growth by 0.3 percentage points, which accounts for almost 10% of the average wage growth in our sample. Second, the magnitude of the pass-through increases with the incidence of minimum wages at the firm level, that is, the minimum wage bite. This effect is not only statistically significant, but also highly economically relevant: for a firm with a bite which is 1 standard deviation above the mean, negative productivity shocks reduce the wage growth of high-paid workers by 0.5 percentage points. Consequently, a 1 standard-deviation increase in the firm bite almost doubles the wage pass-through for a high-paid worker relative to what that worker would experience if employed by a firm with an average minimum wage bite.

When focusing on the wage pass-through of blue collars in Columns (3) and (4), the results are similar, with the only difference that the estimate of the interaction between firm shocks and the minimum wage bite becomes highly statistically significant, and increases in magnitude. Instead, Columns (5) and (6) show that there is no apparent sign of the asymmetric wage pass-through for white collars. The lack of wage adjustment to negative productivity shocks could be due to the fact that our wage measure includes only the base salary, and not bonuses and performance pay. Since these components are much more important for white collars, it is likely that firms adjust the variable pay for white collars upon a negative shock. If this is the case, we should detect evidence on the pass-through for white collars only when firms need to substantially adjust base wages, that is, when firms must cut not only the variable pay. We provide evidence consistent with this notion in Appendix C.2, in which we show that there is a statistically significant wage pass-through into high-paid white collars upon a negative productivity shock when they are hired by a firm with a very high minimum wage bite (i.e., firms with minimum wage bite in the top quartile of the incidence of minimum wages).

These results establish an asymmetric wage pass-through: the wage adjustment to firm negative productivity shocks is concentrated among high-paid workers employed by firms with high incidence of minimum wages.

4.4 Robustness Checks

We perform a comprehensive battery of robustness checks to corroborate how the incidence of wage floors at the worker and firm level shapes the asymmetric pass-through of firm specific shocks into wages. We do so by focusing on blue collars. Appendix C.2 validates our findings over nine key dimensions. Specifically, the asymmetric wage pass-through for blue collars continues to hold in the following cases: (i) when replacing the firm negative productivity shocks with the negative realizations of firm labor-productivity shocks or export shocks, see Table C.1; (ii) when excluding FIAT workers, shortening the sample period to 2011, adding firm controls or considering large negative shocks as in Juhn et al. (2018), see Table C.2; (iii) when deriving productivity shocks by adjusting for variable utilization derived as in Basu et al. (2006), explicitly controlling for heterogeneity in workers' labor inputs across firms, or disentangling the transitory and permanent innovations as in Blundell et al. (2008), see Table C.3; (iv) when defining low-cushion workers as those whose wage is at most either 15% or 20% above their corresponding wage floor, rather than 10% as in the baseline, see Table C.4; (v) when measuring the minimum wage bite by focusing only on the incidence of wage floors for workers with either lower job titles, or higher job titles, as well as when focusing on white collars in firms with a high incidence of minimum wage bite among white collars, see Table C.5; (vi) when saturating the regression with different fixed effects, such as 2-digit sector-year fixed effects, province-year fixed effects, or group fixed effects as in Bonhomme et al. (2019), see Table C.6; (vii) when focusing on key workers' characteristics such as age, excluding workers at the very top of the wage distribution, workers with temporary contracts, or workers in short time work (furlough) schemes, and computing firm incidence of minimum wages focusing only on permanent workers, see Table C.7; $(viii)$ when focusing on key firms' characteristics, such as firms' age, markups, profit ratios, and local labor-market employment shares, see Table C.8; and (ix) when focusing on those characteristics that could proxy worker-firm risk sharing (e.g., Ellul et al., 2018; Lamadon et al., 2022), such as workers' risk aversion, degree of cash needs, and bankruptcy risk, see Table C.9.[15]

[15]We derive a measure of risk aversion in a similar spirit as Guiso et al. (2005), by leveraging a question in the Survey on Household Income and Wealth (SHIW) in which respondents report their own risk-return trade-off. We then impute the risk aversion for the workers of our sample via a matching procedure on common

4.5 The Job-separation and Labor-earnings Pass-through

How does the asymmetric pass-through of firm shocks into workers' wages affect employment outcomes? This section provides direct evidence on how the heterogeneous wage elasticities to firm shocks are mirrored by an asymmetric pass-through of firm shocks into job separations. In what follows, we focus only on blue collars.

We replace the dependent variable in regression (13) with Job $\text{Separation}_{i,f,t}$, which is a dummy variable that equals 1 if blue collar i employed in firm f experiences a job separation by the end of year t. Columns (1) and (2) of Table 2 report the results of this exercise, showing that high-cushion workers do not experience any job separation amidst a negative firm TFP shock, even if they are employed by minimum-wage-intensive firms. Instead, the job separations are concentrated among those low-cushion workers employed by high-bite firms.[16,17]

Table 2: Blue collar job-separation and labor earnings pass-through of negative TFP shocks.

Dependent variable:	Job $\text{Separation}_{i,f,t}$		$\Delta \log$ Labor $\text{Earnings}_{i,f,t}$	
Worker MinW $\text{Cushion}_{i,f,t}$:	0-10%	>10%	0-10%	>10%
	(1)	(2)	(3)	(4)
Negative TFP $\text{Shock}_{f,t}$	-0.016*	0.000	0.017	0.007
	(0.010)	(0.003)	(0.059)	(0.004)
Negative TFP $\text{Shock}_{f,t}$ $\times$ Firm MinW $\text{Bite}_{f,t-1}$	0.050*	0.005	-0.079	-0.145***
	(0.028)	(0.029)	(0.272)	(0.049)
Worker-Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	14,401	420,143	26,985	493,033

Note: The table reports estimates as in Table 1 with the difference that in Columns (1) and (2) the dependent variable is a dummy variable that equals 1 if blue-collar worker i employed by firm f is laid off in year t, and in Columns (3) and (4) is the log-change in labor earnings of a blue-collar worker i.

Our evidence on the asymmetric pass-through of wages and employment outcomes contributes to the general wisdom that minimum wages dampen the variation in wages at the cost of larger employment variations. The opposite applies to high-cushion workers: minimum wages do not influence their employment prospects, but generate additional wage volatility.

The natural question is then whether the variation in job separations outweighs the wage changes so that low-wage workers bear the bulk of the adjustment amidst firm shocks. We show that this is not the case by estimating a regression in which the dependent variable is the log change in workers' labor earnings. Specifically, we consider the variable $\Delta \log \text{Earnings}_{i,f,t}$, that combines the change in wages with that in employment, such that $\log \text{Earnings}_{i,f,t} = 0$

observables in both datasets. The cash needs are derived through a question from the Invind survey, in which firms report the fraction of trade credit claims which has been deferred over the agreed expiration date. Finally, we proxy firms' bankruptcy risk with the Altman (1968)'s Z-score.

[16] Although the first term in Column (1) is negative and statistically significant, job separations for low-cushion workers in a firm with an average bite are not statistically different from zero, with a p-value of 0.293. The job-separation effect kicks in among firms with a higher minimum wage bite than the average value in the sample.

[17] Our analysis uncovers how the presence of a given minimum wage alters employment outcomes following a firm-specific shock. For studies showing how changes in the minimum wage *per se* lead to limited employment losses, see Cengiz et al. (2019), Harasztosi and Lindner (2019), and Dustmann et al. (2022).

if worker i was laid off and has not found a new job at time t. Columns (3) and (4) of Table 2 report the results of this exercise, and highlight that notwithstanding the increased probability of losing a job for low-wage workers, the adjustment in labor earnings amidst firm TFP shocks is still larger among those high-paid workers employed by high-bite firms.

4.6 Summary of the Stylized Facts

To sum up, our empirical analysis reveals that minimum wages shape the pass-through of negative firm productivity shocks into wages. On the one hand, low-cushion workers experience no variation in wages, but face a relatively larger variation in the probability of losing their job. On the other hand, workers whose salary is way above the wage floors – but are employed by high-bite firms – experience a relatively higher wage sensitivity, and no change in employment outcomes. The same pattern holds true also when looking at labor earnings, highlighting that high-paid workers are relatively more exposed to firm shocks. All in all, these results uncover the key role of the incidence of minimum wages at both the individual and firm level in determining the worker-level implications of firm shocks.

5 Quantitative Analysis

This section extends the simple conceptual framework of Section 2 into a fully-fledged quantitative model, so as to show that skill complementarities can account not only qualitatively but also quantitatively for the way in which the incidence of minimum wages at the worker and firm level shapes the pass-through of firm productivity shocks into labor earnings. We then use the model as a laboratory to study the welfare implications of removing minimum wages. The ultimate aim is to provide a proof of concept that the asymmetric pass-through generates heterogeneous welfare implications across the labor-earnings distribution.

5.1 Model Description

We generalize our simple conceptual framework into an incomplete-market neoclassical economy, with heterogeneous households and firms. On the one hand, there is a continuum of households, who are ex-ante heterogeneous in their fixed labor skills, that we map into occupations (i.e., blue collars and white collars). Workers accumulate assets subject to a borrowing constraint. On the other hand, the production side consists of a continuum of firms operating with decreasing returns to scale technologies, as in Hopenhayn (1992). Firms are ex-ante heterogeneous in their fixed markups, which we capture through wedges in total production cost, and face persistent idiosyncratic productivity shocks. Firms produce using capital and labor, and their labor demand feature complementarities across workers with different skill levels. As in the data, firms hire workers subject to occupation-specific wage floors. In this setting, the effect of firm productivity shocks on workers' wages—combined with the borrowing constraint—makes households bear an uninsurable persistent idiosyncratic labor-earnings risk, in the spirit of Aiyagari (1994). We describe the model in detail in Appendix D.

As we explain in Section 2, the asymmetric pass-through emerges due to a technological channel that hinges on the way in which the labor-demand complementarities across skills make the rationing of low-skill workers to affect the wage of high-skill employees. This feature is not just motivated by the empirical relevance of skill complementarities in our data, as reported in Section 4.1, but it proves crucial for our analysis for two main reasons. First, we show that our calibrated model almost matches the magnitude of the pass-through of negative productivity into labor earnings of low-cushion and high-cushion workers. Second, it allows us to build a model with heterogeneity across both (multi-worker) firms and (risk-averse) households within an incomplete-market setting. These features are key to derive the welfare implications of the asymmetric pass-through across the wage distribution as well as across individuals employed in firms with different shares of minimum wage workers.

5.2 Calibration Strategy

When bringing the model into the data, we calibrate the model to the main features of the Italian metalworking sector. We provide all the details on the calibration in Appendix E. Specifically, we discipline firm heterogeneity in productivity and markups to match the dispersion and persistence of log-sales, as well as the dispersion of estimated markups across firms. Then, to calibrate the dispersion of wages across workers' skills, we leverage the employer-employee dimension of our data in a multi-step approach: (i) we estimate workers' fixed effects within a regression featuring firm-time fixed effects, in the spirit of Abowd et al. (1999), (ii) discretize the estimated workers' fixed effects over 7 groups for both blue collars and white collars, and (iii) we set the value of each skill such that the model matches the distribution of both workers and average wages across skill groups. We discipline the relevance of the wage floors by calibrating the minimum wage for blue collars and white collars so that we are consistent with the average firm minimum wage bite for workers in each occupation. In this way, the model is consistent with the fact that white collars on average face wage floors that are 30% higher than those associated with blue collars. However, white collars' wages are on average around 50% higher than blue collars' ones, implying that the incidence of minimum wages—defined as how close actual wages are to wage floors—is relatively larger for blue collars.

We use insights from the model to calibrate the degree of skill complementarities ρ. To do so, we leverage the equilibrium wage conditions, and show that the degree of skill complementarities modulates the dispersion of the wage-to-skill ratio within firms. With skill substitutability (i.e, $\rho = 1$), the wage-to-skill ratio is constant within firms, as it only depends on firm-specific parameters and characteristics. However, the within firm-standard deviation increases with the degree of skill complementarities. This implies that the within-firm standard deviation of the wage-to-skill ratio identifies the elasticity of substitution across skills.

In the data, the within-firm standard deviation of the wage-to-skill ratio is 0.246. The model matches this moment with $\rho = 0.3$. The implied elasticity of substitution between skills is 1.43, in line with the values estimated in the literature (e.g., Ciccone and Peri, 2005). Table 3

Table 3: Identification of ρ, data vs. model.

Moment	Data	Model				
		$\rho = 0.1$	$\rho = 0.3$	$\rho = 0.6$	$\rho = 0.9$	$\rho = 1$
Within-firm std. of wage-to-skill ratio	0.246	0.318	0.248	0.142	0.036	0.004
Std. of wage-to-skill ratio	0.258	0.348	0.268	0.156	0.066	0.055
Std. of log-wages	0.340	0.282	0.258	0.255	0.249	0.248

Note: This table compares the implications of the baseline model with the degree of complementarity equal to $\rho = 0.3$ to four alternative specifications, which span the potential values of the elasticity of substitution across skills. We compute in the model the within-firm standard deviation of the wage-to-skill ratio by dividing wages with x^ρ in each firm, and average across firms. This moment is calculated in the data by dividing wages with the estimated workers' fixed effects recovered from a worker-level regression which features firm-time fixed effects.

confirms also that the within-firm standard deviation of the wage-to-skill ratio decreases with the elasticity of substitution. Interestingly, a model version with a substitutability parameter of $\rho = 0.3$ also matches the overall standard deviation of the wage-to-skill ratio, while it underestimates the overall standard deviation of wages. Appendix F.4 shows that an alternative calibration that also matches the dispersion of wages across firms yields the same identified elasticity of substitution and same quantitative implications on the pass-through.

5.3 Asymmetric pass-through

What are the model quantitative implications on the way in which the incidence of minimum wages at the worker and firm level shapes the pass-through of firm productivity shocks into wages? To answer this question, we construct a measure of wage elasticity to firm TFP:

$$\frac{\log w(x, o, z_k, \tau) - \log w(x, o, z_{k-1}, \tau)}{\log z_k - \log z_{k-1}}. \tag{14}$$

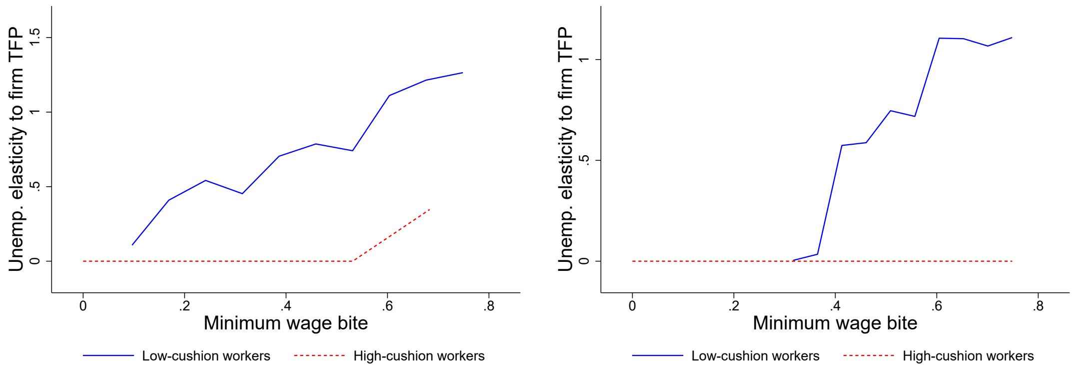
Equation (14) computes the ratio between the change in log-wages associated with a change in firm log-productivity, by considering two consecutive values of firm TFP levels, indexed by k and $k-1$, keeping constant workers' skills x and occupations o, as well as firms' markup levels, τ. In the spirit of our empirical analysis, we compute the wage elasticity to productivity shocks in Equation (14) for two groups of workers: those whose minimum wage cushion is at most 10% (i.e., workers close to the wage floors), and those whose cushion is above 10% (i.e., workers are far from the wage floors). We compute these two measures for each value of firms' minimum wage bite, that is, the firm-level fraction of low-cushion workers.

We start by documenting the model implications on the pass-through of firm negative productivity shocks into job separations. Consistently with our empirical evidence, Figure 1 shows that in the model, high-cushion workers do not experience any increase in the probability of unemployment, independently of their occupation. Instead, low-cushion workers face a surge in job separations which increases in the incidence of minimum wages at the firm level. This dynamics is relatively stronger for blue collars, as the rationing starts at lower level of the firm minimum wage bite, and reaches larger unemployment elasticities.

Figure 2 reports the wage pass-through. Again, the figure shows that the model is consistent with our empirical evidence over three dimensions. First, the wages of low-cushion

Figure 1: Unemployment elasticity to negative firm TFP shocks.

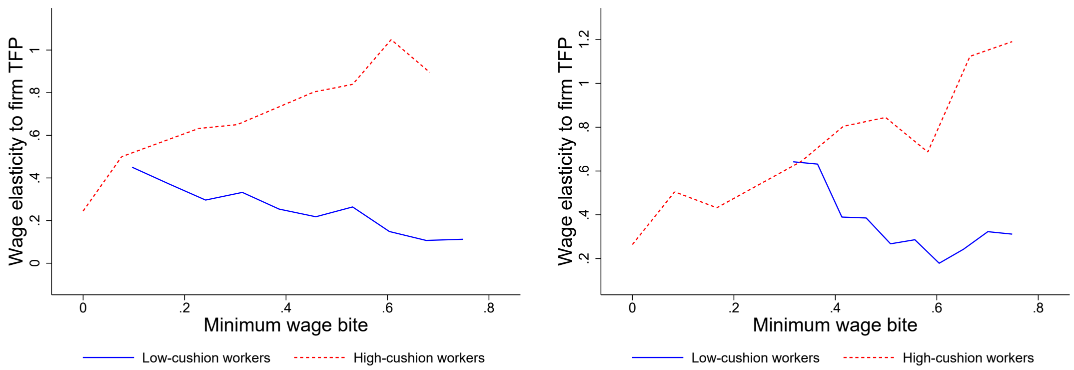
(a) Blue collars (b) White collars



Note: The figures plot the unemployment elasticity to firm negative productivity shocks for blue collars (Panel a) and white collars (Panel b). The blue solid lines are for the low-cushion workers (i.e., workers whose wage is within 10% above the corresponding minimum wage) and the red dashed lines are for high-cushion workers (i.e., workers whose wage is at least 10% above the corresponding minimum wage).

Figure 2: Wage elasticity to negative firm TFP shocks.

(a) Blue collars (b) White collars



Note: The figures are similar to Figure 1, with the difference that in this case we report the change in wages rather than in unemployment.

workers are much less responsive to firm productivity shocks, and this applies for both blue collars and white collars. Second, firms' minimum wage bite crucially determines the wage elasticity of high-cushion worker, as the pass-through becomes substantial in firms with high incidence of minimum wage workers. Third, while the asymmetric wage pass-through applies to workers in each occupation, the relatively larger wage elasticity of high-paid workers emerges for white collars only at very high values of the minimum wage bite. This is consistent with our evidence in Appendix C.2, where the interaction of firm negative productivity shocks and firms' minimum wage bite is a statistically significant factor for the wage pass-through of white collars only in firms in the top quartile of the incidence of minimum wages.

In Appendix F, we report additional results that further validate the implications of the model. We start by showing in Figure F.3 that the positive association between the wage pass-through and the firm minimum wage bite disappears if we consider a model specification in which skills are almost perfect substitutes. Then, Figures F.7 and F.8 highlight that the

Table 4: The blue-collar labor earnings pass-through of negative productivity shocks.

Dependent variable:	Δ log Labor Earnings$_{i,f,t}$			
	Data		Model	
Worker MinW Cushion$_{i,f,t}$:	0-10%	>10%	0-10%	>10%
	(1)	(2)	(3)	(4)
Negative TFP Shock$_{f,t}$	0.017	0.007	-0.045	-0.043
	(0.059)	(0.004)		
Negative TFP Shock$_{f,t}$ $\times$ Firm MinW Bite$_{f,t-1}$	-0.079	-0.145***	-0.097	-0.206
	(0.272)	(0.049)		
Worker-Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No

Note: The table compares the blue-collar labor-earnings elasticities to negative firm productivity shocks estimated in the data, as in Columns (3) and (4) of Table 2, with those implied by the model.

findings of the model do not alter in case we consider an alternative specification for firms' technology in which while there are skill complementarities within occupations, there is a unitary elasticity of substitution between total blue-collar labor and total white-collar labor.

Importantly, the model can replicate the influence of minimum wages in shaping the pass-through of productivity shocks across workers not only qualitatively, but also quantitatively. To uncover this result, we take the model simulated data and closely follow the empirical approach of regression (13), by estimating how the effects of negative productivity shocks into labor earnings vary across low-cushion and high-cushion workers, as a function of firms' minimum wage bites.[18] We focus on labor earnings because this is the key dimension that model has to be consistent with in order to be an ideal laboratory to study the welfare implications of the asymmetric pass-through. Table 4 shows that the model can account for the *magnitude* of the asymmetric pass-through on labor earnings estimated in the data: the role of the interaction term between the negative productivity shock and firms' minimum wage bite as implied by our model almost matches the estimates derived in our data.

5.4 Welfare Implications

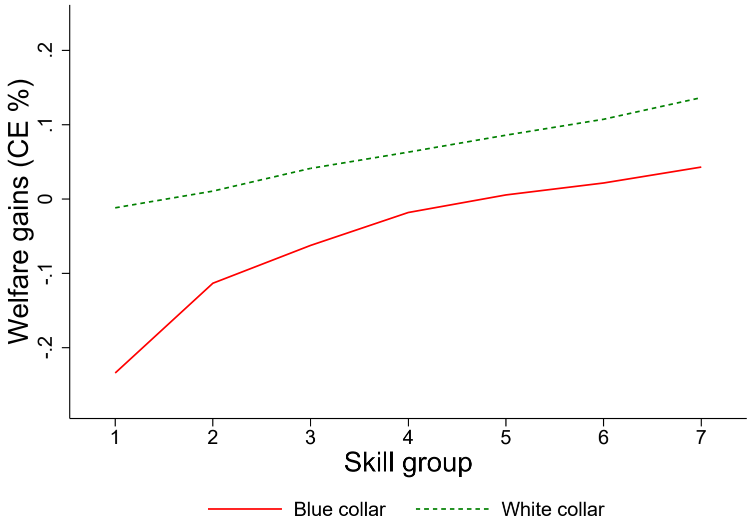
Given that our model accounts for the asymmetric pass-through of firm productivity shocks across workers, we leverage it as an ideal laboratory for the quantification of the welfare gains and losses due to the presence of the minimum wage constraint. Importantly, our analysis does not aim at deriving an optimal level for the minimum wage, as we take no stand on how to aggregate the different welfare changes across households. Rather, we report how welfare changes over the labor earnings distribution if we remove the minimum wage constraint. This section provides a proof of concept that the asymmetric pass-through due to the wage floors generates heterogeneous welfare implications over the labor-earnings distribution.

We compute the gains or losses each worker would experience by moving from the baseline economy to one without the minimum wage.[19] We refer to this version of the model that

[18]The regressions on model simulated data do not include year fixed effects because the model is stationary.

[19]We compute the consumption equivalence term, i.e., the constant rate of change imposed on workers' life-

Figure 3: Welfare gains/losses from removing the minimum wage.



Note: The figures report the welfare gains and losses from removing the minimum wage constraint for each point of the wage distribution. The gains/losses are computed in consumption equivalence terms. The solid line and the dashed line report the welfare gains for the median blue collar and the median white collar, respectively.

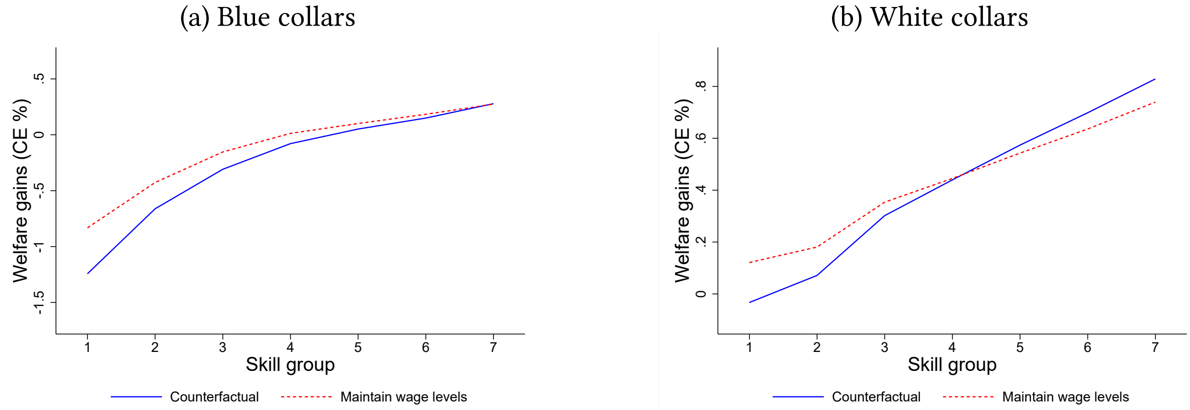
abstracts from wage floors as the "Counterfactual" economy. We report the results of this exercise in Figure 3. While the median welfare change caused by removing the minimum wage is close to zero, this result masks substantial heterogeneity. For both blue collars and white collars, we find welfare losses at the lower end of the skill distribution, and welfare gains at the higher end. The welfare changes of blue collars are tilted towards negative values: low-skill blue collars lose as much as -0.2% in lifetime consumption equivalence terms from the removal of minimum wages, while high-skill collars experience small gains. White collars are mostly better off: low-skill white collars experience a negligible loss from the absence of wage floors, whereas high-skill blue collars gain up to 0.15% in lifetime consumption equivalence terms.

These patterns become more pronounced when looking at workers in high-bite firms. Figure 4 show that low-skill blue collars employed in firms with a high incidence of minimum wages lose substantially from the removal of the wage floors, losing up to -2% in lifetime consumption equivalence terms. These large welfare losses for low-skill blue collars are mirrored by sizable welfare benefits for high-skill white collars, who gain up to 1%.

A potential threat to our approach is the fact that welfare implications not only capture the effect of the minimum wages on the firm productivity pass-through—and thus the *volatility* of wages—across workers, but also the direct effect of minimum wages on the *level* of earnings. To address this concern, we consider a third economy with no wage floors as in the "Counterfactual" case, but with the difference that we recalibrate workers' skill levels to keep wages at the same level as that of the baseline model. We refer to this case as the "Maintain wage levels" economy. Comparing this third case to the baseline model isolates the role of the volatility

time consumption which is necessary to reach the value they would achieve without minimum wages.

Figure 4: Welfare gains/losses from removing the minimum wage: High-bite firms.



Note: The figures compares the welfare gains and losses from removing minimum wages as in Figure 3, but focusing on high-bite firms, with those of an economy in which wages are recalibrated to match the level of earnings of the baseline economy with minimum wages, which we refer to as the "Maintain wage levels" economy. Panel (a) focuses on blue collars and Panel (b) on white collars.

due to the asymmetric pass-through from the level effect. The dashed lines in Figure 4 report the welfare implications of removing the wage floors in the "Maintain wage levels" economy, showing that the volatility effect accounts for the lion's share of the welfare implications of removing wage floors. Thus, although the asymmetric pass-through into wages alters wages' volatility, its welfare implications are of a first-order relevance.

The importance of the volatility effect also helps rationalizing why the welfare gains for white collars are relatively larger than those of blue collars. This is due to the differential asset holdings across workers. Indeed, the model matches the wealth distribution observed in the data (see Table E.2 in Appendix E), so that white collars have higher wealth levels than blue collars. As a result, low-skill white collars can insure relatively more against the higher volatility of their labor earnings absent minimum wages, implying that the welfare losses from eliminating minimum wages for low-skill white collars are substantially curbed.[20]

All in all, the asymmetric pass-through of firm TFP shocks into wages generates a novel channel that tilts the benefits from removing the minimum wage toward high-paid workers.

6 Conclusions

This paper documents that minimum wages shape the allocation of firm-idiosyncratic risk across workers: the pass-through of firm productivity shocks is entirely concentrated on the earnings of high wage individuals employed by firms intensive in minimum-wage workers. Instead, we find a lack of wage adjustment for the workers whose salary is close to the minima. Overall, our evidence provides a novel dimension of the mechanism through which minimum wages shift the cyclicality of wages with respect to firm shocks away from low-paid workers and toward the employees at the high end of the earnings distribution.

[20] Appendix F.3 confirms that the welfare implications crucially vary with households' wealth: low-skill workers are substantially worse off—and high-skill workers are relatively better off—if they hold low asset positions. In other words, when workers have low assets and cannot insure well enough their consumption stream, the welfare implications of the asymmetric pass-through are relatively larger.

We build an incomplete-market economy with heterogeneous households and firms to provide a proof-of-concept that the asymmetric pass-through due to the wage floors generates heterogeneous welfare implications across workers. We provide direct evidence in support of firms' labor demand complementarities across workers of different skills and use this feature to account for the way in which minimum wages modulate the wage pass-through of firm productivity shocks. The model shows that the asymmetric pass-through tilts the benefits of removing minimum wages toward high-paid workers at the expense of low-paid workers. These results highlight a novel channel through which minimum wages asymmetrically affect welfare across workers by altering the wage cyclicality with respect to firm idiosyncratic risk.

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Online Appendix to: "Minimum Wages and Insurance within the Firm"

A More on the Wage Floors

A.1 Institutional Details of Wage Floors

Section 3.1 describes the institutional setting of wage floors in Italy. In this section, we complement this information with additional details.

The wage floors are established via collective bargaining agreements, which in Italy are carried out between unions and employer federations at the sectoral level, and have a national coverage. These agreements also set the conditions for promotions as well as working hours. On average, for the metal-manufacturing industry, the collective agreements tend to last for around 2 years up to 2009, and three years afterwards. While in Italy there is no minimum wage, case law tends to associated the concept of "fair wage" to the wage floors defined by the collective agreements.

In the metal-manufacturing sector, the are four types of collective contracts: (i) the main that covers the vast majority of metal-workers and applies to large privately-owned metal-manufacturing firms; (ii) a contract for workers in state-owned metal-manufacturing firms; (iii) a contract for workers in small and medium enterprises, as well as artisans; and (iv) a contract for workers in co-operative associations. Throughout the paper, we focus on firms which are covered by the first contract for more than 90% of their workforce.

In 2011, Article 8 of Law 148/2011 established the possibility for firms to opt out from the national agreement and determine the contract at the firm level. By doing that, firms would be able to derogate from the conditions set in the national contracts and define the incidence of temporary contracts, and working hours in a bargaining between the firm and workers' representative. Importantly, firms could set wage floors below the ones determined by the sectoral agreements.

One prominent case of a firm opting out is indeed a metal-manufacturing firm, FIAT, which did so starting from 2012. This is the reason why in Table C.2 in Appendix C.2 we consider two cases for our wage pass-through regression in which (i) we exclude FIAT workers from the entire sample period of our analysis, and (ii) we shorten the sample period to 2011, to avoid incurring in the years in which the opt-out possibility has been established.

A.2 Assignment of Wage Floors

Section 3.3 describes the assignment of the relevant wage floor to each metal-manufacturing worker in our sample. In this section, we provide additional details on this procedure. Since in our Invind-INPS data we do not observe the actual job title of each worker which determines its associated wage floor, we imputed it in a multi-step procedure. Notice that blue-collar metal-workers face six potential job titles, while white collars may be associated to up to seven job titles. Our procedure is as follows.

First, we collect actual job titles from an additional data source provided by INPS, which gives us a random and representative 6.5% sample of the Italian workforce, drawn from the universe of private non-farm employees (with available information on job titles). We take the job titles of metal workers as of 2004, and regress them on a set of covariates which are likely determinant of job titles, and that we can also observe in our Invind-INPS data. These covariates are job title, age, sex, tenure, type of contract (permanent or temporary), occupation (blue collar or white collar), firm size (number of employees of the firm in which the worker is employed), and province (location of the firm). We find that regressing the actual job titles in the INPS data on fitted ones in our imputation regression yields a coefficient of 1.28, with a R^2 of 91.84%. This means that our procedure explains almost entirely the variation in job titles—and thus the associated wage floors—across workers in the INPS data.

Second, we further corroborate the validity of the imputation method by comparing the imputed job floors with actual ones for the subsample of workers that we observe both in our Invind-INPS data as well as in the INPS random sample. In this case, the imputation regression yields a coefficient of 1.25 and a R^2 of 93%.

Finally, we validate the assignment procedure by leveraging a firm-level survey of Federmeccanica, the Italian Federation of Metalworking Industries, which gives the breakdown of employment share by job titles. On average, approximately 1,500 firms for a total amount of 225,000 workers are surveyed each year, which accounts for 20% of the total employment of the sector. We compute the employment shares in each job floor at the firm level, and combine them with the imputed employment shares that our assignment procedure implies for those same firms surveyed by Federmeccanica. Regressing the actual firm-level employment shares of each job titles on those imputed for the same firms by our assignment procedure yields a coefficient of 1 with a R^2 of 74%, thus showing that our procedure matches very well the incidence of each wage floor at the firm level.

B Descriptive Statistics

Table B.1 reports some descriptive statistics of our data sample at the firm level, by showing for a set of key variables the mean, standard deviation, as well as the 25th and 75th percentile of the distribution of these variables across firms. Panels A and B in Tables B.2 report the same statistics separately for the sample of firms with low minimum wage bite and high minimum wage bite, respectively. Finally Table B.3 report descriptive statistics at the worker level.

Table B.1: Summary statistics - All firms.

Variable	P25	P75	Mean	S.d.	N
Log monthly nominal wage	7.51	7.88	7.70	0.26	3,004
Monthly nominal wage	1,823.93	2,655.95	2,278.65	598.76	3,004
Firm minimum wage bite	0.01	0.14	0.09	0.12	3,004
Located in north regions (%)	0.00	1.00	0.77	0.42	3,004
Workers' age	22.00	44.00	33.82	16.53	3,004
Size in terms of employees	32.21	106.25	150.79	489.34	3,004
Share blue collar employees (%)	0.50	0.74	0.60	0.21	3,004
Share white collar employees (%)	0.21	0.44	0.35	0.20	3,004
Share temporary employees (%)	0.00	0.07	0.06	0.12	3,004
Log total assets	6.94	8.82	7.84	1.49	3,004
Log turnover	9.19	10.88	10.17	1.30	3,004
Markup	0.81	1.35	1.27	0.82	3,004
Profit to asset ratio	0.04	0.49	0.50	6.88	3,004
Employment share at province level (%)	0.02	0.20	0.19	0.29	3,004
Negative TFP shock (%)	0.00	1.00	0.50	0.50	3,004

Table B.2: Summary statistics - Low and high minimum wage bite firms.

Variable	P25	P75	Mean	S.d.	N
Panel A. Low minimum wage bite firms					
Log monthly nominal wage	7.66	7.99	7.82	0.25	1,502
Monthly nominal wage	2,125.93	2,939.35	2,579.66	646.61	1,502
Firm minimum wage bite	0.00	0.02	0.01	0.01	1,502
Located in north regions (%)	0.00	1.00	0.86	0.34	1,502
Workers' age	23.00	48.00	35.25	17.15	1,502
Size in terms of employees	34.55	191.49	218.24	647.34	1,502
Share blue collar employees (%)	0.47	0.72	0.58	0.21	1,502
Share white collar employees (%)	0.24	0.48	0.38	0.19	1,502
Share temporary employees (%)	0.00	0.06	0.05	0.12	1,502
Log total assets	7.14	9.30	8.17	1.71	1,502
Log turnover	9.71	11.40	10.74	1.45	1,502
Markup	0.84	1.35	1.23	0.67	1,502
Profit to asset ratio	0.06	0.58	1.37	4.93	1,502
Employment share at province level (%)	0.02	0.20	0.19	0.27	1,502
Negative TFP shock (%)	0.00	1.00	0.49	0.50	1,502
Panel B. High minimum wage bite firms					
Log monthly nominal wage	7.45	7.78	7.62	0.22	1,502
Monthly nominal wage	1,720.55	2,387.17	2,084.22	473.10	1,502
Firm minimum wage bite	0.06	0.21	0.15	0.12	1,502
Located in north regions (%)	0.00	1.00	0.71	0.46	1,502
Workers' age	22.00	41.00	32.90	16.05	1,502
Size in terms of employees	29.92	85.62	107.22	344.60	1,502
Share blue collar employees (%)	0.52	0.75	0.61	0.20	1,502
Share white collar employees (%)	0.20	0.43	0.34	0.19	1,502
Share temporary employees (%)	0.00	0.07	0.06	0.13	1,502
Log total assets	6.82	8.58	7.63	1.29	1,502
Log turnover	9.02	10.46	9.81	1.04	1,502
Markup	0.80	1.35	1.29	0.90	1,502
Profit to asset ratio	0.02	0.44	-0.07	7.84	1,502
Employment share at province level (%)	0.02	0.20	0.20	0.30	1,502
Negative TFP shock (%)	0.00	1.00	0.51	0.50	1,502

Table B.3: Summary statistics - All workers.

Variable	P25	P75	Mean	S.d.	N
Daily nominal wage	68.54	106.34	92.24	34.69	635,010
Log daily nominal wage	4.23	4.67	4.47	0.33	635,010
Daily nominal wage growth	0.00	0.08	0.04	0.12	635,010
Minimum-wage cushion	0.22	0.66	0.49	0.43	635,010
Low-cushion workers (%)	0.00	0.00	0.07	0.25	635,010
Probability of job loss	0.00	0.00	0.03	0.17	635,010
Blue collars (%)	0.00	1.00	0.63	0.48	635,010
Permanent workers (%)	1.00	1.00	0.98	0.12	635,010
Part-time workers (%)	0.00	0.00	0.04	0.19	635,010
Age	34.00	48.00	41.13	9.12	635,010
Forlough (%)	0.00	0.00	0.18	0.38	635,010

C More on the Empirical Results

C.1 The Alternative Firm-Specific Shocks

In our empirical analysis, we study how wages react to negative firm productivity shocks. Here, we evaluate the robustness of our findings to three alternative measures that capture exogenous shifts in firm labor demand. In particular, we consider one series of firm-specific labor productivity shocks and two series of firm-specific export shocks.

To back out the firm-specific labor-productivity shocks, we compute the difference between the log-change of firms' sales with the log change of firms' total number of employees,

$$\Delta \text{Labor Productivity}_{f,t} = \Delta[\log(\text{Real Sales}_{f,t}) - \log(\text{Employees}_{f,t})]. \tag{C.1}$$

The first firm-specific export shock is derived as a Bartik-like shift-share variable, in the spirit of Mayer et al. (2021) and Aghion et al. (2018), in which we exploit confidential custom-level information at the firm level, as in Garin and Silvério (2024). Specifically, we retrieve from the Italian Custom Agency database transaction-level data on each product sold abroad by Italian firms. Unfortunately, this information is only available for the later part of our sample period, that is, over 2010-2015. For each product p and destination country d, we compute the variable $\omega_{f,p,d,2010}$:

$$\omega_{f,p,d,2010} = \frac{\text{Exports}_{f,p,d,2010}}{\sum_p \sum_d \text{Exports}_{f,p,d,2010}} \tag{C.2}$$

which is the firm-level share of exports of product p to destination country d in total exports of firm f, measured in the year 2010.

We get information on bilateral trade flows from the BACI-CEPII database. We compute the variable $M_{p,d,t}$, which describes the total imports of a product p that a destination country d receives from all countries, excluding the contribution of Italy, in year t. With this information, we derive the firm-level export shock for the period 2011-2015 as

$$\Delta \text{Export Shock}_{f,t} = \sum_p \sum_d \omega_{f,p,d,2010} \Delta \log M_{p,d,t}. \tag{C.3}$$

The second firm-specific export shock is also derived as a shift-share variable, but this time leverages variation at the market level, defined as the combination of province of location of the firm and its sector of operation. We compute it using data from the Italian National Statistical Institute on the exports from each Italian province p and each sector s to each destination country d in 1995. Again, we complement the data with information from the BACI-CEPII database. This information is available for the entire period of analysis, that is, 1995-2015. We compute the export shock in two steps. First, we compute foreign demand of each destination country at the market level. In this case, we look at total exports, without discriminating between product types. Second, we attribute the province-sector foreign demand to each firm f, using firms' lagged revenue share of exports, $\text{Exports}_{f,t-1}/\text{Sales}_{f,t-1}$.

C.2 Robustness Checks

This section provides a comprehensive battery of robustness checks on the worker-level pass-through of negative firm productivity shocks on the wages of blue collars. We start by ascertaining the validity of our results to alternative specifications for the firm shocks. We complement the analysis of Section 4.3, which has relied on firm TFP shocks, by estimating regression (13) using either firm-specific labor-productivity shocks, or firm-specific export shocks derived from custom level information, or the alternative series of firm-specific export shocks derived by leveraging variation at the market level. In all cases, we keep focusing on the series of negative innovations. We report the results of these robustness exercises in Table C.1.

We also evaluate the robustness with respect to different samples and specifications in Table C.2. In this table, we consider four cases: (i) a regression on blue collars in which we exclude FIAT workers throughout the sample period, to net out the issue that FIAT workers were withdrawn from the sectoral collective bargaining agreement in 2012, (ii), a regression in which we end the sample period in 2011, to avoid considering the period of time in which the possibility of opting out from collective agreements has been established, (iii) a regression in which we also introduce a set of lagged firm controls (i.e, the logarithm of total assets, sales—measured as the logarithm of turnover, markups—estimated when recovering the process of firm TFP shocks, the profit-to-asset ratio, the employment share in the local labor markets—proxied at the 2-digit- sector-region level, and the share of blue collars and white collars), and (iv) a regression which focuses on large realizations of the negative firm productivity shocks, as in Juhn et al. (2018). We define large shocks as the negative realization of firm productivity shock that is above the median.

Table C.3 reports that the asymmetric pass-through holds also when we look at the transitory innovations to firm productivity, which are identified as in Blundell et al. (2008). In this case, we consider the firm productivity shock in its continuous values, thus not isolating only the negative realizations. The asymmetric pass-through does not change in case we consider either TFP shocks adjusted for variable utilization derived as in Basu et al. (2006), in which we use firms' reported utilization of their production inputs (a value between 0 and 1 in the Invind survey), or a series of firm productivity shocks in which we explicitly control for heterogeneity in workers' labor inputs across firms. We do so as in Chan et al. (2023), that is, by absorbing from firms' labor inputs the estimated worker fixed effects, which are recovered in a worker-level regression in the spirit of Abowd et al. (1999). In this case, the number of observations drops because we can only identify the worker fixed effects for the sub-sample of movers.

The baseline analysis in Section 4.3 has characterized the role of the incidence of minimum wages at the worker level by estimating regression (13) on two samples of workers, one whose minimum wage cushion is up to 10%, and one with a cushion above 10%, as well as considering the fraction of workers with the 10% cutoff value to compute the minimum-wage bite at the firm level. Table C.4 confirms the empirical evidence of Table 1 in case we consider either 15% or 20% as the threshold values for the worker minimum wage cushion and the firm minimum wage bite. The asymmetric pass-through continues to hold but becomes smaller in size. This is because the firm level bite is shrinking as we progressively increase the threshold from 10% to 15% and 20%.

We also evaluate the role of different specifications of firms' minimum wage bite in Table C.5. We start by considering two alternative ways of computing the incidence of wage floors at the firm level. In the first one, we take the job title of each worker, and define the set of employees in the same firm that have a job title which is at most as high as that of the worker of interest (e.g., for a worker whose job title is the second one out of the eight possible that apply to blue collars and white collars, we focus solely on the co-workers with the first and second job title). In the second one, we take the complementary approach and define the set of employees in the same firm that have a job title which is higher than that of the worker of interest (e.g., for a worker whose job title is the second one out of the eight possible that apply to blue collars and white collars, we focus solely on the co-workers from the third job title on). We find that the interaction of the minimum wage bite with the firm negative TFP shock is statistically significant when focusing on the below minimum wage bite, while this is not the case when looking at the above minimum wage bite. This result could be due to the fact that insofar both wages and also the average worker's cushion increase with the job title (i.e., the difference between average wage and wage floor is larger for high-skill workers than for low-skill workers), the below minimum wage bite captures the importance of workers' rationing in generating the asymmetric pass-through. We then consider an alternative specification in which: (i) we focus on white collars, (ii) derive the minimum wage bite by considering only white collars, and (iii) focus on firms with the highest incidence of wage floors, by considering the bite in the top quartile of the overall distribution. We find that in this case the asymmetric pass-through also holds for white collars. This in line with the model prediction, showing that for white collars the asymmetric pass-through emerges at high values of firms' minimum wage bite.

We also show that the baseline results are robust to saturating the regression with more granular fixed effects. For instance, Table C.6 reports that the pass-through of firm TFP shocks into the wages of high-cushion workers holds in case we substitute the year fixed effects with either 2 digit sector-year fixed effects, or with province fixed effects, or with three different sets of fixed effects defined at the year level, firm level, and group level as in Bonhomme et al. (2019). The magnitude of the pass-through barely changes when using the relatively more granular fixed effects.

Next, we study the role of some key workers' characteristics in shaping the pass-through of the firm-specific shocks into the wages of high-paid workers. We do so over five dimensions. First, we split the samples by workers' age: one with all the employees whose age is between 20 and 41, and one with those employees whose age is between 41 and 65. We find that the relatively larger pass-through applies almost indistinguishably to the two groups of workers. Second, we exclude the workers at the top 20% of the wage distribution, to provide further evidence that bonuses or heterogeneity in job performance at the top end of the wage distribution (Juhn et al., 2018) are not driving our result. Third, we exclude all those workers who have been subject to furlough policies. Fourth, to rule out any consideration due to the duality of the Italian labor market, we exclude all workers with a temporary contract and focus exclusively on the employees with a permanent position. Fifth, we repeat the previous case and now compute also the incidence of minimum wages at the firm level by excluding all workers with temporary contracts. We report all these cases in Table C.7.

We also evaluate the role of firms' characteristics. Table C.8 reports the wage elasticity of high-cushion workers by splitting the firms into two samples depending each time on one key firm characteristic. We start by considering characteristics that proxy for firms' financial conditions. Indeed, firms' financial constraints could determine how minimum wages affect the wage distribution (Arabzadeh et al., 2024). Columns (1) and (2) consider the wage elasticity in a sample of low-markup and high-markup firms, respectively. These markups are estimated jointly with the productivity levels when recovering the firm productivity shocks. Columns (3) and (4) evaluate how the pass-through relates to firms' profits-to-asset ratio, and Columns (5) and (6) analyze the role of firms' age. In all these cases, the magnitude of the pass-through is fairly constant across samples, thus revealing that this phenomenon cannot be fully explained by worker-firm rent sharing (e.g., Card et al., 2014; Matano and Naticchioni, 2017). For the last set of characteristics, we consider firms' monopsony power. Specifically, Columns (7) and (8) study whether the pass-through depends on firms' employment share in their local labor market of operation, which is defined at the 2 digit sector-region level. These cases highlight that the asymmetric pass-through is not closely tied to firms' monopsony power. Indeed, while the magnitude of the pass-through decreases with firms' local monopsony power, in line with Chan et al. (2023) and Berger et al. (2022a), we find that the wage elasticity keeps being statistically significant in the sample of firms with high employment shares in their local labor markets.

Finally, we study the role of risk-sharing in shaping the asymmetric pass-through (Guiso et al., 2005; Ellul et al., 2018; Lamadon et al., 2022), and find that our results hold above and beyond any risk consideration. Table C.9 establishes this result by looking at four dimensions. The first one is workers' risk aversion. In the spirit of Guiso et al. (2005), we leverage a question of the SHIW which asks whether workers manage their financial investments either (i) to aim at very high gains, even though this implies that a substantial part of the invested capital could be likely lost, or (ii) to aim at a good gain, while facing a discrete degree of safety for the invested capital, or (iii) to aim at a discrete gain, while facing a good degree of safety for the invested capital, or (iv) to aim at a low gain, with no risk for the invested capital. Following closely Guiso et al. (2005), we impute the risk aversion of all the workers in our sample through a matching procedure based on the observable characteristics that appear both in our dataset and in the SHIW. We then define as lowly risk-averse workers all those who are associated to answers (i)-(iii), while answer (iv) defines highly risk-averse workers. Second, we consider firm uncertainty and proxy it with the time-series volatility of firm TFP shocks. We define that a firm has a low volatility if the standard deviation of its TFP shocks is below the median value in our sample. As a third dimension, we consider firm bankruptcy risk, and measure it with Altman (1968)'s Z-score. The score is measured in a 9-point scale and we define as the firms with high bankruptcy risk those in the highest three buckets. The last dimension we consider is firm cash needs. We measure them by exploiting a question in the Invind survey, in which firms have to report the fraction of their trade credit claims that has been deferred over the agreed expiration date. The answer to this question then measures the amount of liquid resources that firms could have got should their customers have paid them on due time. We then define low cash-need firms as those who have reported a fraction of deferred trade credit claims which is below the median value in our sample. Table C.9 shows that the asymmetric pass-through of firm negative productivity shocks into the wages of high-cushion workers holds always above and beyond the variation in these four ways of capturing risk considerations.

Table C.1: The role of alternative firm-specific shocks.

Dependent variable:	$\Delta \log \text{Wage}_{i,f,t}$					
	Labor Productivity Shocks		Export Shocks		Alternative Export Shocks	
Worker MinW Cushion$_{i,f,t}$:	0-10%	>10%	0-10%	>10%	0-10%	>10%
	(1)	(2)	(3)	(4)	(5)	(6)
Shock$_{f,t}$	-0.010*	-0.008***	-0.011	0.054	0.007	0.005
	(0.005)	(0.003)	(0.007)	(0.006)	(0.008)	(0.004)
Shock$_{f,t}$ × Firm MinW Bite$_{f,t-1}$	0.025	-0.067**	0.016	-0.035**	-0.027	-0.069*
	(0.017)	(0.032)	(0.012)	(0.017)	(0.037)	(0.036)
Worker-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,530	375,058	2,141	67,194	6,430	240,083

Note: The table reports panel-regression estimates as in Table 1 with the difference that we replace the negative realizations of firm productivity shocks with the negative realizations of labor productivity shocks in Columns (1) and (2), the negative realizations of export shocks derived from custom-level information in Columns (3) and (4), and the negative realizations of an alternative export shocks series derived using variation at the market level in Columns (5) and (6).

Table C.2: The role of alternative specifications and samples.

Dependent variable:	$\Delta \log \text{Wage}_{i,f,t}$							
	Excluding FIAT		Until 2011		Firm Controls		Large Shocks	
Worker MinW Cushion$_{i,f,t}$:	0-10%	>10%	0-10%	>10%	0-10%	>10%	0-10%	>10%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Negative TFP Shock$_{f,t}$	0.005	0.002	0.003	0.004	0.004	0.003	0.001	0.002
	(0.006)	(0.003)	(0.005)	(0.003)	(0.006)	(0.003)	(0.009)	(0.003)
Negative TFP Shock$_{f,t}$ × Firm MinW Bite$_{f,t-1}$	-0.016	-0.077***	-0.025	-0.082**	-0.016	-0.078***	0.018	-0.088**
	(0.020)	(0.030)	(0.022)	(0.034)	(0.020)	(0.029)	(0.031)	(0.034)
Worker-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,012	366,690	8,930	288,218	13,108	391,410	13,108	391,410

Note: The table reports panel-regression estimates as in Table 1 with the difference that Columns (1) and (2) excludes FIAT workers, Columns (3) and (4) further exclude all observations after 2011, Columns (5) and (6) introduce a set of lagged firm controls (i.e, the logarithm of total assets, sales—measured as the logarithm of turnover, markups—estimated when recovering the process of firm TFP shocks, the profit-to-asset ratio, the employment share in the local labor markets—proxied at the 2-digit- sector-region level, and the share of blue collars and white collars), and Columns (7) and (8) looks only at large negative firm productivity shocks.

Table C.3: The role of alternative productivity shocks.

Dependent variable:	$\Delta \log \text{Wage}_{i,f,t}$					
	Transitory Shocks		Shocks Adjusted Variable Utilization		Shocks Adjusted Labor Inputs	
Worker MinW Cushion$_{i,f,t}$:	0-10%	>10%	0-10%	>10%	0-10%	>10%
	(1)	(2)	(3)	(4)	(5)	(6)
Shock$_{f,t}$	0.023	0.011	0.068***	0.048***	0.094**	0.061***
	(0.016)	(0.010)	(0.024)	(0.016)	(0.043)	(0.022)
Shock$_{f,t}$ $\times$ Firm MinW Bite$_{f,t-1}$	-0.058	0.143*	-0.190	0.310*	-0.122	0.400*
	(0.070)	(0.080)	(0.116)	(0.164)	(0.126)	(0.221)
Worker-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,302	344,662	11,786	380,161	8,884	187,373

Note: The table reports panel-regression estimates as in Table 1 with the difference that in this case the series of firm-productivity shocks, Shock$_{f,t}$, is either the continuous realizations of temporary productivity shocks estimated as in Blundell et al. (2008), in Columns (1) and (2), or the continuous realizations of firm productivity shocks adjusted for variable utilization derived as in Basu et al. (2006), in Columns (3) and (4), or the continuous realizations of firm productivity shocks adjusted for heterogeneity in workers' inputs, by absorbing from firm labor the workers' fixed effects estimated in a regression in the spirit of Abowd et al. (1999), in Columns (5) and (6).

Table C.4: The role of alternative workers' minimum wage cushion.

Dependent variable:	$\Delta \log \text{Wage}_{i,f,t}$			
Worker MinW Cushion$_{i,f,t}$:	0-15%	>15%	0-20%	>20%
	(1)	(2)	(3)	(4)
Negative TFP Shock$_{f,t}$	-0.001	0.002	-0.005	0.002
	(0.006)	(0.003)	(0.006)	(0.004)
Negative TFP Shock$_{f,t}$ $\times$ Firm MinW Bite$_{f,t-1}$	0.010	-0.041**	0.016	-0.026*
	(0.017)	(0.018)	(0.013)	(0.014)
Worker-Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	31,002	369,693	58,754	337,948

Note: The table reports panel-regression estimates as in Table 1 with the difference that this table focuses on blue-collar workers, and considers different cut-off values for defining low-cushion and high-cushion workers. The cutoff changes from 10% in the baseline model to 15% in Columns (1) and (2), and 20% in Columns (3) and (4).

Table C.5: The role of alternative firms' minimum wage bite.

Dependent variable:	Δ log Wage$_{i,f,t}$					
	Job Titles Below		Job Titles Above		White Collars	
Worker MinW Cushion$_{i,f,t}$:	0-10%	>10%	0-10%	>10%	0-10%	>10%
	(1)	(2)	(3)	(4)	(5)	(6)
Negative TFP Shock$_{f,t}$	0.008	0.002	0.002	-0.002	-0.029	-0.002
	(0.007)	(0.003)	(0.004)	(0.002)	(0.028)	(0.005)
Negative TFP Shock$_{f,t}$ $\times$ Firm MinW Bite$_{f,t-1}$	-0.017	-0.049**	0.003	-0.021	0.006	-0.012*
	(0.018)	(0.021)	(0.022)	(0.164)	(0.027)	(0.007)
Worker-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,072	386,019	13,076	386,023	5,609	182,774

Note: The table reports panel-regression estimates as in Table 1 with the difference that it considers different ways of measuring firms' minimum wage bite. In Columns (1) and (2), we measure the bite for each worker by focusing only on its co-employees with a job title at most as high as its. In Columns (3) and (4), we take the complementary approach, and measure the bite for each worker by focusing only on its co-employees with a job title at least as high as its. In Columns (5) and (6), we focus on white collars, compute the minimum wage bite only focusing on white collars, and consider the highest quartile of the distribution of the incidence of minimum wages across firms.

Table C.6: The role of alternative fixed effects.

Dependent variable:		$\Delta \log \text{Wage}_{i,f,t}$		
	Baseline	Sector-Year FE	Province-Year FE	Firm, Year, Group FE
Worker MinW Cushion$_{i,f,t} > 10\%$	(1)	(2)	(3)	(4)
Negative TFP Shock$_{f,t}$	0.002	0.003	0.001	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Negative TFP Shock$_{f,t}$ $\times$ Firm MinW Bite$_{f,t-1}$	-0.077***	-0.074***	-0.070**	-0.067**
	(0.030)	(0.027)	(0.028)	(0.033)
Worker-Firm FE	Yes	Yes	Yes	No
Year FE	Yes	No	No	Yes
Sector-Year FE	No	Yes	No	No
Province-Year FE	No	No	Yes	No
Firm FE	No	No	No	Yes
Group FE	No	No	No	Yes
Observations	391,410	391,410	391,250	342,336

Note: The table reports in Column (1) the baseline panel-regression estimate of Table 1 for high-cushion blue collars, that is, those workers whose minimum wage cushion is above 10%. Column (2) substitutes the year fixed effects with 2 digit sector-year fixed effects, Column (3) substitutes the year fixed effects with province-year fixed effects, and Column (4) features firm fixed effects, year fixed effects, and group fixed effects as in Bonhomme et al. (2019).

Table C.7: The role of key worker characteristics.

Dependent variable:	Δ log Wage$_{i,f,t}$					
	Young Workers	Old Workers	Excluding Top 20%	Excluding Furlough	Permanent Workers	Permanent-Workers Firm Bite
Worker MinW Cushion$_{i,f,t}$:>10%	(1)	(2)	(3)	(4)	(5)	(6)
Negative TFP Shock$_{f,t}$	0.004	0.001	0.003	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Negative TFP Shock$_{f,t}$ $\times$ Firm MinW Bite$_{f,t-1}$	-0.084**	-0.075**	-0.083***	-0.050**	-0.075**	-0.077**
	(0.034)	(0.030)	(0.029)	(0.024)	(0.030)	(0.031)
Worker-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	206,865	178,882	350,686	257,574	384,060	384,060

Note: The table reports panel-regression estimates as in Table 1 for high-cushion blue collars, that is, those workers whose minimum wage cushion is above 10%, and studies the role of some key worker characteristics. Columns (1) and (2) split the sample by the age of the workers, such that Column (1) is estimated on a sample of young employees, whose age is between 20 and 41 years old, Column (2) focuses on a sample of old employees, whose wage is above 41 years old, Column (3) excludes the workers whose wage is in the top 20% of the sample, Column (4) excludes the workers who have been subject to furlough policies, Column (5) excludes workers with temporary contracts, and Column (6) excludes workers with temporary contracts also when computing the minimum wage bite at the firm level.

Table C.8: The role of key firm characteristics.

Dependent variable:	Δ log $\text{Wage}_{i,f,t}$							
	Markups		Profits/Assets Ratio		Age		Empl. Share in Local Labor Market	
	Low	High	Low	High	Low	High	Low	High
Worker MinW $\text{Cushion}_{i,f,t} > 10\%$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Negative TFP $\text{Shock}_{f,t}$	0.002	0.002	0.007	0.006	0.011*	-0.001	0.002	0.002
	(0.004)	(0.004)	(0.005)	(0.004)	(0.007)	(0.003)	(0.003)	(0.005)
Negative TFP $\text{Shock}_{f,t}$ $\times$ Fir MinW $\text{Bite}_{f,t-1}$	-0.059*	-0.078*	-0.103***	-0.094*	-0.087*	-0.072**	-0.070*	-0.080*
	(0.033)	(0.040)	(0.038)	(0.056)	(0.050)	(0.034)	(0.041)	(0.048)
Worker-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	319,906	56,133	204,856	139,410	81,672	294,073	220,297	161,074

Note: The table reports panel-regression estimates as in Table 1 for high-cushion blue collars, that is, those workers whose minimum wage cushion is above 10%, and studies the role of some key firm characteristics. Columns (1) and (2) estimate the regressions for the samples of firms with low and high markup levels, Columns (3) and (4) estimate the regressions for the samples of firms with low and high profit ratios, Columns (5) and (6) estimate the regressions for the samples of young and old firms, and Columns (7) and (8) estimate the regressions for the samples of firms with low and high local labor-market employment shares, respectively. The local labor market is defined at the 2 digit sector-region level.

Table C.9: The role of risk.

Dependent variable:	$\Delta \log \text{Wage}_{i,f,t}$							
	Worker Risk Aversion		Firm Uncertainty		Firm Bankruptcy Risk		Firm Cash Needs	
	Low	High	Low	High	Low	High	Low	High
Worker MinW Cushion$_{i,f,t} > 10\%$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Negative TFP Shock$_{f,t}$	0.002	0.003	0.000	0.005	0.002	0.018**	0.006	0.000
	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)	(0.008)	(0.004)	(0.004)
Negative TFP Shock$_{f,t}$ $\times$ Firm MinW Bite$_{f,t-1}$	-0.069*	-0.089**	-0.059*	-0.112*	-0.086**	-0.101*	-0.093**	-0.071*
	(0.039)	(0.039)	(0.034)	(0.063)	(0.035)	(0.059)	(0.044)	(0.042)
Worker-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	141,876	135,331	189,681	193,651	322,022	16,310	230,024	149,009

Note: The table reports panel-regression estimates as in Table 1 for high-cushion blue collars, that is, those workers whose minimum wage cushion is above 10%, and studies the role of risk. Columns (1) and (2) estimate the regressions for low and high risk-averse workers, respectively, where risk aversion is derived from a question in the SHIW survey about households' financial investment attitude. Columns (3) and (4) estimate the regressions for low and high volatile firms, respectively, where volatility is the time-series standard deviation of firm TFP shocks, and firms are split in two groups of low and high volatility around the median value of the TFP shock standard deviation. Columns (5) and (6) estimate the regressions for firms with low and bankruptcy risk, respectively. Bankruptcy risk is measured using Altman's Z-score. High risk firms are those featuring a score that defines a firm to be in financial distress. Columns (7) and (8) estimate the regressions for firms with low and high cash needs, respectively. Cash needs are derived from a question in the Invind survey in which firms report the fraction of trade credit claims which have been referred over the due expiration date. We define low cash-need firms as all those reporting a fraction which is below the median value in the sample.

D Description of the Quantitative Model

This section details the structure of our quantitative model, that extends the simple conceptual framework of Section 2 into a fully-fledged incomplete-market model with heterogeneous households and heterogeneous firms.

D.1 Firms

The production side of the economy consists of a continuum of firms of unit measure. Firms are characterized by an idiosyncratic time-varying TFP level, z, and an idiosyncratic fixed markup, captured by τ. The former is a discrete random variable following an arbitrary stationary stochastic process with transition matrix $\Gamma_z(z, z')$. We denote the discrete set of possible values of z by $\mathbb{Z} = \{z_1, \ldots, z_{N_z}\}$. The variable τ, that denotes firm markup, is fixed for each firm and take N_τ levels within the set $\mathbb{T} = \{\tau_1, \ldots, \tau_{N_\tau}\}$. We capture firms' markups as exogenous wedges that apply to firms' total production costs.

The relevance of the heterogeneity in markups is twofold. First, it breaks the one-to-one mapping between firms' TFP and minimum wage bite. Without the variation in markups, the model would counterfactually imply that the minimum wage relevance at the firm level uniquely depends on its productivity. Second, markups heterogeneity generates variation in wages that goes above and beyond that implied by the dispersion in firms' TFP. Without the variation in markups, the pass-through implied by the model could be biased upwards as it would derive the response of wages with respect to changes to their sole determinant, firms' productivity.

Firms produce the final good of the economy, Y, with the technology

$$Y = z(K^\alpha L^{1-\alpha})^\eta, \tag{D.1}$$

where K denotes capital, and L is labor. Finally, the span-of-control parameter η is assumed to be less than 1, such that the technology features decreasing returns to scale. As in Krusell et al. (2000) and Caselli and Coleman (2006), firms' labor consists of an aggregator that allows for imperfect substitutability between workers of different skills. Formally, firms' effective labor aggregates the supply of different skills as follows

$$L = \left(\sum_{i=1}^{N_x} [x_i \mu(x_i)]^\rho \right)^{\frac{1}{\rho}}, \tag{D.2}$$

where $\mu(x)$ is the firm-specific measure of workers with skills x. These skills are fixed and heterogeneous across workers, and can take N_x levels within the set $\mathbb{X} = \{x_1, \ldots, x_{N_x}\}$. We then map skills into occupations $o(x)$. Specifically, we consider a set of occupations $\mathbb{O} = \{\text{bc}, \text{wc}\}$, such that workers can be either blue collars, bc, or white collars, wc. We then assign the first $N_{x,1}$ values of workers' skills to blue collars, and the next $N_{x,2}$ values to white collars, such that $N_{x,1} + N_{x,2} = N_x$. Thus, the skills for blue collars take value within the subset $\mathbb{X}_1 = \{x_1, \ldots, x_{N_{x,1}}\}$, and the skills for white collars take value within the subset

$\mathbb{X}_2 = \{x_{N_{x,1}+1}, \ldots, x_{N_x}\}$. Hereafter, we refer to both workers' skills x and occupations o as individual state variables, even though the latter depends entirely on the former.

The strength of complementarities across skills in firm labor demand is pinned down by the parameter ρ of Equation (D.2). When $\rho = 1$, there is perfect substitutability across skills. However, insofar $\rho < 1$, the economy is characterized by skill complementarities, and the degree of complementarities is stronger the lower is the value of parameter ρ. The functional form of the labor aggregator follows the specification of Ciccone and Peri (2005) and Caselli and Coleman (2006). This technology then implies that workers are perfectly substitutable within each skill level, and imperfectly substitutable across skills.

We assume that there is anonymity in firms and workers conditional on z, τ, and x. Workers who are going to work in a (z, τ)-firm in a period are pooled together and drawn randomly into firms. This rules out firms' dynamic considerations when attracting workers, so that firms decide on the measure of workers from each skill independently of the past. In addition, upon the values of a (x, o, z, τ)-tuple, the worker is fully mobile between firms of productivity z and markup τ. This implies that the wage for a given skill x in occupation o is the same for each (z, τ)-firm.[21] We denote this wage by $w(x, o, z, \tau)$.

Firms' profit-maximization problem is static: firms choose how much capital to rent, the measure of workers of each skill level, $\{\mu(x_i)\}_{i=1}^{N_x}$, and their output, as follows,

$$\pi(z,\tau) = \max_{K, \{\mu(x_i)\}_{i=1}^{N_x}, Y} \quad Y - (1-\tau)[(r+\delta)K - \sum_{i=1}^{N_x} w(x_i, o, z, \tau)\mu(x_i)] \tag{D.3}$$

$$\text{s.t.} \quad Y = z\left[K^{\alpha}\left\{\left(\sum_{i=1}^{N_x}(x_i\mu(x_i))^{\rho}\right)^{\frac{1}{\rho}}\right\}^{1-\alpha}\right]^{\eta}. \tag{D.4}$$

As in the data, the economy features occupation-specific minimum wage constraints

$$w(x, o, z, \tau) \geq \underline{w}(o), \qquad \forall x, z, \tau, \tag{D.5}$$

which impose the same wage floor $\underline{w}(o)$ for workers with occupation o independently of their skills x, as well as the productivity, z, and markup τ, of the firm at which they are employed. Importantly, the wage floors vary across occupations in line with what we observe in the metal-manufacturing sector in Italy. Note that firms' maximization problem does not include the presence of of the minimum wage constraints, meaning that in this setting firms do not directly take their hiring decisions by explicitly accounting for the role of minimum wages. Rather, this restriction emerges in equilibrium, since firms take wages as given.

[21] This would also be the implication of a take-it-or-leave-it offer from the worker to the firm in each period.

D.2 Workers

The economy is populated by a continuum of households of unit measure. Households have standard CRRA preferences in consumption, so that life-time utility equals

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\gamma}}{1-\gamma}, \tag{D.6}$$

where γ captures the degree of risk aversion, and β is the time discount factor.

Workers are endowed with a fixed skill level, x, whose properties are described above. The variation in skills make households ex-ante heterogeneous. In addition, workers face a source of idiosyncratic uncertainty: with probability $1-s$, workers are obliged to work in their employer of last period. In this case, their wage varies with the realizations of the productivity shocks of their employer, moving along the same TFP-ladder of their firm, which is governed by the transition matrix Γ_z. Instead, with probability s, workers receive the opportunity to decide on which firm-level productivity and markup to work for.[22]

Conditional on the own labor skill, x, and occupation, o, as well as firm characteristics, z and τ, workers face a probability $U(x, o, z, \tau)$ of not being hired due to the rationing implied by the presence of the minimum wage constraints. If households are not hired, they receive an exogenous unemployment income, b, that is assumed uniform within the economy. If they are hired, they receive the wage rate $w(x, o, z, \tau)$. Although the function $U(x, o, z, \tau)$ is endogenous, workers take it as given. The unemployment spell of a worker, conditional on x, o, z, and τ, is independently drawn over time. The dependence of workers' wages on firm TFP and the possibility of being unemployed generates a source of idiosyncratic labor-earnings risk for the households.

Workers can accumulate a risk-free asset, a, but cannot have negative positions due to the presence of a borrowing constraint. In addition, workers hold infinitesimal shares of each firm in the economy. In each period, the profits are uniformly rebated back to all workers. We denote this flow of profit with Π. Consequently, we can define the value function $V(a, x, o)$ associated with a worker with asset holdings a, skill level x, and occupation o, starting a period with the opportunity to decide on which firm to work for, as:

$$V(a, x, o) = \max_{(z,\tau)\in\mathbb{Z}\times\mathbb{T}} V^m(a, x, o, z, \tau). \tag{D.7}$$

When maximizing the value function in Equation (D.7), workers consider the value associated with matching to each particular firm, $V^m(a, x, o, z, \tau)$. Specifically, when deciding to match to a particular firm with TFP level z and markup level τ, workers take into account that with a probability that depends on both the worker efficiency level and the firm productivity and markup levels, $U(x, o, z, \tau)$, they will end up unemployed (i.e., $u = 1$), and with the remaining probability, $1 - U(x, o, z, \tau)$, the match becomes active (i.e., $u = 0$). Thus, the function

[22] If we set idiosyncratic probability s to one, workers would change firms in every period and there would not be a well-defined notion of the pass-through of firm productivity shocks into wages. The quantitative analysis disciplines this modeling feature by matching the turnover of workers across firms.

$V^m(a, x, o, z, \tau)$ averages the values associated with each employment status, weighted by the respective probabilities, as follows:

$$\begin{aligned} V^m(a, x, o, z, \tau) = [1 - U(x, o, z, \tau)]\, \tilde{V}(a, x, o, z, \tau \mid u = 0) \\ + U(x, o, z, \tau)\tilde{V}(a, x, o, z, \tau \mid u = 1), \end{aligned} \tag{D.8}$$

where $\tilde{V}(a, x, o, z, \tau; u)$ denotes the value function conditional on the unemployment realization in the current period. The latter is characterized as follows:

$$V(a, x, o, z, \tau; u) = \max_{a' \geq 0} \frac{c^{1-\gamma}}{1-\gamma} + \beta E\Big\{ sV(a', x, o) + (1-s) E_{z'|z}\left[V^m(a', x, o, z', \tau)\right] \Big\} \tag{D.9}$$

$$\text{s.t. } c = (1-u)w(x, o, z, \tau) + ub + a(1+r) - a' + \Pi \tag{D.10}$$

$$a \geq 0. \tag{D.11}$$

Equation (D.9) takes into account that, in the next period, with probability $1 - s$ workers keep being attached to the current firm at which they are employed, and thus are associated with the continuation expected value $E_{z'|z}\left[V^m(a', x, o, z', \tau)\right]$, that depends on the transition of firm productivity shocks. With the remaining probability s, workers can reset their occupational choice, which yields the value of $V(a', x, o)$. Equation (D.10) is the budget constraint, and posits that workers finance their consumption expenditures with either their labor earnings, $w(x, o, z, \tau)$, in case they are hired by a firm, or their unemployment benefit b, and also receives the net proceeds from the risk-free assets, $a(1 + r) - a'$, as well as firms' profits, Π. Finally, Equation (D.11) is the borrowing constraint on the holdings of the risk-free asset.

The only reason for a positive unemployment rate in this model is the presence of the occupation-specific minimum wage constraints, which ration the employment of those workers whose marginal product of labor is below the wage floors $\underline{w}(o)$. As shown in Section 5.3, the presence of the minimum wage alters the wage sensitivity to firm TFP shocks of high-cushion employees by affecting the rationing of low-cushion workers.

D.3 Convexifying the Workers' Problem

The firm matching problem is non-convex, as workers can choose between a discrete set of different labor markets, characterized by TFP, z, and the inverse of markup, τ. To convexify this problem, we assume that – in addition to the wages offered by different groups of firms – a worker's occupational choice is affected by taste shocks for working for each of these groups. In particular, in the beginning of each period, a worker realizes a vector of taste shocks $\boldsymbol{\epsilon}$. Each component of this vector corresponds to a different additional level of firm TFP and markup, adding to the original value of the match. Technically, these shocks facilitate the model solution by convexifying the maximization problem of workers over different jobs. The policy functions that are otherwise discrete in nature become continuous probabilities before the realization of these shocks. This smooths out the value functions and facilitates the convergence of the model's numerical solution.[23] Nevertheless, these shocks are relevant beyond the technical aspect. As discussed in Card et al. (2018), they make firms imperfect substitutes from the workers' point of view, adding motives for workers to sort into firms beyond the differences in the wages they are offered.

The presence of the taste shocks implies that the value function $V(a,x,o,\boldsymbol{\epsilon})$ of a worker with asset level a, skills x, occupation o, and taste shock vector $\boldsymbol{\epsilon}$, starting a period with the opportunity to decide on which firm to work for is:

$$V(a,x,o,\boldsymbol{\epsilon}) = \max_{(z,\tau)\in\mathbb{Z}\times\mathbb{T}} \{V^m(a,x,o,z,\tau) + \epsilon_{z,\tau}\}, \tag{D.12}$$

where $V^m(a,x,o,z,\tau)$ denotes the value that workers with skill level x, occupation o, and asset holdings x receive from matching to a firm with productivity level z and markup τ, as defined in Equation (D.8).

In the calibration, we posit that the ϵ-shocks capturing the taste of workers for working in different productivity firms follow a Generalized Extreme Value distribution:

$$F(\boldsymbol{\epsilon}) = \exp\left[-\left(\sum_{k=1}^{K}\exp\left(-\frac{\epsilon_k}{\pi_\epsilon\sigma_\epsilon}\right)\right)^{\pi_\epsilon}\right]. \tag{D.13}$$

We set the parameter π_ϵ, which captures the correlation between the shocks for the different productivity levels, to 1, and then calibrate σ_ϵ to the smallest value that achieves the convergence of the workers' problem, which is 0.015. Importantly, the quantitative implications of the model on the asymmetric pass-through of firm-specific shocks into wages – and the associated welfare changes in removing the minimum wage constraint – do not vary with the value of σ_ϵ.

D.4 Definition of Equilibrium

This section reports the definition of a stationary general equilibrium (SGE) for the model. We start by introducing some notation: we denote the wealth policy function as $A(a,x,o,z,\tau;u)$, and the firm-matching policy function as $M(a,x,o,z,\tau,\boldsymbol{\epsilon})$. This latter policy depends on the realization of the $\boldsymbol{\epsilon}$ vector, and thus implies a probability of choosing each occupation before the realization of the $\boldsymbol{\epsilon}$-shocks. We denote this probability vector by $\mathbf{M}(a,x,o,z,\tau)$.

The SGE is a set of policy functions $A(a,x,o,z,\tau;u)$, $\mathbf{M}(a,x,o,z,\tau)$ for the workers, factor demands $K^\star(z,\tau)$ and $\mu^\star(x,o,z,\tau)$, firms' profit function $\pi(z,\tau)$, a probability distribution of workers $\lambda(a,x,o,z,\tau)$, an interest rate r, a wage function $w(x,o,z,\tau)$, an unemployment probability function $U(x,o,z,\tau)$, and total profits received by workers, Π, such that:

- The policy functions $A(a,x,o,z,\tau;u)$ and $\mathbf{M}(a,x,o,z,\tau)$ solve the worker problem (D.9) for each (a,x,o,z,τ) given the prices, the unemployment probability function, and total profits.

[23] These shocks have been used in many different contexts in economic research for the same motive, see for instance Iskhakov et al. (2017) for an overview.

- Firms' demand choices $K^{\star}(z,\tau)$ and $\mu^{\star}(x,o,z,\tau)$ solve their static profit maximization for each z and τ given the prices.

- The profits received by households are consistent with the profits of each firm, given the prices:
$$\Pi = \sum_{l=1}^{N_\tau}\sum_{j=1}^{N_z} \pi(z_j,\tau_l)\phi(z_j,\tau_l).$$

- The wages satisfy the occupation-specific minimum wage constraints: $w(x,o,z,\tau) \geq \underline{w}(o), \forall x,z,\tau$.

- The labor demand for each worker efficiency and firm productivity pair is equal to the number of workers who supply labor and are not unemployed in the corresponding market:
$$\Phi(z,\tau)\mu^{\star}(x,o,z,\tau) = [1 - U(x,o,z,\tau)]\sum_a \lambda(a,o,x,z,\tau), \forall x,o,z,\tau \tag{D.14}$$
with $U(x,o,z,\tau) \geq 0$. Moreover, $U(x,o,z,\tau) > 0$ if and only if $w(x,o,z,\tau) = \underline{w}(o)$.

- The asset market clears:
$$\sum_{l=1}^{N_\tau}\sum_{j=1}^{N_z} \Phi(z_j,\tau_l)K^{\star}(z_j,\tau_l) = \sum_{l=1}^{N_\tau}\sum_{j=1}^{N_z}\sum_{i=1}^{N_x}\sum_{k=1}^{2}\sum_a \lambda(a,x_i,o_k,z_j,\tau_l)a.$$

- Workers' asset positions satisfy the borrowing constraint, $a \geq 0$.

- The distribution across worker states is time-invariant: $\lambda(a',x,z',\tau) =$
$$\sum_{l=1}^{N_\tau}\sum_{j=1}^{N_z}\sum_{i=1}^{N_x}\sum_{k=1}^{2}\sum_a \lambda(a,x_i,o_k,z_j,\tau_l) \times \sum_{u=0}^{1}\Big\{(uU(x,o,z,\tau) + (1-u)\left[1 - U(x,o,z,\tau)\right])\times$$
$$\times\, \mathbb{I}_{\{A(a,x,o,z,\tau;u)=a'\}}\Big[\Big(1-s\Big)\Gamma_z(z,z') + s\mathbf{M}(a',x,o,z',\tau')\Big]\Big\}. \tag{D.15}$$

E More on the Calibration

In our quantitative analysis, we calibrate the model to the main features of the Italian metal-working sector. This section provides additional information of this procedure.

We start by first describing the parameter values that are defined following the standard in the literature, and then explain the calibration of the rest of the parameters which are set to match features of the data.

We calibrate the parameters governing the standard features of the model to values widely used in the literature. In particular, we set the risk aversion, γ, to 1.5, and the discount rate, β, to 0.94. The capital share in the production function, α, is set to equal 0.33, and we set the span-of-control, η, to 0.85. The capital depreciation rate, δ, equals 0.06.

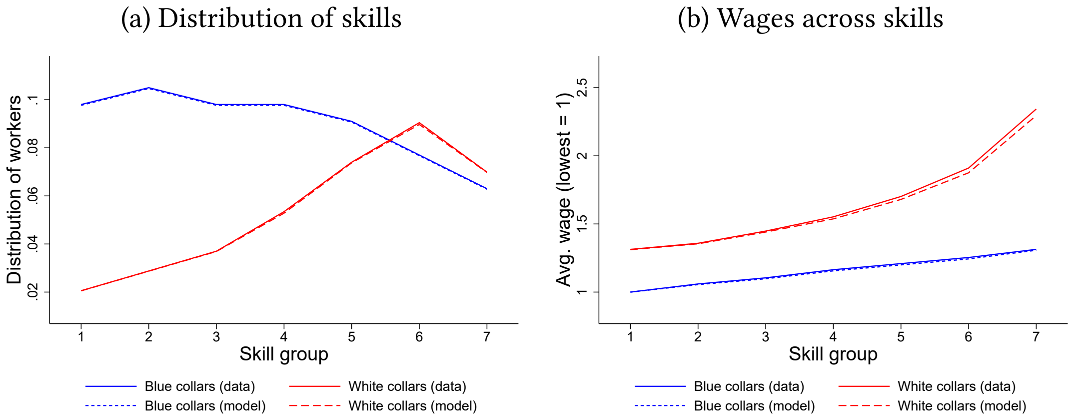
We calibrate the workers' probability of having an option to choose a new firm productivity and markup, s, to match the fraction of metalworkers changing firms in Italy, estimated at 10%.[24] Then, we turn to the parametrization of workers' skill levels x. To do so, we leverage the employer-employee dimension of our data, and estimate workers' fixed effects within a regression featuring firm-time fixed effects, in the spirit of Abowd et al. (1999). We discretize the estimated workers' fixed effects over 7 groups for both blue collars and white collars, and map the value of each of these total 14 groups into 14 different levels for workers' skill x. We set the value of each skill such that the model matches the distribution of both workers and average wages across skill groups, after normalizing the average wage of the lowest skill level within the blue collar group to unity.

Figure E.1 illustrates how the model replicates exactly the distribution and the average wage across skill groups observed in the data. In particular, Panel (a) shows that the model can exactly replicate the distribution of workers across skills as derived in the data. Indeed, the dashed lines, which denote the model implications on the skill distributions for blue collars (blue line) and white collars (red line) perfectly coincide with the respective solid lines, which indicate the patterns of the density of workers across skills in the data. To empirically measure workers' skills, we use the workers' fixed effects estimated in a regression that features firm-year fixed effects.

Regarding the cross-section of firms, we calibrate the heterogeneity in markups and productivity. We start by setting the variation of the total production-cost wedges, τ, in the model to replicate that of markups in the data. For the empirical counterpart, we use the distribution of markups across firms that we estimate when recovering firm productivity shocks. This approach yields a standard deviation of the total production-cost wedges which equals $\sigma_\tau = 0.124$. With respect to the firm productivity process, we construct the transition matrix for the discrete Markov chain governing the dynamics of firm TFP, Γ_z, to resemble an AR(1) process with persistence parameter π_z and standard deviation for the innovations σ_z. We do

[24] In the model, workers change firms only to work in a company with distinct TFP and markup levels. Accordingly, we target the fact that workers move to firms with different TFP and markup levels every period with a 10% probability.

Figure E.1: Calibration of workers' skills.



Note: The left panel plots the distribution of skills x in the baseline model calibration (dashed line) and in the data (solid line). We measure skills in the data with the estimated workers' fixed effects in a regression featuring firm-year fixed effects, in the spirit of Abowd et al. (1999). The figure shows the distribution of skills separately for blue and white-collar workers. The right panel does the same for the wages, normalized by the lowest skill group within blue collars.

so following the Tauchen (1986) algorithm, which gives us two parameters for the calibration. We set these parameters targeting the autocorrelation and standard deviation of log-sales in our sample of metal manufacturing firms.

We consider two minimum wage constraints, one for blue collars and one for white collars. While in the data wage floors vary also within occupations, they do so through dimensions which are absent in the model, such as seniority and education. To calibrate these two minimum wage constraints, we replicate the ratio between the average wage and the (average) wage floor for both blue collars and white collars, $\underline{w}(\mathrm{bc})$ and $\underline{w}(\mathrm{wc})$, which equal 66% and 50%, respectively. To set the amount of unemployment benefits, OECD data show that for a worker earning 67% of the average wage in the economy, the income if unemployed in the next two quarters equals 60% of the current income. Since the unemployment income is uniform in our model, we replicate this statistic by calibrating the unemployment income parameter b to equal 40% of the average worker labor earnings.

Table E.1 reports the details on the entire set of calibrated parameters. Panel (a) refers to the set of parameters that are externally calibrated, that is, whose value is defined according to the standard used in the literature. Then, Panel (b) shows the set of parameters that are internally calibrated, that is, whose value is defined to match a specific data moment. The panel shows not only the value for each parameter, but also reports the moment (and its value) associated to each of them. Table E.3 shows how the model compares to data with respect to the targeted moments.

Table E.2 compares the model implications on a set of key untargeted moments with respect to the data. While we have calibrated the model only to match the dispersion – and the persistence – of log-sales and markups across firms, our economy can also almost perfectly account for the auto-correlation of firms' log-employment, and explain also the dispersion

Table E.1: Parameters.

Parameter	Value	Description/Target
		Panel A: Calibrated outside of the simulations
γ	1.5	Risk aversion
β	0.94	Discount factor
α	0.33	Capital share
η	0.85	Span of control
δ	0.06	Capital depreciation
r	0.05	Risk-free interest rate
		Panel B: Calibrated targeting moments
ρ	0.3	Within-firm standard deviation wages-to-skill ratio $= 0.25$
π_z	0.98	Autocorrelation of log-sales $= 0.99$
σ_z	0.115	Standard deviation of log-sales $= 1.8$
σ_τ	0.124	Standard deviation of markups $= 0.124$
$\underline{w}(\text{bc})$	250.0	Firm minimum wage bite - blue collars $= 5.0\%$
$\underline{w}(\text{wc})$	331.5	Firm minimum wage bite - white collars $= 4.3\%$
b	226.0	Replacement rate $= 40\%$
s	0.10	Probability of changing firms $= 0.10$

Note: Panel A reports the parameters that are set before solving the model (i.e., the parameters that are calibrated outside the model). Panel B reports the parameters that are set to match specific targets with the model solution (i.e., the parameters that are calibrated within the model).

of log-employment across firms. These results give further credence on the capacity of the model to replicate the cross-sectional distribution of Italian metalworking firms.

The welfare consequences of the asymmetric pass-through crucially depend on the model implications on both the magnitude of the wage elasticities to firm productivity shocks, and workers' wealth levels. Indeed, the latter defines the extent to which workers can self-insure against the variability in their labor earnings. Although the model is calibrated to match the distribution of wages across workers' skills for both blue collars and white collars, the economy replicates also the distribution of wealth across Italian manufacturing workers. In particular, we compare the ratios of the 25th, 75th, 90th, and 99th percentiles with respect to the median both in the model and in the data. The empirical counterpart of workers' wealth distribution comes from information of the Survey on Household Income and Wealth, by focusing only on the wealth of manufacturing workers, and excluding the self-employed. Table E.2 shows that our economy accounts well for most percentiles of the wealth distribution, while over-estimating the asset holdings at its lower end. Consequently, our model provides a lower bound for the welfare changes due to the asymmetric pass-through for wealth-poor workers.

Table E.2: Non-targeted moments, data vs. model.

Moment	Data	Model
Panel A. Firm heterogeneity		
Autocorrelation of log-employment	0.99	0.96
Standard deviation of log-employment	1.49	1.61
Autocorrelation of of log-wage	0.94	0.98
Panel B. Wealth distribution		
P99/P50	10.2	10.0
P90/P50	4.3	4.3
P75/P50	2.5	2.3
P25/P50	0.04	0.3

Note: The model statistics are computed using the stationary distributions of workers and firms. Sales in the data are computed as revenues, and in the model as output. Employment in the data and in the model is the number of workers. Wealth in the data is from the Survey on Household Income and Wealth. We report the ratios of 99th, 90th, 75th and 25th percentiles of wealth relative to the median.

Table E.3: Targeted moments, data vs. model.

Moment	Data	Model
Within-firm standard deviation of wage-to-skill ratio	0.25	0.25
Autocorrelation of log-sales	0.99	0.97
Standard deviation of log-sales	1.80	1.77
Standard deviation of markups	0.124	0.124
Minimum wage / average wage – blue collars	0.66	0.71
Minimum wage / average wage – white collars	0.50	0.55
Replacement rate	40%	40%

Note: The table compares the model implications on the set of targeted moments with the data. The model statistics are computed using the stationary distributions of workers and firms. The within-firm standard deviation of the wage-to-skill ratio is computed in the model as standard deviation of the difference between log-wages and the logarithm of x^{ρ} across all workers in each firm, and then by averaging across firms. In the data, we compute this statistics as the difference between log-wages and the logarithm of workers' fixed effects estimated in a regression with firm-year fixed effects. Sales are computed in the model as output, Y, and in the data as revenues. Markups in the model correspond to the total production-cost wedge τ, while the empirical counterpart comes from the estimation of firm TFP shocks. The replacement rate in the data is taken from the OECD, and in the model it is the ratio of parameter b to the average wage.

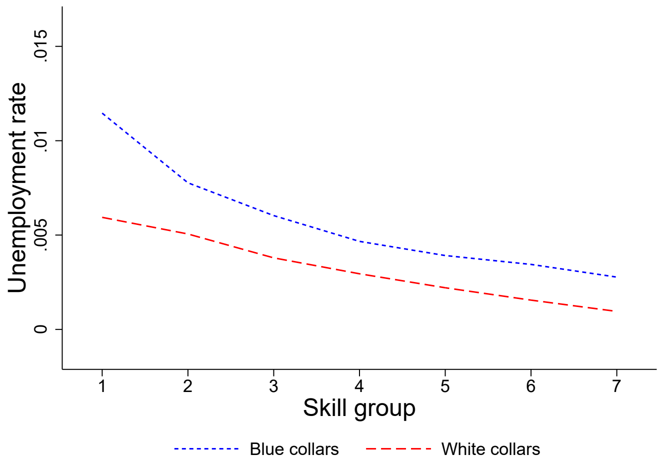
Finally, the fact that white collars earn higher wages than blue collars and are relatively less subject to the rationing implied by the minimum wage bears implications also for the wealth distribution. This is especially the case when comparing wealth-rich workers across occupations: in the model the 95th wealth percentile for white collars is roughly twice as large as that of blue collars. Workers' wealth strongly covaries with firms' TFP, with a correlation of about 0.4.

F More on the Quantitative Results

F.1 Employment rationing due to the minimum wages

We start the inspection of the model predictions by showing how the minimum wages shape the rationing of low-skills workers. Since we calibrate the variation of skills x to guarantee that wages increase with skills within each occupation, the wage floors bind relatively more at low values of x, in line with the data. Thus, low-skill workers face a relatively higher unemployment rate as it is more likely that their MPL is below the minima. Figure F.1 shows that, within each occupation, moving from the lowest to the highest skill level halves the probability of being unemployed. In addition, the rationing is relatively lower for white collars. Indeed, while the minimum wage of blue collars accounts for 66% of their average wage, this statistics is just 50% for white collars. This different incidence of the wage floors explains why the unemployment rate of blue collars is around one-third higher than that of white collars.

Figure F.1: Unemployment rate across skills.



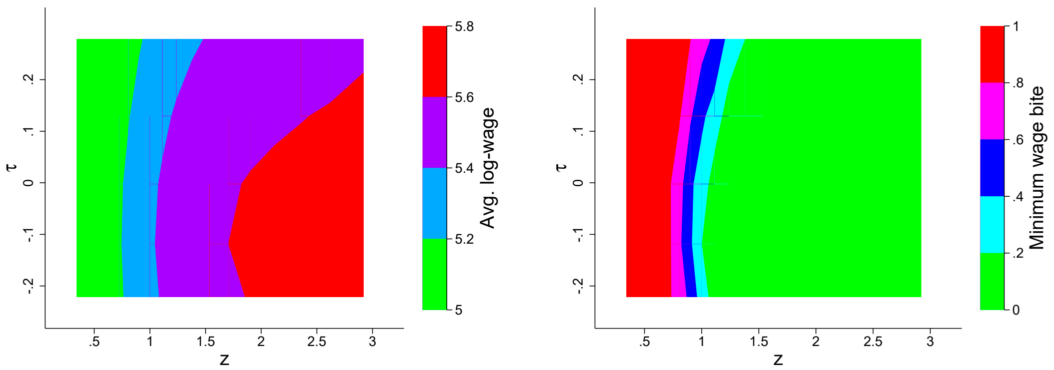
Note: The figure plots the unemployment rate across skill groups, x for blue collars (blue short dashed line) and white collars (red long dashed line).

To understand how the rationing varies across firm characteristics, we start by reporting in Panel (a) of Figure F.2 the heat map of wages as a function of firm productivity z and markup, τ. The panel shows that wages are relatively higher in high-TFP and in low-markup companies (i.e., high-z and low-τ firms). This relationship then implies that firms' minimum wage bite depends negatively on productivity and positively on markups: Panel (b) shows that the relatively lower wages in firms with low TFP and high markups raise the incidence of the wage floors. Consequently, workers are more likely to be laid off by firms at the lower end of the productivity distribution and at the higher end of the markup distribution. Thus, negative TFP shocks amplify the rationing of low-skill workers, even more so in firms with low productivity and/or high markups.

Section F.2 shows that the complementarities across workers' skills in firms' labor demand are the key feature that allows our model to account for the asymmetric pass-through of firm

Figure F.2: The effect of firm productivity and markup on wages and the minimum wage bite.

(a) Wage (b) Minimum Wage Bite



Note: The figures plot how firms' average log-wage (in Panel a) and firms' minimum wage bite (in Panel b) vary with productivity z and markup τ.

productivity shocks into wages. Indeed, the analysis in section F.2 below, reveals that if we abstract from the labor-demand complementarities, that is, if we set the parameter $\rho = 1$ so that the elasticity of substitution across skills is infinite, then the model counterfactually implies that the wage elasticity of high-cushion workers does not vary with firms' minimum wage bite.

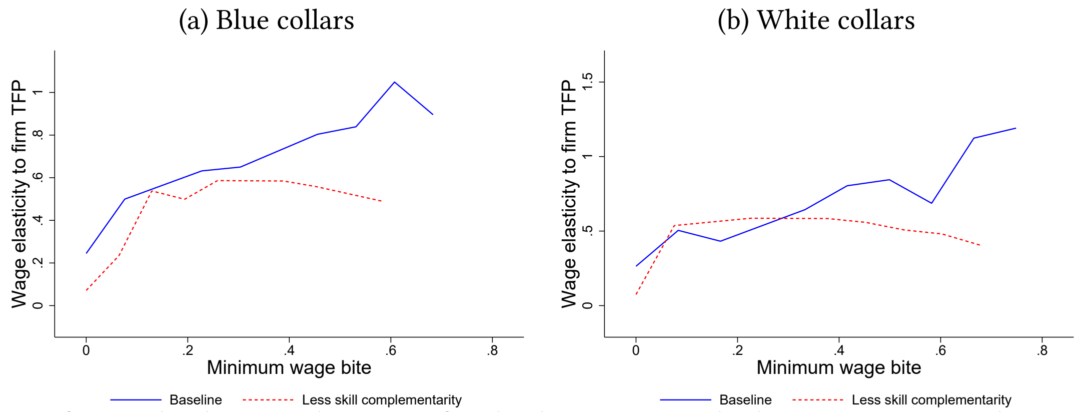
F.2 The role of complementarities

What is the role of complementarities in firm labor demand in shaping the asymmetric pass-through of the firm productivity shocks? This section isolates the role of this key modeling feature by focusing on the wage elasticity of high-cushion workers. To do so, we repeat the analysis of Figure 2 and compare how the wage elasticity to firm negative TFP shocks varies with firms' minimum wage bite both in the baseline model and in an alternative calibration in which skills are almost perfectly substitutable, that is, an economy with $\rho = 0.9$. We calibrate the alternative economy so that (i) the minimum wages lead to the same unemployment across occupations, (ii) the unemployment benefit maintains the ratio of unemployment income to the average wage; and (iii) the dispersion of skills across workers maintains the dispersion of log-wages.

The results of this exercise in Figure F.3 show that while in the baseline economy the wage elasticity of high-cushion workers to firm productivity shocks increases with firms' minimum wage bite, in the alternative economy which abstracts from the labor-demand complementarities, the wage elasticity of high-cushion workers barely changes with the firm-level incidence of the wage floors. In other words, the labor-demand complementarities across skills are the essential feature that allows the model to be consistent with our empirical evidence.

We then leverage the insights derived in our calibration strategy on the identification of the labor-demand complementarities to provide direct evidence on the role of this key modeling feature in the asymmetric pass-through of firm productivity shocks into the wages of high-cushion workers. Since the elasticity of substitution across skills maps directly into

Figure F.3: Wage elasticity to firm TFP shocks, the minimum wage, and the complementarities.



Note: The figures plot the wage elasticity to firm-level negative TFP shocks as in Figure 2. In this case, we focus only on high-cushion workers (i.e., the workers whose wage is 10% above the minimum wage). The blue solid line denotes the wage elasticity implied by the baseline model, and the dashed red line is the wage elasticity of the alternative economy with almost full substitutability across workers' skills (i.e., $\rho = 0.9$).

the dispersion of the wage-to-skill ratio, we use the variation in this measure across firms in the data to verify that the pass-through increases with the degree of the complementarities. Specifically, we compute the standard deviation of the wage-to-skill ratio for each firm, and estimate regression (13) for high-cushion blue collars by splitting the sample in the workers employed by firms with either below-average or above-average dispersion in the ratio. In this way, we can test directly whether the magnitude of the asymmetric pass-through increases with the degree of the labor-demand complementarities.

Table F.1: The role of labor-demand complementarities in the asymmetric pass-through.

Dependent variable:	$\Delta \log \text{Wage}_{i,f,t}$	
	Within-Firm Standard Deviation of Wage-to-Skill Ratio	
	Low	High
Worker MinW Cushion$_{i,f,t} > 10\%$	(1)	(2)
Negative TFP Shock$_{f,t}$	-0.001	0.003
	(0.003)	(0.005)
Negative TFP Shock$_{f,t}$ $\times$ Firm MinW Bite$_{f,t-1}$	-0.007	-0.120**
	(0.036)	(0.046)
Worker-Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	173,727	207,084

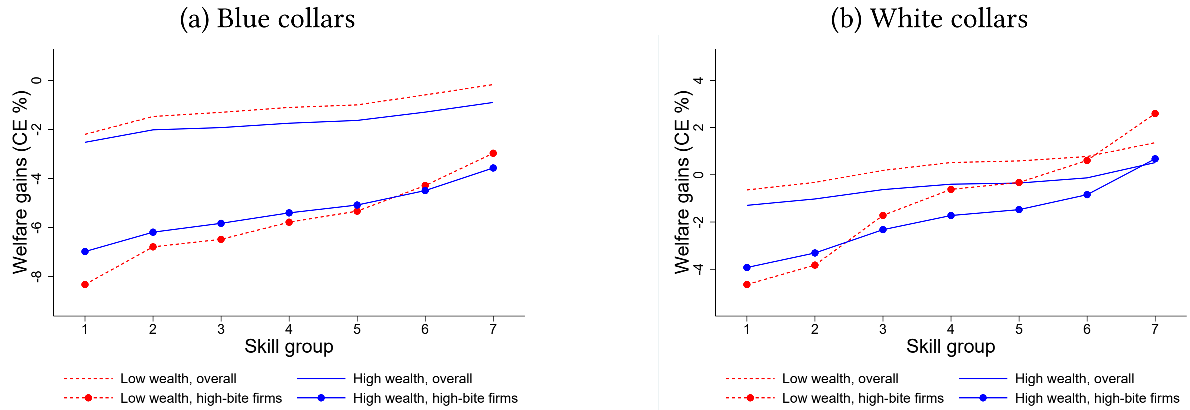
Note: The table reports panel-regression estimates as in Table 1 focusing on a sample of only high-cushion blue collars, that is, those workers whose minimum wage cushion is above 10%. Column (1) focuses on firms with below-average within-firm standard deviation of the wage-to-skill ratio, and Column (2) focuses on firms with above-average within-firm standard deviation of the wage-to-skill ratio.

We report the estimates of this exercise in Table F.1. The results show that the pass-through of firm productivity shocks into the wages of high-cushion workers is entirely concentrated in those high-bite firms featuring a high standard deviation of the wage-to-skill ratio. Consequently, the data support the model prediction that the asymmetric pass-through holds only as long as there is a sufficiently low elasticity of substitution across workers' skills (i.e., a sufficiently high degree of the labor-demand complementarity).

F.3 Welfare Implications: The Role of Wealth

We then leverage the distribution of asset holdings across households to highlight how the welfare implications vary with wealth. To do so, Figure F.4 reports the welfare changes for blue collars and white collars by differentiating between those in the lower end of the wealth distribution and those in the higher end of asset holdings. Specifically, we consider the households in the bottom and top deciles of the wealth distribution.

Figure F.4: Welfare gains/losses from removing the minimum wage: The role of wealth.



Note: The figures report the welfare gains and losses from removing minimum wages as in Figure 3, isolating the role of workers' wealth. Low and high wealth refer to the gains for workers in top and bottom wealth decile of their skill group-occupation, respectively.

The graphs show that the welfare changes crucially depend on workers' wealth positions: within the blue collars, the welfare losses for those employed in high-bite firms can be twice as large when comparing workers with low wealth levels vis-à-vis wealth-rich ones. Similarly, the welfare gains from removing the minimum wages for white collars are substantially larger if workers have low asset positions. This is due to the fact that the variation in the wage pass-through of firm productivity shocks generated by the presence of minimum wages maps relatively more into consumption if workers' wealth is low. In other words, when workers have low assets and cannot insure well enough their consumption stream, the welfare implications of the asymmetric pass-through are relatively larger. These dynamics explain why the model implies that the welfare losses for the median blue collar in high-bite firms are in absolute value twice as large as the welfare gains of the analogous median white collar.

F.4 Model Calibrated to Wage Dispersion

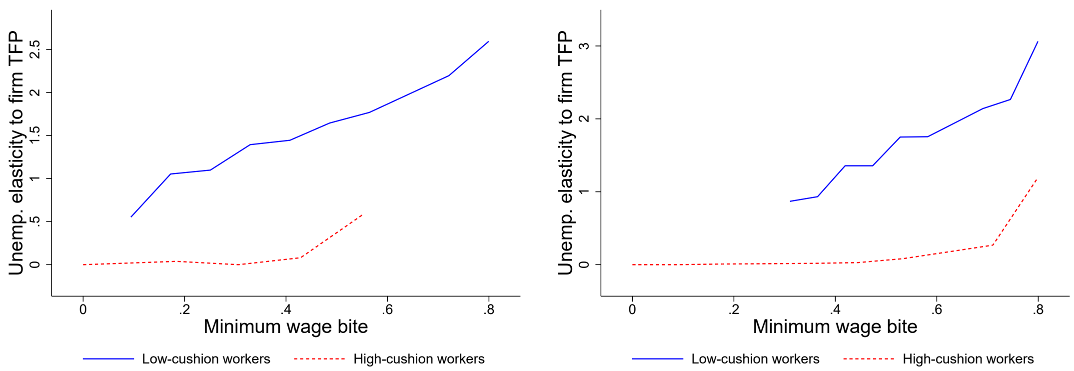
As we describe in Section 5.2, the quantitative model is calibrated to match the within-firm dispersion of the wage-to-skill ratio, since this moment is the one that identifies the degree of complementarities in labor demand. By doing that, we also incidentally match the overall standard deviation of the wage-to-skill ratio, while we account for 76% of the overall standard deviation of log wages across firms.

In this section, we present an alternative calibration strategy that allows the quantitative model to match also the overall standard deviation of log wages across firms. We do so by explicitly leveraging the taste shocks introduced in Section D.3. Indeed, in the baseline model we assume that—in addition to the wages offered by different groups of firms—a worker's occupational choice is affected by taste shocks for working for each of these groups. In particular, in the beginning of each period, a worker realizes a vector of taste shocks $\boldsymbol{\epsilon}$. Each component of this vector corresponds to a different additional level of firm TFP and markup, adding to the original value of the match. This model dimension is required just as a technical step, with the aim of convexifying workers' maximization problem.

We now explicitly leverage this dimension by considering these taste shocks as representing any pecuniary and non-pecuniary attributes of wages that are not captured by the rest of the model structure, and calibrate the standard deviation of these shocks to match the overall standard deviation of log wages across firms. Importantly, we keep the calibrated parameters for the skill complementarities as in the baseline, and we just add this extra dimension in our matching procedure. In doing so, the model becomes consistent with: (i) the within-firm standard deviation of the wage-to-skill ratio, (ii) the overall standard deviation of the wage-to-skill ratio across firms, and (iii) the overall standard deviation of log wages across firms.

Figure F.5: Unemployment elasticity to firm-level TFP shocks.

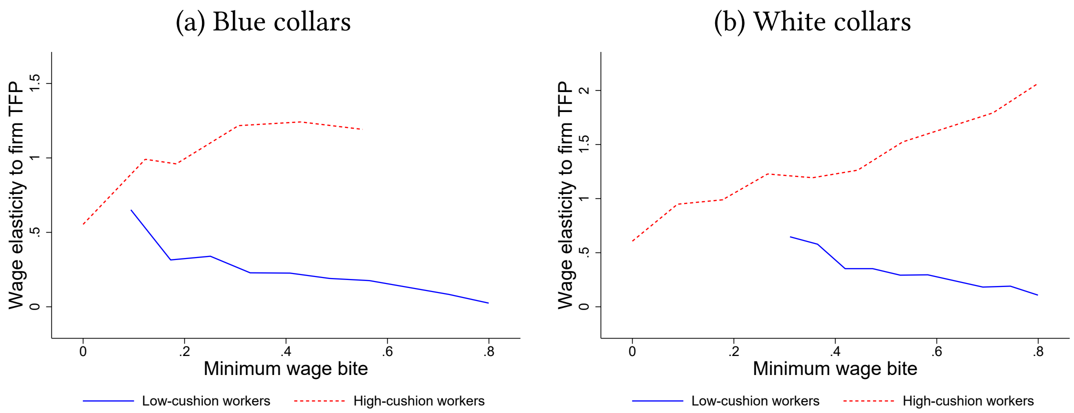
(a) Blue collars (b) White collars



Note: The figures plot the unemployment elasticity to firm negative TFP shocks similarly to Figure 1, with the only difference that the model is calibrated to match also the dispersion of wages across firms.

We then use the model under this alternative calibrated strategy to replicate the analysis of the unemployment and wage pass-through of Figures 1 and 2. We report these exercises in Figures F.5 and F.6. The results indicate that calibrating the model to match also the dispersion of wages across firms does not alter the quantitative implications with respect to our baseline economy.

Figure F.6: Wage elasticity to firm-level TFP shocks.



Note: The figures plot the wage elasticity to firm negative TFP shocks similarly to Figure 2, with the only difference that the model is calibrated to match also the dispersion of wages across firms.

F.5 Model with Within-Occupation Complementarities

The key mechanism through which our model can account for the asymmetric pass-through of firm productivity shocks across workers is the complementarities across skills in firm demand. The main idea is that, in order to produce, a firm requires the joint work of workers with different skills. In our baseline quantitative model, we posit a technology in which the degree of complementarities between low-skill and high-skill workers is the same independently of whether they are blue collars or white collars. This means that the degree of complementarity between a low-skill and high-skill blue collar is the same as that between a low-skill blue collar and a high-skill white collar. In this section, we present an alternative specification of our quantitative model that relaxes this restriction, and posits that skill complementarities are relevant within occupations, but not across occupations.

Specifically, we posit that firms produce the final good of the economy, Y, with the technology

$$Y = z(K^{\alpha} L_{\text{bc}}^{\theta} L_{\text{wc}}^{1-\alpha-\theta})^{\eta}, \tag{F.1}$$

where L_{bc} denotes total blue-collar labor, L_{wc} is total white-collar labor, and θ is the share of blue-collar labor in value added. We then set the two labor aggregators as follows:

$$L_{\text{bc}} = \left(\sum_{i=1}^{N_{bc}} [x_i \mu(x_i)]^{\rho} \right)^{\frac{1}{\rho}}, \tag{F.2}$$

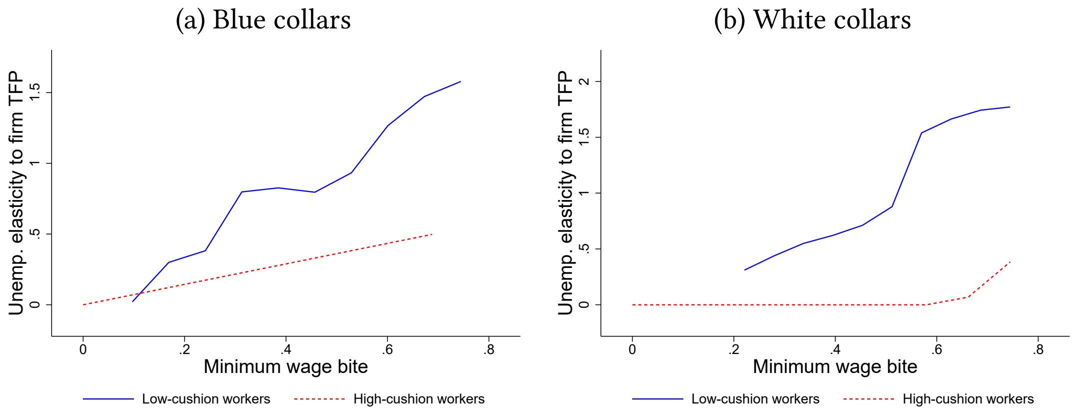
and

$$L_{\mathrm{wc}} = \left(\sum_{i=N_{bc}+1}^{N_x} [x_i \mu(x_i)]^{\rho} \right)^{\frac{1}{\rho}}, \tag{F.3}$$

where N_{bc} denotes the number of skill levels that are set to be associated with blue-collar workers, and N_x is the total number of skill levels. Note that white collars have relatively higher levels of skills.

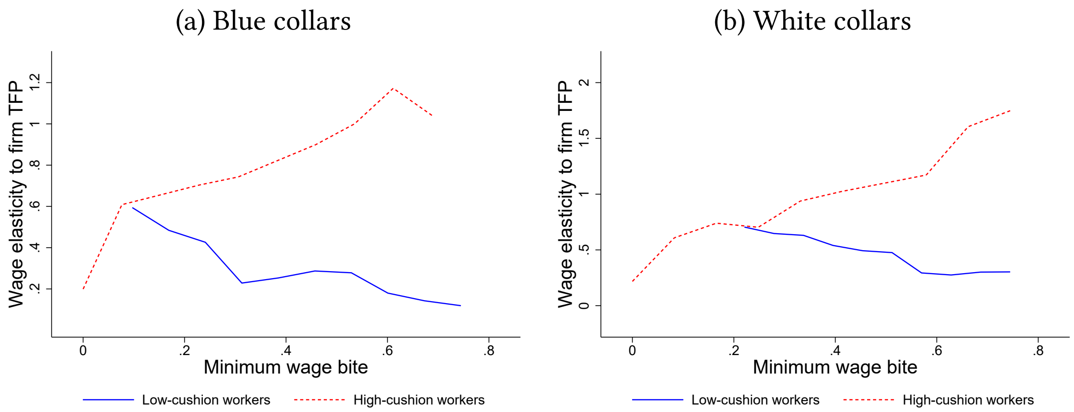
In this setting, skill complementarities are captured by the parameter ρ as in the baseline model, they are set to the same value within each occupation, but this specification implies that low-skill blue collars are not anymore complementary to high-skill white collars. That is, skill complementarities only hold within each occupation.

Figure F.7: Unemployment elasticity to negative firm TFP shocks.



Note: The figures plot the unemployment elasticity to firm negative TFP shocks similarly to Figure 1, with the only difference that they are produced by a version of the model in which skill complementarities are relevant within occupations, but not across occupations.

Figure F.8: Wage elasticity to negative firm TFP shocks.



Note: The figures plot the wage elasticity to firm negative TFP shocks similarly to Figure 2, with the only difference that they are produced by a version of the model in which skill complementarities are relevant within occupations, but not across occupations.

We consider the same calibration of the baseline model, also in terms of skill values (see Appendix E), and set θ to match the share of the compensation of blue collars in value added observed in our data. We then use the model to derive the unemployment and wage pass-through of negative firm TFP shocks, and study how these moments vary across low-cushion and high-cushion workers, across blue collars and white collars, and across firms with different incidence of minimum wages. To do so, we replicate the analysis of Figures 1 and 2. We report these exercises in Figures F.7 and F.8. The results indicate that the asymmetric pass-through of this model specification is similar to that of the baseline model.

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ZEW – Leibniz-Zentrum für Europäische Wirtschaftsforschung GmbH Mannheim

ZEW – Leibniz Centre for European Economic Research

L 7,1 · 68161 Mannheim · Germany
Phone +49 621 1235-01
info@zew.de · zew.de