Understanding High Wage and Low Wage Firms*

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December 2021

Abstract

Some firms pay higher wages than others for identical workers. To unpack the firm wage premium distribution, I develop and implement a new structural decomposition using rich administrative data on employers and employees in France. Existing research shows that firm wage premia depend on firms' *labor productivity* and *wage-setting power*. This paper shows that they also depend on firms' *product market power* and *labor elasticity of output*. My findings suggest that: (i) without accounting for the latter, workhorse models overestimate the contributions of firms' labor productivity and wage-setting power to firm wage premia; (ii) conventional measures of input misallocation overestimate the degree of labor misallocation; (iii) high productivity firms have lower labor shares of revenue not only because of greater product market power, but also greater labor market power and lower labor elasticities of output; and (iv) firms' product market power and labor elasticity of output reduce the pass-through of firm productivity to wages.

Keywords: wage inequality, firm heterogeneity, market power, production technology
JEL codes: D24, D33, E2, J3, J42

*First version: August 2019. Special thanks to Thijs van Rens, Roland Rathelot, and Dennis Novy for their invaluable guidance, support, and patience. I am very grateful to Jan Eeckhout, Francis Kramarz, Tim Sang Yoon Lee, Jay Euijung Lee, Isabelle Mejean, Aviv Nevo, Andrew Oswald, Vincent Sterk, and anonymous reviewers for very helpful comments. For insightful conversations, I thank Jesper Bagger, Pablo Beker, Dan Bernhardt, Christine Braun, Luis Candelaria, Danilo Cascaldi-Garcia, Dita Eckardt, James Fenske, Joaquin García-Cabo, Basile Grassi, Daniel Habermacher, Omiros Kouvavas, Alice Kuegler, Thomas Le Barbanchon, Timo Leidecker, Norman Loayza, Roberto Pancrazi, Ayush Pant, Carlo Perroni, Josep Pijoan-Mas, Fabien Postel-Vinay, Camilla Roncoroni, Federico Rossi, Alessandro Ruggieri, Marta Santamaria, Jesse Shapiro, Ben Smith, Douglas Staiger, Liliana Varela, Marija Vukotic, Jonathan Yeo, and the many seminar and conference participants. I gratefully acknowledge financial support from the ESRC and the ERC TRADENET grant (714597), and data access from DARES, DGFiP, INSEE, and CASD.

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1 Introduction

Some firms pay higher wages than others for identical workers. This is known as the *firm wage premium*. Following the pioneering work of Slichter (1950) and Abowd, Kramarz, and Margolis (1999), a large body of empirical research confirms this finding. Firm wage premia are a key prediction of models of frictional labor markets (Burdett and Mortensen, 1998). They allocate workers across firms and are systematically related to firm size and productivity (Haltiwanger, Hyatt, Kahn, and McEntarfer, 2018). Firm wage premia also offer an important answer to many questions about the labor market, from the long-term wage loss of displaced workers (Schmieder, Von Wachter, and Heining, 2018) and the gender wage gap (Card, Cardoso, and Kline, 2015), to recent questions about how globalization (Dauth, Findeisen, and Suedekum, 2021) and the rise of large firms (Song, Price, Guvenen, Bloom, and Von Wachter, 2019) impact the wage distribution.

What explains firm wage premia? To make sense of them, I build a structural framework to interpret standard regression-based estimates of firm wage premia. In my framework, labor market frictions prevent firm wage premia from being competed away. Firm heterogeneity then determines how much a firm is willing to pay to hire a given worker.

The main innovation is to introduce a notion of firms common in industrial organization and macroeconomics into workhorse frictional labor market frameworks (Burdett and Mortensen, 1998): firms have non-isoelastic revenue functions with respect to factor inputs. This non-isoelasticity comes from imperfect product market competition and imperfect substitutability between labor and other factor inputs. Under this notion of firms, I show that firm wage premia depend two sets of firm characteristics. The role of the first set – *labor productivity* and *wage-setting power* – is well-explored in research on firm wage premia.[1] The role of the second set – *product market power* and *labor elasticity of output* – has received little attention so far. Using rich administrative datasets on employers and employees in France, I estimate these firm characteristics and combine them with the model to study the firm wage premium distribution.

My central finding is that differences in product market power and labor elasticities of output have important implications for understanding firm wage premia, the allocation of labor across firms, the labor share of revenue, and the pass-through of firm productivity to wages. Product market power and labor elasticities of output account for 11% and 17% of firm wage premia. These firm characteristics are correlated with labor productivity and wage-setting power. Therefore, without taking them into account, workhorse models of frictional labor markets overestimate the role that labor productivity and wage-setting power differences play in explaining firm wage premia. More productive firms tend to pay

[1] See Card, Cardoso, Heining, and Kline (2018) for a survey of the literature.

higher wages that reallocate workers from less productive firms (Haltiwanger et al., 2018), while dispersion in wage-setting power leads to misallocation of labor (Azkarate-Askasua and Zerecero, 2020; Berger, Herkenhoff, and Mongey, 2020). Correctly accounting for their role in firm wage premia is therefore important for understanding the allocative efficiency of labor across firms and the extent to which there is room for labor market policy interventions.

My estimates reveal that more productive firms have a lower labor elasticity of output. This finding: (i) implies that conventional measures of labor misallocation (Hsieh and Klenow, 2009) based on revenue per hour overstate the extent of aggregate productivity gains from removing dispersion in wage-setting power; (ii) provides a new explanation for why high wage, high productivity firms have low labor revenue shares apart from market power (De Loecker, Eeckhout, and Unger, 2020); (iii) provides a new source of incomplete pass-through from firm productivity to wages (Guiso, Pistaferri, and Schivardi, 2005).

Section 2 develops a structural framework to interpret statistical estimates of firm wage premia. In the model, labor market frictions sustain firm wage premia and firms endogenously differ from each other along multiple characteristics. As in workhorse frictional labor market models such as Burdett and Mortensen (1998), firms differ in labor productivity and wage-setting power. Wage-setting power is defined as a *markdown* of wages below the marginal revenue product of labor. Compared to these models, the new features of my framework are differences in product market power and the labor elasticity of output. Product market power refers to firms' *price-cost markups* and the labor elasticity of output refers to the rate of diminishing marginal returns with respect to labor inputs. These new features introduce (i) firm-specific downward-sloping labor demand curves that are (ii) non-isoelastic into a standard frictional labor market framework.[2] I then obtain a structural equation linking firm wage premia to these firm characteristics.[3] Since these firm characteristics are equilibrium outcomes, I also refer to them as "channels of firm heterogeneity".

To estimate these firm characteristics, particularly the distribution of wage markdowns across firms, in Section 3 I develop a new approach by combining empirical methods from industrial organization and labor economics. I do so by building on the production-based approach of De Loecker and Warzynski (2012) to accommodate imperfectly competitive labor markets and worker heterogeneity, which involves panel data methods widely used

[2] In standard frictional labor market models such as Burdett and Mortensen (1998), revenue functions are linear in labor inputs, implying that labor demand curves are isoelastic and horizontal. Some important recent exceptions include Elsby, Michaels, and Ratner (2018) and Bilal, Engbom, Mongey, and Violante (2019), who develop labor search models with concave isoelastic revenue functions.

[3] Allowing non-isoelasticity in labor demand implies that average and marginal revenue products of labor are not necessarily proportional to each other.

in labor economics (Abowd et al., 1999; Bonhomme, Lamadon, and Manresa, 2019). This approach has the advantage that it does not require the researcher to specify particular market structures in a wide array of product and labor markets. To separately estimate output elasticities from productivity, I estimate production functions using a control function approach (Ackerberg, Frazer, and Caves, 2015), in which I use firms' past input choices to instrument for their current choices under the following timing assumption: firms' past input choices are orthogonal to current productivity shocks. To separately identify firms' wage markdowns from price-cost markups, I exploit the fact that wage-setting power is a distortion only on labor demand, while product market power is a common distortion on the demand for each input.

The estimation procedure requires detailed information about workers and firms, which is discussed in Section 4. I use large administrative datasets from France that covers the population of employers and employees between 1995 and 2018. I estimate the firm wage premia using matched employer-employee panel data, which includes key information on hourly wages. I estimate the relevant firm characteristics using firm balance sheet panel data, which contains information such as revenue, employment, and capital. I complement the balance sheet data with administrative data on firm-product level prices for manufacturing firms, available between 2009 and 2018. The key advantage of the latter is that it allows me to address the common but challenging issue of unobserved input and output prices in production function estimation (De Loecker and Goldberg, 2014; Bond, Hashemi, Kaplan, and Zoch, 2021). My main empirical analysis therefore focuses on the manufacturing sector.[4]

In Section 5, my estimates confirm well-established deviations from the law of one wage. High wage firms at the 90^{th} percentile of the firm wage premium distribution pay a wage that is 30% higher than firms at the 10^{th} percentile, with an interquartile range of 15%. Consistent with models of imperfect labor market competition, wage premia are higher at larger, more productive, and low labor share firms. How much wage-setting power do firms have?

French manufacturers hold considerable wage-setting power. Even with a high national minimum wage by international standards and near universal coverage of collective bargaining agreements, my baseline estimates suggest that the median firm marks down wages by approximately 40%. These wage markdowns are far from uniform. Firms at the 75^{th} percentile of the wage markdown distribution pay 71% of the marginal revenue product of labor as wages, while those at the 25^{th} percentile pay 46%.

French manufacturers also display large differences in the labor elasticity of output,

[4] An important advantage of these distinct datasets is that they can be linked using unique firm tax identifiers.

price-cost markup, and labor productivity, with most of these differences occuring within narrowly defined sectors (Syverson, 2011; De Loecker et al., 2020). The considerable dispersion of price-cost markups and labor elasticities of output suggest sizable deviations from isoelasticity in firms' labor demand.

To gauge the importance of these firm characteristics for firm wage premia, I use the structural firm wage premium equation to implement a number of statistical decompositions. I find that wage markdowns, labor productivity, price-cost markups, and labor elasticities of output account for 24%, 48%, 11%, and 17% of firm wage premium dispersion. Price-cost markups and labor elasticities of output are quantitatively important for firm wage premia. Under the assumption of isoelastic revenue functions, these two channels of underlying latent firm heterogeneity would be absent. This finding suggests that, when structurally estimating a model of imperfectly competitive labor markets to study wages, one should consider whether non-isoelasticities in labor demand could be important for the particular question or setting. This is because the four firm characteristics are correlated with each other and could lead to overestimating the explanatory power of heterogeneity in wage-setting power and labor productivity.[5]

Among these correlations, the decompositions reveal a strong negative correlation between labor productivity and labor elasticities of output. At the same time, more productive firms appear to have higher intermediate input and capital elasticities of output. Through the lens of the structural framework, this empirical pattern suggests that more productive firms are more likely to substitute labor with other factor inputs. The reason is that more productive firms have higher labor demand, but the presence of labor market frictions imply that firms face upward-sloping labor supply curves: firms must pay higher wages to attract more workers. If labor and other inputs are (imperfect) substitutes, then more productive firms tend to substitute away from labor inputs to avoid a higher relative cost of labor. This partially offsets their higher labor demand relative to less productive firms, reducing their willingness to pay higher wage premia to compete in hiring workers. This result highlights the importance of studying firms' input substitution decisions in imperfectly competitive labor markets.

In Section 6, I show that this negative correlation between firms' labor productivity and labor elasticity of output has important implications for measuring the allocative efficiency of labor inputs. The variance of the marginal revenue product of labor is an indicator of labor misallocation (Hsieh and Klenow, 2009), commonly proxied for by the average revenue product of labor (value-added or revenue per worker or per hour) under

[5]For example, structurally estimating a model with isoelastic labor demand while simultaneously matching the joint distribution of wages and labor productivity would overstate the explanatory power of differences in wage-setting power and labor productivity.

the assumption of isoelastic revenue functions. While this proxy is widely available, it overstates the variance of the marginal revenue product of labor by over two times. It is an accurate proxy only when labor elasticities of output and price-cost markups are constant across firms within a given sector. However, the inverse relationship between labor productivity and labor elasticities of output suggests that more productive firms that are more constrained by labor market frictions can circumvent these frictions by substituting labor with other inputs. This mismeasurement overstates the aggregate productivity and output gains of removing labor market power distortions.

High productivity firms also matter for the labor market because they play a key role in driving the aggregate labor income share (Autor, Dorn, Katz, Patterson, and Van Reenen, 2020). My previous finding offers a new explanation for their low labor shares of revenue: lower labor elasticities of output. This finding adds to other channels advanced by existing literature: low labor share firms have greater product market power (De Loecker et al., 2020) and labor market power (Gouin-Bonenfant, 2020). Quantitatively, a decomposition exercise suggests that low labor elasticities of output explain much of why high productivity manufacturers in France have low labor shares of revenue, with important contributions from wage markdowns and price-cost markups.

Finally, I show that the non-isoelasticity of labor demand matters for the degree of pass-through from firm productivity to wages. To do so, I estimate and decompose the pass-through of changes in firms' total factor productivity to wage premia.[6] Theories of imperfectly competitive labor markets predict that firm productivity shocks transmit into wages, a prediction with strong empirical support (Manning, 2011; Card et al., 2018). My findings show that firms that experience a positive change in their total factor productivity also experience an increase in their price-cost markups and a decline in their labor elasticity of output. Both of these channels of adjustment partly offset the increase in labor demand and hence the pass-through of TFP to wage premia.

Contributions to related literature. A large literature in labor economics estimates the separate contribution of workers and firms to the wage distribution (Abowd et al., 1999). The finding that different firms pay identical workers differently has been replicated across countries, such as Brazil (Alvarez, Benguria, Engbom, and Moser, 2018), Denmark (Bagger, Christensen, and Mortensen, 2014), Portugal (Card et al., 2018), USA (Song et al., 2019), and Sweden (Bonhomme et al., 2019). A few recent papers provide structural interpretations of firm wage premia (Barlevy, 2008; Bagger et al., 2014; Engbom and Moser, 2018; Lamadon, Mogstad, and Setzler, 2019; Haanwinckel, 2020). These papers provide fully microfounded models to study counterfactual scenarios. My pa-

[6] I allow firm wage premia to vary over time within firms.

per differs by imposing just enough structure on the data to allow labor demand to be non-isoelastic. My findings suggest that departures from isoelasticity are quantitatively important for understanding firm wage premia.

By embedding a richer notion of a firm, the structural firm wage premium decomposition in this paper also speaks to broader recent work on the impact of productivity dispersion (Berlingieri, Blanchenay, and Criscuolo, 2017), labor market power (Azar, Marinescu, Steinbaum, and Taska, 2020), product market power (De Loecker et al., 2020), and the production technology (Karabarbounis and Neiman, 2014) on wages and labor shares. I discuss each below. Methodologically, this paper is closely related to Lochner and Schultz (2020), who combine matched employer-employee data and production function estimation to investigate the drivers of worker-firm sorting. I show that these types of datasets can be used to disentangle firms' market power in product and labor markets. Conceptually, this paper is closely related to Mertens (2020), who studies how manufacturing firms' production technology and market power explain the decline of the German manufacturing labor share. I focus on how the non-isoelasticity of labor demand matters for understanding firm wage premia, the pass-through of firm productivity to wages, labor misallocation, as well as labor shares.

If firms share rents with their employees, then this opens the door for the productivity of individual firms to influence the wages they pay. A large body of work provides evidence for rent-sharing and explores their implications for wage determination (Faggio, Salvanes, and Van Reenen, 2007; Manning, 2011; Barth, Bryson, Davis, and Freeman, 2016; Kline, Petkova, Williams, and Zidar, 2019; Card et al., 2018; Garin and Silverio, 2019). My paper shows that firm productivity account for sizable shares of cross-sectional dispersion of firm wage premia. Yet, I find that both price-cost markups and labor elasticities of output attenuate the impact of firm productivity shocks on wage premia.

Motivated by high levels of concentration in product and labor markets, a growing number of researchers study the causes and consequences of market power. Among research that focus on product market power, Barkai (2020) and De Loecker et al. (2020) make the case for growing product market power. Autor et al. (2020) and Kehrig and Vincent (2020) show that the falling US labor share is due to firms whose labor shares fell as they grew larger. De Loecker et al. (2020) show that firms with low labor shares charge high markups, with implications for aggregate labor shares and wages.

Among research that focus on labor market power, Dube, Jacobs, Naidu, and Suri (2018) provide evidence for monopsonistic labor markets and Azar et al. (2020) show that U.S. labor markets are highly concentrated. Recent papers by Gouin-Bonenfant (2020), Berger et al. (2020), Jarosch, Nimczik, and Sorkin (2021), and Brooks, Kaboski, Li, and Qian (2021) study the effects of labor market power on wages, labor shares, and productivity. Caldwell and Danieli (2019), Caldwell and Harmon (2019), and Schubert, Stansbury, and Taska (2019) study the effects of outside options on wages. Hershbein, Macaluso, and Yeh (2020) show that labor market power is rising among U.S. manufacturing firms.

Recent work focused on understanding movements in the aggregate labor share also highlight the role of production technology. Elsby, Hobijn, and Şahin (2013) discuss the role of outsourcing in the US labor share decline, while Karabarbounis and Neiman (2014) and Hubmer (2019) focus on capital-labor substitution.

Broadly, the focus of macro-IO on product market power and production technologies – sources of non-isoelastic labor demand – provides a deeper understanding of aggregate labor shares, wages, and productivity. However, by largely abstracting from labor market frictions, it is silent on firm wage premia. On the other hand, research focused on understanding firm wage premia provides a deeper understanding of imperfect competition in the labor market, but largely abstract from non-isoelastic labor demand. A contribution of this paper is to show that non-isoelastic labor demand combined with imperfectly competitive labor markets generates new implications for understanding firm wage premia, labor misallocation, labor shares, and the pass-through of firm productivity to wages.

2 Framework to Decompose Firm Wage Premia

To derive a structural interpretation of regression-based estimates of firm wage premia, I present a wage-posting framework with frictional labor markets in the tradition of Burdett and Mortensen (1998).[7] The framework is a dynamic version of the Manning (2006) monopsony model. The main innovation is to augment it with imperfectly competitive product markets and a general production function with capital, labor, and intermediate inputs. The model therefore introduces a notion of firms common in industrial organization and macroeconomics – revenue functions are non-isoelastic. This non-isoelasticity implies that average and marginal revenue products of labor are no longer proportional.

I impose just enough structure to allow a number of channels of firm heterogeneity, while attempting to remain agnostic about many of the primitives governing the equilibrium outcome of the model, such as parametric distribution functions for firms' latent total factor productivity or the product market structure.

[7] In the Online Appendix D, I show that the firm wage premium equation can be derived from a wage-bargaining protocol and under different microfoundations for imperfectly competitive labor markets. I pursue some degree of flexibility here because both wage-setting protocols are used by firms in reality (Hall and Krueger, 2012).

2.1 Model environment

The model is set in partial equilibrium. Two main ingredients generate wage dispersion in this framework – labor market frictions and firm heterogeneity. Labor market frictions imply that workers cannot instantaneously find another job and hiring is costly for firms, allowing a distribution of firm-specific wage premium to survive. Firm heterogeneity then determines the wage premium a firm is willing to pay to hire workers of a given skill level.

Time is discrete. Capital and intermediate input markets are perfectly competitive. Firms can hire more workers by posting higher wages, as in monopsony models such as Burdett and Mortensen (1998). In addition, firms can also increase recruitment effort, as in job search models such as the Diamond-Mortensen-Pissarides model.

I focus on wage-setting protocols that are contemporaneous in nature. In this wage-posting model, this assumption implies that firms only commit to paying a given wage for one period. Firms also face within-firm equity constraints in wage-setting (Rudanko, 2021). Together, these assumptions imply that there is a firm-specific wage in each period t. This is also true in a wage-bargaining model in which wages are renegotiated every period (Stole and Zwiebel, 1996), as shown in Online Appendix D.[8]

Each firm j posts piece-rate wages per efficiency unit of labor denoted Φ_{jt} (Barlevy, 2008). A worker i with efficiency E_{it} obtains a wage $W_{it} = E_{it}\Phi_{jt}$. Taking logs, this wage equation has a log-additive structure reminiscent of the two-way fixed effect regression due to Abowd et al. (1999) ("AKM" henceforth), $w_{jt} = e_{jt} + \phi_{jt}$, where lowercase letters denote variables in logs. The piece-rate wage (ϕ) is the *firm-specific wage (premium)*.

Firm j's effective labor is subject to the following law of motion:

$$H_{jt} = (1 - s_{jt})H_{jt-1} + R_{jt} \tag{1}$$

where $s_{jt} = s(\Phi_{jt})$ denotes its worker separation rate, which is allowed to depend on the firm-specific wage premium Φ_{jt}. I assume that $s(.)$ is twice differentiable in $\frac{\partial s}{\partial \Phi} < 0$ and $\frac{\partial^2 s}{\partial \Phi^2} > 0$. Firms' recruitment size in efficiency units ($R_{jt} = R(\Phi_{jt}, V_{jt})$) depends on its posted wage and its recruitment effort (V_{jt}). I assume that the recruitment function $R(.)$ is twice differentiable and monotonically increasing in its wages and recruitment effort, with diminishing marginal returns. All else equal, firms that offer higher wages have a higher recruitment rate and lower separation rate. Equation (1) is therefore the firm-specific labor supply function.

[8] In Online Appendix C, I show that my findings presented in Section 5 are robust to focusing on hiring wages only, allowing incumbent workers to be paid a different premium, as in Di Addario, Kline, Saggio, and Solvsten (2020).

The assumption that firm-specific separation and recruitment rates depend on the wages offered is informed by models of on-the-job search such as Mortensen (2010). Firms' recruitment efforts are subject to recruitment costs $c(V_{jt})$. I assume that the recruitment cost function is twice differentiable, and that $c_V(.) > 0$ and $c_{VV}(.) > 0$, so that the marginal cost of recruitment effort is increasing in recruitment.

2.2 Departures from standard labor market search models

I first depart from canonical search models by introducing an imperfectly competitive goods market. Each firm j faces a downward-sloping (inverse) product demand curve and sets their own prices:

$$P_{jt} = \tilde{D}_s(Y_{jt}, D_{jt}) \tag{2}$$

where P_{jt} denotes the price charged by firm j in sector s at time t, Y_{jt} denotes the firm's output, and D_{jt} denotes the firm's idiosyncratic demand. The demand function is twice differentiable, with $\frac{\partial \tilde{D}_s}{\partial Y} < 0$ and $\frac{\partial^2 \tilde{D}_s}{\partial Y^2} > 0$. The firm's idiosyncratic demand D_{jt} can depend on aggregate, sectoral, or firm-specific demand shifters. The assumption of imperfectly competitive goods markets generates a distribution of firm-specific price-cost markups, an important determinant of firms' labor demand (Peters, 2020).

The second departure is that firms operate a general production function with diminishing marginal returns to each input, instead of a constant-returns-to-labor production function:

$$Y_{jt} = \Omega_{jt} F_{st}(K_{jt}, H_{jt}, M_{jt}) \tag{3}$$

I assume that this production function is sector-specific and twice differentiable. Ω_{jt} is the Hicks neutral productivity term, which is subject to the following autoregressive process $\omega_{jt} = g(\omega_{jt-1}) + \eta_{jt}$ where $\omega = \log \Omega$ and η_{jt} is a random productivity shock.[9] K_{jt}, H_{jt}, and M_{jt} denote capital, efficiency units of labor, and intermediate inputs, at firm j at time t. Efficiency units of labor can be written as $H_{jt} = \bar{E}_{jt} L_{jt}$, where $\bar{E}_{jt}$ denotes average efficiency and L_{jt} denotes amount of labor. By allowing diminishing marginal returns to labor and not restricting the elasticity of substitution between any pair of factor inputs, I allow the elasticity of output with respect to each input to differ across firms. I discuss what these output elasticities and price-cost markups depend on in the next subsection.

[9] In contrast with search models such as Burdett and Mortensen (1998) in which firms are in their steady states, firms in my framework are subject to idiosyncratic productivity shocks. This will be useful for estimating the model, as I discuss in Section 3.

2.3 Deriving the firm-specific wage premium equation

Firm j maximizes profits subject to (1), (2), and (3):

$$\Pi(\Lambda_{jt}) = \max_{P_{jt}, K_{jt}, M_{jt}, \Phi_{jt}, V_{jt}} P_{jt}Y_{jt} - P_t^K K_{jt} - P_t^M M_{jt} - \Phi_{jt}H_{jt} - c(V_{jt})V_{jt} + \beta E_t[\Pi(\Lambda_{jt+1})]$$

where $\Lambda_{jt} = \{\Omega_{jt}, D_{jt}, H_{jt-1}\}$. Let P_t^K and P_t^M denote the competitive price of capital and intermediate inputs. The timing of events is as follows. First, firms obtain an idiosyncratic draw of productivity and demand. Then, firms post wages, exert recruitment effort, and employ workers and other inputs. Finally, firms produce.

Solving for the first-order condition with respect to Φ gives the *firm wage premium equation*:

$$\Phi_{jt} = WM_{jt} \cdot ARPH_{jt} \cdot PM_{jt}^{-1} \cdot LEO_{jt} = WM_{jt} \cdot MRPH_{jt} \tag{4}$$

which is log-linear in four channels of firm heterogeneity. The wage markdown (WM) captures the firm's wage-setting power, defined as the fraction of the marginal revenue product of labor paid as wages. The average revenue product of labor ($ARPH$) is a commonly-used measure of firm productivity – revenue per unit of effective labor ($ARPH_{jt} = \frac{P_{jt}Y_{jt}}{H_{jt}}$).[10] The price-cost markup (PM) is a markup over marginal costs. The labor elasticity of output (LEO) measures a firm's percentage increase in output from a one percent increase in labor inputs ($LEO_{jt} = \frac{\partial \ln Y_{jt}}{\partial \ln H_{jt}}$). The last three components form the marginal revenue product of labor ($MRPH$). In equilibrium, each component of equation (4) depends on the joint distribution of latent firm heterogeneity in primitives (such as idiosyncratic TFP (Ω) and demand (D)).

Wage markdown (WM). It can be written as:

$$WM_{jt} = \frac{\xi_{jt}}{1 + \xi_{jt} - \beta E_t\left(\frac{(1-s_{jt+1})J_{jt+1}}{\frac{\partial c_{jt}}{\partial V_{jt}}V_{jt} + c(V_{jt})}\right)\frac{\partial R_{jt}}{\partial V_{jt}}} \tag{5}$$

where $\xi_{jt} = \xi(\Phi_{jt}, V_{jt})$ is the firm-specific labor supply elasticity, $\frac{\partial c_{jt}}{\partial V_{jt}}V_{jt} + c(V_{jt})$ is the marginal recruitment cost, and J_{jt+1} is the marginal profit to the firm of having an additional worker next period. Equation (5) shows that firms facing lower labor supply elasticities possess stronger wage-setting power: they mark down wages more. The second component in the denominator is the expected discounted marginal profits of having an additional worker next period relative to recruitment costs. This component shows that

[10] This component is also commonly referred to as "labor productivity".

firms expecting a high marginal value of a worker next period are willing to pay a higher wage markdown in the current period. Equation (5) therefore nests static monopsony models (Burdett and Mortensen, 1998), in which wage markdowns depend only on labor supply elasticities. The specific functional form for labor supply elasticities depends on the microfoundation for the labor supply curve. In the Online Appendix D, I present a few common microfoundations for wage markdowns.

Average revenue product of labor (ARPH). This is the theory-consistent measure of productivity for the firm wage premium. It can be written as:

$$ARPH_{jt} = \frac{P_{jt}Y_{jt}}{H_{jt}}$$

which is the ratio of sales revenue over efficiency units of labor. The firm wage premium equation (4) shows that, all else equal, more productive firms pay a higher wage premium. This is because more productive firms make larger profits from an employment relationship due to labor market frictions.

Price-cost markup (PM). This component captures firms' price-setting power. It can be written as:

$$PM_{jt} = \frac{\upsilon_{jt}}{\upsilon_{jt} - 1}$$

where $\upsilon_{jt} = \upsilon(P_{jt}, D_{jt})$ is the firm-specific price elasticity of demand. The specific functional form for the price elasticity of demand depends on the microfoundation for the product demand curve (2). For example, with an oligopolistic competition market structure and a nested constant elasticity of substitution (CES) demand system, it depends on the firm's market share of sales (Edmond, Midrigan, and Xu, 2015). Equation (4) shows that, all else equal, firms with higher markups pay a lower wage premium. The intuition is that firms that are able to charge positive markups maximize profits by producing less than they would in the perfectly competitive benchmark, which reduces their labor demand and the wage premium they are willing to pay.

Labor elasticity of output (LEO). This component measures a firm's percentage increase in output from a one percent increase in labor inputs:

$$LEO_{jt} = \frac{\partial \ln Y_{jt}}{\partial \ln H_{jt}}$$

Equation (4) shows that firms for which output is highly elastic with respect to labor inputs pay a higher wage premium, all else equal. This is because firms with a higher labor elasticity of output have a higher labor demand.

To see what the firm-specific labor elasticity of output depends on, compare a sector-specific Cobb-Douglas and CES production function. For simplicity, assume that firms produce with only capital and labor inputs. The Cobb-Douglas production function is $Y_j = H_j^{\alpha_s} K_j^{1-\alpha_s}$, where α is the weight on labor inputs. The labor elasticity of output in this case is then sector-specific:

$$LEO_s = \alpha_s$$

The CES production function is $Y_j = (\alpha_s H_j^{\sigma_s} + (1-\alpha_s) K_j^{\sigma_s})^{\frac{1}{\sigma_s}}$, where σ_s is the elasticity of substitution between inputs. The labor elasticity of output is:

$$LEO_j = \frac{\alpha_s}{\alpha_s + (1-\alpha_s)(K_j/L_j)^{\sigma_s - 1}}$$

This comparison shows that the firm-specific labor elasticity of output depends on the (i) sector-specific input weights, (ii) sector-specific elasticity of substitution between any pair of inputs, and (iii) the firm-specific factor intensities. If capital and labor are substitutes ($\sigma > 1$), then the labor elasticity of output is decreasing in the capital-labor ratio, implying a faster rate of diminishing returns to labor.

2.4 Discussion

The firm wage premium equation (4) shows that, by allowing revenue functions to be non-isoelastic, firm wage premia depend on a standard set of firm characteristics – wage markdowns and average revenue products of labor – and a new set of firm characteristics – price-cost markups and labor elasticities of output. The log-linear structure substantially simplifies a decomposition of firm wage premia without requiring the researcher to fully specify and estimate the underlying primitives of the model. On the worker side, worker mobility in the model is also consistent with the identifying assumption behind estimating firm wage premia in AKM regressions: conditional on the worker and firm types, worker mobility is exogenous. On the firm side, firms differ in underlying TFP, which follows an autoregressive process, consistent with the identifying assumption behind production function estimation techniques explained in the next section.

However, the following caveats apply. First, I only consider wage-setting protocols of a static nature: wages are posted (or bargained over) each period. In doing so, I abstract from important wage-setting mechanisms such as the sequential auctions mechanism (Postel-Vinay and Robin, 2002). On the theoretical front, introducing of diminishing returns to labor in a frictional labor market model comes with additional modelling challenges. In particular, one will need to take into account the fact that the marginal product of labor changes when a worker leaves or joins a firm, which potentially triggers a renegotiation between the firm and other incumbent employees (Stole and Zwiebel, 1996). On the empirical front, the sequential auctions mechanism implies that worker mobility depends on the previous employer, a channel ruled out by standard AKM identifying restrictions.[11] This restriction implies that I do not consider within-firm wage differentials due to within-firm worker heterogeneity in outside options. However, within-firm wage dispersion due to differences in human capital is allowed for. In Online Appendix C, I show that my findings are robust to considering only hiring wages following Di Addario et al. (2020), allowing incumbents to be paid different wages.

Second, implicit in the efficiency units specification of the production function, I assume that worker types are perfect substitutes, although average worker efficiency and firm productivity are complements. This restrictive assumption implies that the model abstracts from worker-firm sorting based on production complementarities (Eeckhout and Kircher, 2011). In return, this assumption (i) delivers a close mapping between AKM regressions and the structural firm wage premium equation; and (ii) keeps the production function estimation procedure computationally feasible. This is because the estimation strategy involves estimating flexible production functions without restrictions on the elasticity of substitution between pairs of factor inputs. Relaxing this assumption by introducing multiple (or a continuum of) worker types exponentially increases the number of parameters to be estimated. When workers are imperfect substitutes, the log-additive AKM regression is misspecified – an interaction term between the worker and firm effect needs to be present. I address this issue in two ways. First, I estimate an AKM regression augmented with this interaction term, following Bonhomme et al. (2019), but find a limited role for it. Second, I extend the analysis to include high and low-wage occupations in Online Appendix E. I find that the results of this extension are similar to those reported in Section 5.[12]

3 Estimating the Firm Wage Premium Equation

3.1 Empirical approach

To implement the structural decomposition, I first estimate firm wage premia, then estimate firm-specific measures of the wage markdown, average revenue product of effective labor, price-cost markup, and labor elasticity of output. One approach to estimating these firm characteristics is to estimate a fully-specified structural framework. However, this

[11] Di Addario et al. (2020) find little evidence for a past-employer effect on worker mobility.

[12] a systematic assessment of worker-firm sorting and its relationship with firms' product and labor market power is beyond the scope of this paper.

requires the researcher to specify the market structure in each product and labor market. Alternatively, a common approach is to measure firm-specific price-cost markups is the cost share approach. This approach measures firm-specific markups using sales to total variable cost ratios. However, at least two key assumptions are required to implement the cost share approach: (i) firms use constant returns-to-scale production technologies and (ii) all input markets are perfectly competitive, which precludes the estimation of wage markdowns.

To overcome these challenges, I adapt the production-based markup estimation approach by De Loecker and Warzynski (2012) and De Loecker et al. (2020) to accommodate imperfectly competitive labor markets. In the original approach, one first estimates the output elasticities, then computes price-cost markups from a variable input's expenditure share of revenue. I show that when labor markets are imperfectly competitive, the same approach can be used to measure firms' wage markdowns.[13] Once output elasticities are obtained, I show that price-cost markups and wage markdowns can be disentangled by exploiting the fact that price-cost markups distort each input demand, while wage markdowns distort only labor demand. Methodologically, this builds on Dobbelaere and Mairesse (2013), who estimate price-cost markups and monopsony power at the firm level. My approach differs by: (i) allowing technology to be labor-augmenting; (ii) allowing labor elasticities of output to vary across firms; (iii) using a flexible control function estimation approach.

3.2 Estimating firm wage premia

A common way of estimating firm wage premia is to estimate firm effects from an AKM regression (Abowd et al., 1999). The firm effects are fixed over time and are identified from worker mobility between firms. However, equation (4) shows that firm wage premia (Φ_{jt}) can vary over time. Further, a key practical issue in estimating firm effects is the lack of between-firm worker mobility in short panels, which leads to noisy firm effects estimates that upward-bias the variance of firm effects. To address the lack of worker mobility and to allow time-variation in firm wage premia, I implement the k-means classification approach of (Bonhomme et al., 2019) ("BLM" henceforth).[14]

I first classify firms into groups using a k-means clustering algorithm, then estimate a version of the AKM regression replacing firm effects with firm-group effects. Specifically,

[13] Morlacco (2019) exploits a similar idea to estimate firms' market power in foreign intermediate input markets.

[14] I also compare the estimated variance of firm wage premia using the Bonhomme et al. (2019) k-means clustering and Kline, Saggio, and Solvsten (2020) leave-out approaches in Table 1. I find the estimated variance to be similar between the two approaches. Bonhomme, Holzheu, Lamadon, Manresa, Mogstad, and Setzler (2020) have similar findings using datasets from other countries.

I estimate the following regression:

$$\ln W_{it} = \chi_{it}'\beta + \iota_i + \phi_{g(j(i,t),t)t} + \nu_{it}$$

where i denotes the individual, j denotes the firm, $g(j)$ denotes the group of firm j at time t, ι_i are worker fixed effects, $\phi_{g(j(i,t),t)}$ are firm-group fixed effects, and χ_{it} is a vector of time-varying worker characteristics, including age polynomials and part-time status. When there are as many firm-groups as there are firms, this regression converges to the classic AKM regression. The firm-group fixed effects are then identified by workers who switch between firm-groups. Relative to the AKM regression, this procedure has the advantage that it substantially increases the number of switchers used to identify firm-group effects, which enables firm wage premia to be precisely estimated.

To classify firms with similar firm wage premia into the same group, I group firms based on the similarity of their internal wage distributions. The idea is that, conditional on the AKM regression, firms with similar firm effects and worker effects should have similar internal wage distributions. If two firms have internal wage distributions of very similar shapes, but their average wages differ significantly, then the AKM wage equation suggests that they have very different firm effects. If two firms have similar average wages, but the shape of their internal wage distributions differ substantially, they are clustered into different groups. In practice, I apply the clustering algorithm by 2-digit sectors for every overlapping 2-year window, allowing firm wage premia to vary over time for a given firm-group. Online Appendix B provides more detail on how I cluster firms and addresses the main restrictions underlying the AKM regression.

3.3 Estimating the channels of firm heterogeneity

Estimation approach in theory. My estimation approach for the four channels of firm heterogeneity has three steps. First, I compute the average revenue product of labor in efficiency units $ARPH = \frac{PY}{\bar{E}L}$. To do so, I first compute the average labor productivity $\frac{PY}{L}$ as the total revenue per hour, and then compute the model-consistent average efficiency of workers per hour as the difference between the firm's average wage and the firm wage premium, $\bar{E} = \frac{\bar{W}}{\Phi}$. The log of the firm-specific average worker efficiency is normalized to have a mean of 0 in the cross-section.

The second and third steps extend the production-based approach of De Loecker and Warzynski (2012). In the second step, I estimate sector-specific production functions for each sector s: $y_{jt} = f_s(k_{jt}, h_{jt}, m_{jt}; \beta) + \omega_{jt}$. Lowercase letters represent the natural log counterparts of variables written in uppercase letters, β represents the set of production function parameters, and ω_{jt} is the firm's Hicks-neutral productivity. This step generates estimates of firm-specific output elasticities with respect to capital, effective labor, and intermediate inputs: $KEO_{jt} := \frac{\partial y_{jt}}{\partial k_{jt}}$, $LEO_{jt} := \frac{\partial y_{jt}}{\partial h_{jt}}$, and $MEO_{jt} := \frac{\partial y_{jt}}{\partial m_{jt}}$.

In the final step, I separately disentagle firms' price-cost markups from their wage markdowns. I exploit the fact that price-cost markups are common distortions to the demand of each input while wage markdowns distort only labor demand to separately identify price-cost markups and wage markdowns. Under the assumption that intermediate inputs are variable inputs and that firms take their prices as given, markups represent the only distortion to intermediate input demand (De Loecker and Warzynski, 2012). One can then express price-cost markups as a function of the intermediate input expenditure share and intermediate input elasticity of output:

$$PM_{jt} = MEO_{jt} \frac{P_{jt} Y_{jt}}{P_t^M M_{jt}}$$

I then obtain wage markdowns using the wage bill to intermediate input expenditure ratio and the output elasticities:

$$WM_{jt} = \frac{\Phi_{jt} H_{jt}}{P_t^M M_{jt}} \cdot \frac{MEO_{jt}}{LEO_{jt}} = \frac{\bar{W}_{jt} L_{jt}}{P_t^M M_{jt}} \cdot \frac{MEO_{jt}}{LEO_{jt}} \tag{6}$$

Since the price-cost markup is a common input distortion, it cancels out and therefore does not feature in this equation. Further, under the assumption that intermediate inputs are flexible inputs, the only remaining distortion is the wage markdown.

Estimation approach in practice. There are a few practical considerations when estimating production functions. First, firm productivity ω_{jt} are unobserved but they determine firms' input choices. Since more productive firms have a higher demand for inputs, OLS estimates of production function parameters will be upward-biased – a transmission bias. To address this issue, I use a control function approach (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015). This approach allows the researcher to "observe" the firms' productivity by inverting their optimal input demand function for a fully flexible variable input. In practice, I assume that intermediate inputs are flexible inputs. I further discuss this choice at the end of this section.

Second, firms' output prices are rarely observed by the researcher but they are correlated with firms' input choices, potentially introducing an *output price bias* on estimated production function parameters (De Loecker and Goldberg, 2014).[15] In practice, the

[15] When output prices are observed, they are typically for specific industries, e.g. beer brewing (De Loecker and Scott, 2016).

estimated production function is often:

$$p_{jt} + y_{jt} = f_s(k_{jt}, h_{jt}, m_{jt}; \beta) + p_{jt} + \omega_{jt}$$

where $p_{jt} + \omega_{jt}$ is the revenue TFP. The potential negative correlation between output prices and input demand could lead to a downward bias of estimated output elasticities. The intuition is that, all else equal, firms that set higher prices tend to sell less output, which in turn requires less inputs. To address this issue, I measure firm level prices p_{jt} using French administrative data on firm-product-year level prices for manufacturing firms and compute firm-year level output as revenue divided by prices.[16] I provide additional detail in Section 4.

Third, firms' input prices are also rarely observed by the researcher, therefore (deflated) input expenditures are often used in place of input quantity. This potentially introduces an *input price bias* on estimated production function parameters (De Loecker and Goldberg, 2014). Conditional on observing firms' output prices, the commonly estimated production function is then:

$$y_{jt} = f_s(\tilde{k}_{jt}, \tilde{h}_{jt}, \tilde{m}_{jt}; \beta) + B(\mathbf{p}^{\mathbf{x}}_{jt}, \tilde{\mathbf{x}}_{jt}; \beta, \zeta) + \omega_{jt}$$

where $\tilde{\mathbf{x}}_{jt} = \{\tilde{k}_{jt}, \tilde{h}_{jt}, \tilde{m}_{jt}\}$ represents the set of input expenditures (denoted with a tilde) and $\mathbf{p}^{\mathbf{x}}_{jt} = \{p^k_{jt}, \phi_{jt}, p^m_{jt}\}$ the set of input prices. The function $B(.)$ is present because of unobserved input prices. The specific functional form of $B(.)$ depends on the functional form of $f(.)$. Note that ζ is the set of parameters that must be estimated due to unobserved input prices. Since higher input prices are likely to lead to lower input demand, unobserved input prices may bias the estimated β downwards.

Relative to most datasets, the French DADS employer-employee data includes hours and wages at the worker level, allowing me to measure effective labor h_{jt}, as detailed above. Therefore, the production function I estimate is:

$$y_{jt} = f_s(\tilde{k}_{jt}, h_{jt}, \tilde{m}_{jt}; \beta) + B_s(\mathbf{p}^{\mathbf{x}}_{jt}, \tilde{\mathbf{x}}_{jt}, h_{jt}; \beta, \zeta) + \omega_{jt}$$

where the set of input expenditures now become $\tilde{\mathbf{x}}_{jt} = \{\tilde{k}_{jt}, \tilde{m}_{jt}\}$ and the set of unobserved input prices become $\mathbf{p}^{\mathbf{x}}_{jt} = \{p^k_{jt}, p^m_{jt}\}$. The prices of intermediate and capital inputs are unobserved in most existing datasets. I therefore work under the standard assumption that firms are price-takers in intermediate and capital input markets (De Loecker and

[16] See De Loecker and Goldberg (2014), De Loecker and Syverson (2021), and De Ridder, Grassi, and Morzenti (2021) for systematic discussions of production function and markup estimation with and without output price information.

Goldberg, 2014).

To the extent that firms in different sectors and locations face different intermediate and capital input prices, I control for sector and location fixed effects in the production function estimation routine. I also allow firms within a sector-location to face different intermediate and capital input prices due to differences in input quality. As De Loecker, Goldberg, Khandelwal, and Pavcnik (2016) show, under a large class of consumer demand functions used in International Trade, Industrial Organization, and Macroeconomics, output prices are monotonically increasing in output quality, which are themselves monotonically increasing in input quality. Under the assumption that higher quality inputs come with higher input prices, one can then build a control function for unobserved input prices using output prices.

Specifically, let input prices $\mathbf{p}^{\mathbf{x}}_{jt} = \mathbf{p}^{\mathbf{x}}(\vartheta_{jt}, \mathbf{G}_j)$ depend on output quality ϑ_{jt} and fixed sector-location characteristics $\mathbf{G}_j$. Then, De Loecker et al. (2016) show that the control function for input prices $\mathbf{p}^{\mathbf{x}}_{jt} = \mathbf{p}^{\mathbf{x}}(p_{jt}, \mathbf{Z}_{jt})$ can be written as a function of output prices p_{jt} and a vector $\mathbf{Z}_{jt}$ containing sector-location fixed effects $\mathbf{G}_j$, export status, and controls for markup heterogeneity such as market shares (more details on markup controls are below). In contrast with De Loecker et al. (2016), in this paper labor markets are also imperfectly competitive. Therefore, for output prices to be a valid proxy for input prices, I also include firm wage premia ϕ_{jt} to control for wage-setting power in $\mathbf{Z}_{jt}$.[17] The function $B(.)$ can then be written as:

$$B_s((p_{jt}, \mathbf{Z}_{jt}) \times \{1, \tilde{\mathbf{x}}_{jt}, h_{jt}\}; \beta, \zeta)$$

which is a function of output prices p_{jt} and the controls vector $\mathbf{Z}_{jt}$, and their interactions with input expenditures $\tilde{\mathbf{x}}_{jt}$ and effective labor h_{jt}. Since input expenditures $\tilde{\mathbf{x}}_{jt}$ only enter the function $B(.)$ as interaction terms with output prices and other controls $\mathbf{Z}_{jt}$, the production function parameters β are identified. This identification insight from De Loecker et al. (2016) does not hinge on functional form assumptions for $f(.)$.[18]

I now build a control function to address the transmission bias stemming from unobserved firm productivity ω_{jt}. The first step towards obtaining a control function for firm productivity is to obtain the optimal intermediate input demand function using the

[17] This is because firms' wage-setting power affect their marginal costs when labor markets are imperfectly competitive.

[18] I refer interested readers to De Loecker et al. (2016) for derivations of this identification result. The reason that input expenditure shares do not enter $B(.)$ lone variables is that the control function for input prices is built only from the consumer demand side.

first-order conditions for intermediate inputs:

$$\tilde{m}_{jt} = m_s(\omega_{jt}, \tilde{k}_{jt}, h_{jt}, pm_{jt}, p_{jt}, \mathbf{Z}_{jt})$$

Next, I invert the intermediate input demand function under the assumption that, conditional on the variables in the control function, intermediate input demand is monotonically increasing in idiosyncratic productivity ω_{jt}. The control function expresses firm productivity as a function of observed variables:

$$\omega_{jt} = \omega_s(h_{jt}, \tilde{k}_{jt}, \tilde{m}_{jt}, pm_{jt}, p_{jt}, \mathbf{Z}_{jt}) \tag{7}$$

The control function points to an important challenge in production function estimation when goods markets are imperfectly competitive – it includes price-cost markups $pm_{jt} = pm(P_{jt}, D_{jt})$, which are unobserved (Bond et al., 2021). If firm heterogeneity in markups is driven by differences in firm productivity ω_{jt} or regional and sectoral differences product market competition, these are controlled for in the control function. However, differences in idiosyncratic demand uncorrelated with TFP could still drive markup variation *beyond* what is controlled for in the control function. Therefore, I additionally include controls for markup heterogeneity. Informed by oligopolistic competition trade models such as Edmond et al. (2015), I include export status and market shares as additional controls. Informed by models of customer capital (Gourio and Rudanko, 2014), which predict that firms accumulate customers over time, I also include firm age. Finally, to capture the potentially nonlinear relationship between markups and output prices, and to capture differences in markups due to demand shocks D_{jt} that are orthogonal to TFP, I include a third-order polynomial of output prices. The key assumption here is that these additional controls sufficiently capture variation in markups uncorrelated with TFP. In Tables 14 and 15, I compare the markup and markdown estimates across various specifications with and without these additional controls for demand shifters.

The production function can then be estimated following the two-step GMM approach described in Ackerberg et al. (2015). In step 1, I combine (7) with the production function and estimate the following by OLS:

$$y_{jt} = \Psi_s(\tilde{k}_{jt}, h_{jt}, \tilde{m}_{jt}, pm_{jt}, p_{jt}, \mathbf{Z}_{jt}; \beta, \zeta) + \epsilon_{jt} \tag{8}$$

The vector $\mathbf{Z}_{jt}$ contains 5-digit sector-location fixed effects, year effects, export status, market shares, and firm age. This step estimates and removes the residual term ϵ_{jt}, capturing measurement error and productivity shocks that are unobserved by the firm and are therefore orthogonal to input choices.[19]

In step 2, I estimate the production function parameters β and input-price-related parameters ζ by forming moment conditions. Firm productivity ω_{jt} can be written as a function of the parameters to be estimated $\{\beta, \zeta\}$:

$$\omega_{jt}(\beta, \zeta) = \hat{\Psi}_{jt} - f_s(\tilde{k}_{jt}, h_{jt}, \tilde{m}_{jt}; \beta) - B_s(\mathbf{p}^{\mathbf{x}}(p_{jt}, \mathbf{Z}_{jt}), \tilde{\mathbf{x}}_{jt}, h_{jt}; \beta, \zeta) \tag{9}$$

Specify law of motion for the log of Hicks-neutral productivity as:

$$\omega_{jt} = g_s(\omega_{jt-1}) + \eta_{jt} \tag{10}$$

where $g_s(.)$ is a flexible function and η_{jt} is a productivity shock.[20] Combining equation (9) and the law of motion for productivity (10), I obtain productivity shocks η_{jt} as a function of the parameters of interest:

$$\eta_{jt}(\beta, \zeta) = \omega_{jt}(\beta, \zeta) - g_s(\omega_{jt-1}(\beta, \zeta))$$

I then form the following moment conditions:

$$E[\eta_{jt}(\beta, \zeta)\mathbf{X}_{jt}] = \mathbf{0}$$

where $\mathbf{X}_{jt}$ includes current and lagged capital, lagged effective labor, lagged intermediate inputs, lagged interaction terms between factor inputs, lagged output prices, lagged export status, lagged market share, lagged firm age, and the interaction terms with the lagged factor inputs. This moment condition is consistent with the timing assumption of the structural framework in the previous section. Firms' input demand and posted wages in the current period are orthogonal to future productivity shocks. In addition, capital inputs are assumed to be dynamic and pre-determined, so firms' current capital input demand are orthogonal to current productivity shocks. I combine the two steps into one and implement Wooldridge (2009). I estimate production functions for each 2-digit manufacturing sector.

Implementation decisions by the researcher. In practice, there at least two main choices to be made when estimating equation (4). I explain these choices below and report the results for each possible choice in Tables 8, 9, 10. I also inspect the similarity

[19] I approximate $\Psi(.)$ with a third-order polynomial using each variable except dummy variables. Dummy variables enter linearly.

[20] I let $g_s(.)$ be linear. I approximate $B(.)$ with a third-order polynomial using each variable except dummy variables. Dummy variables enter linearly.

of my estimates by reporting their cross-specification correlations in Tables 14 and 15.

Which production function to estimate? The simplest production function to estimate is a sector-specific Cobb-Douglas production function: $y = \beta_{s,k}k + \beta_{s,h}h + \beta_{s,m}m + \omega$. However, this restricts the output elasticities to a constant.[21] As equation (4) shows, this imposes the constraint that within sectors labor elasticities of output are constant across firms. In addition, as equation (6) shows, in this case all variation in LEO are attributed to wage markdowns, while variation in intermediate input elasticities of output are attributed to price-cost markups. My preferred approach is therefore to estimate a translog production function, which is a second-order approximation of any well-behaved production function:

$$\begin{aligned} y_{jt} = {} & \beta_{k,s}k_{jt} + \beta_{h,s}h_{jt} + \beta_{m,s}m_{jt} + \beta_{kk,s}k_{jt}^2 + \beta_{hh,s}h_{jt}^2 + \beta_{mm,s}m_{jt}^2 \\ & + \beta_{kh,s}k_{jt}h_{jt} + \beta_{km,s}k_{jt}m_{jt} + \beta_{hm,s}h_{jt}m_{jt} + \beta_{khm,s}k_{jt}h_{jt}m_{jt} + \omega_{jt} \end{aligned}$$

The translog function does not restrict the elasticity of substitution between any pair of inputs, allowing output elasticities to vary across firms depending on input composition.

The choice of production functions also have implications for the functional form of $B(.)$. Under Cobb-Douglas, $B_s(\mathbf{p}^{\mathbf{x}}(p_{jt}, \mathbf{Z}_{jt}); \beta)$, so output prices p_{jt} do not interact with input expenditures $\tilde{\mathbf{x}}_{jt}$. Under translog, $B_s(\mathbf{p}^{\mathbf{x}}(p_{jt}, \mathbf{Z}_{jt}), \tilde{\mathbf{x}}_{jt}, h_{jt}; \beta, \zeta)$, as described before. It is also worth noting that the production function parameters β are identified. The reason is that input expenditures and effective labor only appear in $B(.)$ as interaction terms with output prices.[22]

Which variables are inputs into production? The conventional approach is to estimate a three-input production function with capital, labor, and intermediate inputs, such as the one specified above. However, the French firm balance sheet data reports two types of intermediate inputs – materials and services. The conventional specification uses materials as a factor input, while services are assumed to be fixed overhead costs. I begin with this specification as my baseline, but also consider an alternative four-input production function in which services are factor inputs.

4 Data Description

[21] In this paper, I focus on gross output production functions. I refer interested readers to Rubens (2021) for a method of estimating markups and markdowns when production functions are Leontief.

[22] For more details on production function and markup estimation under unobserved input prices, I refer the interested reader to De Loecker et al. (2016).

4.1 Administrative datasets from France

Estimating the structural firm wage premium equation using the approach described above requires three types of datasets. Firm wage premia are estimated using matched employer-employee data, which follow workers over time and employment spells at different firms. The four channels of firm heterogeneity are estimated using firm balance sheet panel data and data on firm-product level output prices. While these types of datasets have become increasingly accessible, they are typically not jointly available. I therefore use matched employer-employee, balance sheet, and firm-product-level output price panel data from France.

My sources for firm balance sheet information is the *Fichier approché des résultats d'Esane* (FARE) datasets, available from 2008 to 2019. FARE is compiled by the fiscal authority of France, *Direction Générale des Finances Publiques* (DGFiP), from compulsory filings of firms' annual accounting information. These datasets contain balance sheet information for all firms in France without restrictions on the size of firms. From these datasets, I obtain information on variables such as sales, employment, intermediate input and capital expenditure. I provide details on measurement in Online Appendix A.

To obtain output price information at the firm level, I use the *Enquête Annuelle de Production* (EAP), available from 2009 to 2019. This dataset contains firm-product-level sales revenue and output for all manufacturing firms with at least 20 employees or with sales revenue exceeding 5 million Euros. The dataset also includes a representative sample of manufacturing firms with less than 20 employees. These are survey data compiled by the national statistical institute of France, *Institut National de la Statistique et des Études Économiques* (INSEE). To compute firm level output prices, I follow De Ridder et al. (2021). I first compute the revenue-to-quantity ratio for each firm-product-year combination, then normalize the price measure by dividing it by the sales-weighted average price of the particular product across all firms in a given year. The firm-specific output price is then the sales-weighted average of the price index across all products sold by a given firm.

I also use annual French administrative data on employed workers, available from 1995 to 2018, under the umbrella *Déclarations Annuelles de Données Sociales* (DADS). The DADS datasets are compiled by INSEE from compulsory reports of employee information to the French authorities. They contain information at the job level, such as age, gender, earnings, hours, and occupational category. One advantage of the DADS datasets is that work hours are observed, allowing researchers to construct and study variation in hourly wages. This addresses concerns that variation in earnings simply reflect variation in hours worked. They also include employer identifiers, called SIREN, which enables linking with firm balance sheet data. One disadvantage is that information about workers' education is not available.

The first DADS dataset is the DADS-Panel, which provides information on all employed workers in the private sector born in October in a panel structure.[23] Because workers are followed over time and their employer identifiers are observed, I use this dataset to estimate the AKM-BLM regressions.

The second DADS dataset is the DADS-Postes, which contains information on all existing jobs in France. Unlike the DADS-Panel, this is not a proper panel dataset. It is organized in an overlapping structure – each observation appears in the dataset under the same identifier for at most two periods. Therefore, this dataset cannot be used to estimate firm wage premia directly. Instead, to maximize the number of firms for which firm wage premia are estimated using the DADS-Panel, I first use the DADS-Postes to k-means cluster firms into groups of similar firms following the procedure described in the previous section. This approach has the advantage that firm wage premia can be estimated for firms that exist in the firm balance sheet data but not in the DADS-Panel because they do not have an employee who is born in October.

4.2 Estimation sample

I restrict firm level observations from the FARE balance sheet data to manufacturing firms whose output price data are observed in the EAP. I include only firms with at least 5 employees. I harmonize all industry codes to the latest available version (Nomenclature d'activités Française – NAF rév. 2). I drop 2-digit sectors with less than 500 observations. This is important when estimating flexible production function specifications, such as the translog, as this procedure would be demanding on small sample sizes and could lead to imprecise estimates of the production function parameters. In practice, few two-digit sectors have less than 500 observations.

For both of the DADS datasets, I focus on workers between the age of 16 to 65, who hold either a part-time or full-time job principal job (side jobs are dropped). I use only years 2009-2016, since INSEE reports that wages are recorded with errors in 2017 and 2018. I keep workers in the following one-digit occupational categories: (a) Top management, such as chief executive officers or directors; (b) senior executives, such as engineers, professors, and heads of human resources; (c) middle management, such as sales managers; (d) non-supervisory white-collar workers, such as secretarial staff and cashiers; and (e) blue-collar workers, such as foremen and fishermen. Occupation codes

[23] Only October-workers born in even years are observed prior to 2002.

are harmonized and updated to the latest version provided by INSEE (PCE-ESE 2003). Observations whose wages fall outside three standard deviations of the mean are excluded.

Firm wage premia in the AKM-BLM regression are only identified for the sets of firms connected by worker mobility. I focus on the largest connected set of firms. In practice, due to the clustering of firms into groups using the DADS-Postes, my analysis pertains to the largest connected set of firm-groups, of which very few firms are not a part. This group consists of 158,163,180 people-year observations, an average of 7,908,159 per year. After clustering firms into groups, I link the DADS-Postes and DADS-Panel via the firm identifier to allocate each firm-year observation a firm-group identifier and construct the estimation sample for firm wage premia. I estimate firm wage premia on this sample.

After estimating firm wage premia, I collapse the dataset to the firm level and link it to the FARE-EAP firm balance sheet and output price data to construct the estimation sample for the four firm characteristics. I implement the production function estimation routine on this sample. There are 130,246 firm-year observations in total and an average of 16,501 firms per year in this sample. Summary statistics for worker and firm characteristics are reported in Table 6 in Online Appendix C.

5 Decomposing Firm Wage Premia

5.1 The distributions of estimated firm characteristics

My estimates of the firm characteristics in equation (4) display considerable heterogeneity, with and without adjusting for potential measurement error. I find firm wage premia to be dispersed and positively correlated with measures of firm size and firm level labor productivity. Firm wage premia are also negatively correlated with labor shares, implying incomplete pass-through of firms' labor productivity to wages. Similarly, wage markdowns, price-cost markups, and labor elasticities of output are dispersed and systematically related to firm size and firm level labor productivity, indicating deviations from isoelastic labor demand. In levels, wage markdowns are significant, suggesting that the average French manufacturer possesses considerable market power in labor markets.

Table 1 reports statistics about firm wage premia in 2016. The variance of firm wage premia (ϕ) is modest (0.007), accounting for 4.6% of wage dispersion, similar to the numbers for the United States, Sweden, Austria, Norway, and Italy from Bonhomme et al. (2020). Nevertheless, the dispersion of firm wage premia is a quantitatively important deviation from the law of one wage. Column 2 in Table 1 shows that a firm at the 90th percentile of the firm wage premium distribution pays a given worker a wage that is on

Table 1: Dispersion of firm wage premia in 2016.

	AKM-BLM		AKM		AKM-KSS	
	MN	Overall	MN	Overall	MN	Overall
$\frac{Var(\phi)}{Var(w)}$	4.6%	6.9%	9.2%	15.9%	4.3%	7.2%
$Var(\phi)$	0.007	0.011	0.016	0.026	0.006	0.012
90-10 ratio	1.23	1.30	1.33	1.43	-	-
75-25 ratio	1.10	1.15	1.16	1.20	-	-
90-50 ratio	1.11	1.14	1.14	1.21	-	-
50-10 ratio	1.11	1.14	1.17	1.19	-	-
# firms	15,934	369,091	13,289	343,470	13,289	343,470
# firm-groups	418	4,156	13,289	343,470	13,289	343,470
# workers	1,128,966	10,737,479	123,952	1,829,455	123,952	1,829,455

Columns below 'MN' are estimates for manufacturing firms in my estimation sample. Columns below 'Overall' are estimates for all firms in the private sector. The first and second columns report statistics for AKM firm effects estimated at the firm-group level following BLM. The columns under AKM report the AKM firm effects without grouping firms. The columns under AKM-KSS report AKM firm effects corrected for limited mobility bias following the Kline et al. (2020) leave-out approach.

average 30% more than a firm at the 10th percentile. This gap is approximately three times as large as the gender wage gap in France. Among manufacturing firms, the 90-10 wage premium difference of 23% is also substantial.

Figure 7 shows that, within two-digit sectors, high wage firms are systematically larger, more productive, and have lower labor shares. Classifying firms into deciles of size (log employment), labor productivity (log ARPH), and labor shares, Table 13 reports how much firm wage premia vary across these deciles. Overall, within sectors, firms at the highest decile of size and productivity pay a wage premium about 7-8% higher than firms at the lowest decile. Similarly, firms in the decile with the lowest labor shares pay a wage premium that is 2% higher than those with the highest labor shares. The latter empirical relationship suggests that the pass-through of labor productivity to wages is incomplete.

These empirical regularities can be explained by workhorse and recent models of imperfectly competitive labor markets. A key prediction of the Burdett and Mortensen (1998) model is that high wage firms grow large, even if firms are ex-ante identical.[24] In Burdett-Mortensen style models with ex-ante heterogeneous firm productivity, more productive firms pay higher wages and grow larger, but they face a more inelastic labor supply, which implies a larger markdown of wages and a lower labor share (Postel-Vinay

[24]However, this model would imply that there is no relationship between wage premia and firm productivity, and that high wage firms have high labor shares.

and Robin, 2002; Barlevy, 2008; Gouin-Bonenfant, 2020). Recent oligopsonistic models of variable wage markdowns are also able to jointly explain these empirical patterns (Berger et al., 2020). In these models, the key to explaining why high wage firms have lower labor shares is that high wage firms markdown wages more.

However, labor demand is often modelled as isoelastic in these models. Table 2 shows that both labor elasticities of output and price-cost markups are dispersed, suggesting sizable deviations from isoelasticity.[25]

Table 2: Summary statistics for estimated firm characteristics in 2016.

	Mean	Median	25^{th} Pct	75^{th} Pct	Var	Var (i)	Var (ii)
WM	0.62	0.58	0.46	0.72	0.13	0.09	0.05
PM	1.50	1.38	1.18	1.70	0.08	0.05	0.02
LEO	0.43	0.42	0.33	0.53	0.20	0.15	0.08
$\log ARPH$	0.00	-0.04	-0.35	0.32	0.27	0.20	0.08
$\log MRPH$	0.00	0.00	-0.22	0.22	0.13	0.10	0.05
Number of firms				15,934			

This table reports the summary statistics for the firm characteristics estimated in my baseline specification: three-input translog production function taking into account input prices, output prices, and markup heterogeneity. Variances for wage markdowns, price-cost markups, and labor elasticities of output are reported for the logarithms of those variables ($\log WM$, $\log PM$, and $\log LEO$). The log of average and marginal revenue products of labor ($\log ARPH$ and $\log MRPH$) are normalized to have a mean of 0. The column Var (i) reports the variances corrected for measurement error following Krueger and Summers (1988) and Kline et al. (2020), while the column Var (ii) reports the variances for firm-groups. The distribution of joint market power ($\log \frac{WM}{PM}$) is trimmed by 1% on either side.

Existing estimates for labor elasticities of output (LEO) are usually at an aggregated level, for example, at the sector level (Basu, Fernald, Fisher, and Kimball, 2013; Oberfield and Raval, 2021). My estimates for firm-specific labor elasticities of output reported in the third row of Table 2 display substantial heterogeneity across firms. The interquartile range for labor elasticities of output is 0.20. However, my estimates are consistent with existing estimates that find moderate dispersion of labor elasticities of output across sectors: the within-sector (two-digit) interquartile range is 0.18.

Consistent with existing findings, the second row of Table 2 reports that price-cost markups (PM) are heterogeneous across firms. The median markup among French manufacturers is 1.38. This is somewhat higher than existing estimates. De Loecker and Warzynski (2012) estimate markups using Slovenian manufacturing firm data and find median markups between 1.10 and 1.28. De Loecker et al. (2020) find markups at the 75^{th} percentile between 1.3 and 1.6 in 2016 in the US, while my estimates for France is 1.70

[25]Tables 8 to 11 in Online Appendix C reports these summary statistics for various specifications of the production function.

in 2016. Edmond, Midrigan, and Xu (2018) report an interquartile range for markups of 1.31-0.97=0.34. My estimates for the interquartile range is 0.52.

Most French manufacturers appear to have significant wage-setting power. The first row of Table 2 describes the distribution of wage markdowns (WM). France has one of the highest national minimum wages and an almost universal coverage of collective bargaining agreements that define sectoral wage floors. Nevertheless, half of the firms in my sample pay less than 0.60 of the marginal revenue product of labor as wages. I also find substantial dispersion of wage markdowns across firms. Firms at the 75^{th} percentile of the wage markdown distribution pay a wage that is 72% of the marginal revenue product of labor. At the 25^{th} percentile, workers obtain less than half of their marginal revenue productivity.

The set of direct estimates of wage markdowns is small. I start by comparing my estimates to those of Hershbein et al. (2020) and Mertens (2020), whose estimates are methodologically the closest to mine. They find that the median US and German manufacturing firm pay 0.73 and 0.68 of the marginal revenue product of labor as wages. For the median French manufacturing firm the wage markdown is 0.58, implying more wage-setting power than their US or German counterparts.[26] Kroft, Luo, Mogstad, and Setzler (2021) find a markdown of 20% below marginal product in the US construction sector. Another way to do such a comparison is to assume that my wage markdown estimates are generated by a static wage-posting model. As discussed in Section 2, wage markdowns in this case are entirely determined by labor supply elasticities, $\frac{\epsilon^H}{1+\epsilon^H}$. This gives firm-specific labor supply elasticities of 0.85, 1.38, 2.57 at the 25^{th}, 50^{th}, and 75^{th} percentiles. This is somewhat higher than estimates for the US based on the Burdett-Mortensen model by Webber (2015), who find firm-specific labor supply elasticities of 0.44, 0.75, 1.13, at the 25^{th}, 50^{th}, and 75^{th} percentiles. Berger et al. (2020) find firm-specific labor supply elasticities driven by differences in market shares in an oligopsonistic model between 0.76 and 3.74 in the US.

The second-to-last row of Table 2 reports the summary statistics for the average revenue product of labor ($ARPH$) in logs. The dispersion of firm productivity is well-documented (Syverson, 2011). I find that the average revenue product of labor has an interquartile range of $\exp(0.32 + 0.35) = 1.95$. Most of the dispersion in productivity occurs within sectors, consistent with existing work. The average interquartile range within two-digit sectors is 1.84.

[26] However, it should be noted that my sample of French manufacturers consists of firms with at least 20 employees or sales revenue in excess of 5 million Euros and a representative sample of smaller firms.

5.2 Variance decompositions of firm wage premia

I now implement a number of statistical decompositions using the firm wage premium equation (4). The main message of this section is that product market power and labor elasticities of output account for sizable shares of the variation in firm wage premia. At the same time, firms with a high labor productivity tend to have a low labor elasticity of output, which constrains the dispersion of firm wage premia. Non-isoelasticity in labor demand is therefore important to understand firm wage premia. Since wage premia are estimated at the firm-group level, my decompositions henceforth are also implemented for firm-groups.

Recall that the structural firm wage premium equation is a log-linear function of the four channels of firm heterogeneity:

$$\phi_{gt} = wm_{gt} + arph_{gt} - pm_{gt} + leo_{gt} \tag{11}$$

where g represents the firm-group and lowercase letters are variables in logs.

I start with a parsimonious statistical decomposition of the variance of firm wage premia – a Shapley decomposition (Shorrocks, 1982, 2013).[27] This decomposition partitions the variance of firm wage premia into four components, corresponding to the four firm characteristics. The decomposition does so by calculating the Shapley value associated with each firm characteristic and assigns a percentage value between 0 and 1 to each variance component, known as the partial R^2. Because each firm characteristic is exactly identified in my estimation approach, my decomposition is also exact. Table 16 presents the Shapley decomposition results.[28]

Table 16 shows that approximately 30% of the variation in firm wage premia can be accounted for by price-cost markups and labor elasticities of output. If labor demand were isoelastic, these components would account for none of the variation in firm wage premia. The rest of the variation can be accounted for by wage markdowns and average revenue products of labor.

To see the importance of the covariance terms in accounting for firm wage premia, I

[27] Section D.1 in Online Appendix D explains the Shapley decomposition in detail.

[28] Table 17 reports the results from emsemble decompositions: $V(\phi) = CV(\phi, wm) - CV(\phi, pm) + CV(\phi, leo) + CV(\phi, arph)$. So, $1 = \frac{CV(\phi,wm)}{V(\phi)} - \frac{CV(\phi,pm)}{V(\phi)} + \frac{CV(\phi,leo)}{V(\phi)} + \frac{CV(\phi,arph)}{V(\phi)}$ This decomposition paints a similar picture of the importance of price-cost markups and labor elasticities of output.

Table 3: Shapley decomposition of the firm wage premium distribution.

Firm characteristics	Partial R^2
Wage markdown (wm)	0.24
Average revenue product of labor ($arph$)	0.48
Price-cost markup (pm)	0.11
Labor elasticity of output (leo)	0.17
Number of firm-years	130,246

This table reports the results of a Shapley decomposition of firm wage premia within two-digit sectors using firm characteristics estimated in my baseline specification: three-input translog production function taking into account input prices, output prices, and markup heterogeneity. Sample period: 2009-2016.

do a standard variance decomposition. Using equation (11), this can be written as:

$$\begin{aligned} 1 \ = & \frac{V(wm)}{V(\phi)} + \frac{V(arph)}{V(\phi)} + \frac{V(pm)}{V(\phi)} + \frac{V(leo)}{V(\phi)} + 2\frac{CV(wm, arph)}{V(\phi)} + 2\frac{CV(wm, pm)}{V(\phi)} \\ & - 2\frac{CV(wm, leo)}{V(\phi)} - 2\frac{CV(arph, pm)}{V(\phi)} + 2\frac{CV(arph, leo)}{V(\phi)} - 2\frac{CV(pm, leo)}{V(\phi)} \end{aligned}$$

Table 18 reports the results of the standard variance decomposition.

While most covariance terms play an important role, one that stands out is the negative correlation between average revenue products of labor and labor elasticities of output. Row eight in the second-to-last column of Table 18 shows that it is the most quantitatively important among the set of cross-terms. Table 4 shows that the correlation coefficient between them is -0.66. This negative correlation offsets the effects of firm heterogeneity on firm wage premium dispersion. At the same time, the correlation between labor productivity and the material elasticity of output is positive (0.69). The correlation between labor productivity and the capital elasticity of output is also positive (0.23).

Table 4: Correlation between firm characteristics.

	wm	$arph$	pm	leo
wm	1			
$arph$	-0.26	1		
pm	0.51	-0.22	1	
leo	-0.25	-0.66	0.35	1

This table reports the Pearson correlation coefficients within two-digit sectors using firm characteristics estimated in my baseline specification: three-input translog production function taking into account input prices, output prices, and markup heterogeneity. Sample period: 2009-2016.

Conditional on my production function estimates, the structural framework in Section 2 contains two channels through which more productive firms can have lower labor elasticities of output: (i) non-homotheticities in the production function; (ii) labor input substitution.

The non-homotheticity channel posits that as firms become larger, their production process becomes more intensive in certain factor inputs – in this case, factor inputs other than labor. Therefore, as more productive firms wish to grow larger, their labor demand grows by less-than-proportionately compared to less productive firms. In my estimates, the prevalence of this channel appears to be limited as I find moderate deviations from constant returns to scale – 98% of firms fall within 5 percentage points of constant returns to scale.

The labor input substitution channel works as follows. Since firms face upward-sloping labor supply curves due to labor market frictions, firms must offer higher wages to hire more workers. Because more productive firms wish to grow larger than less productive firms, the former face higher relative costs of labor. If labor and other inputs are (imperfect) substitutes, more productive firms substitute labor with other inputs to avoid higher relative costs of employing labor. In this case, the labor elasticity of output is decreasing in the firm's input intensity of other inputs, reducing the firm's labor demand and offered wage premium.

An implication of these findings is that one should consider whether non-isoelasticities in labor demand could matter for the question of interest. As an example, if one were to estimate a standard frictional labor market model with isoelastic labor demand to match the distribution of wages and labor productivity, the model would overestimate the explanatory power of firms' labor productivity and wage markdowns for firm wage premia. This matters for two reasons. First, if models overestimate the extent to which the firm wage premium distribution reflects heterogeneous wage markdowns, then they also overestimate the role of wage markdowns in the misallocation of labor inputs across firms. This would overstate the extent to which labor market policies can address distortions due to labor market power. For example, when firms' wage markdowns are quantitatively important distortions to labor demand, the minimum wage can be an effective tool to correct such distortions and lead to welfare improvements.

Second, if models overestimate the role of firm productivity in driving firm wage premia, then they also overestimate the extent to which firm wage premia reallocate workers from less productive firms to more productive firms, as workers search on-the-job for better-paying firms. This worker reallocation role of wage dispersion is a key driver of aggregate productivity and wage growth (Haltiwanger et al., 2018; Bilal et al., 2019).

6 Implications

6.1 Input substitution reduces labor misallocation across firms

In a frictionless labor market, the marginal revenue product of labor is identical across firms. Differences in latent TFP heterogeneity leads firms to adjust their size until the marginal revenue product of labor equals the competitive wage.[29] The cross-sectional dispersion of the marginal revenue product of labor is therefore an indicator of misallocation of labor inputs (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009).

However, when labor demand is non-isoelastic, the average ($arph$) and marginal revenue product of labor ($mrph$) are no longer proportional. The wedge between the two reflects price-cost markups (pm) and labor elasticities of output (leo). Conventional measures of labor misallocation approximate the $mrph$ with the $arph$. However, the finding that $arph$ and leo are strongly negatively correlated implies that the $mrph$ is considerably less dispersed than the $arph$. Consequently, conventional measures of labor misallocation overstate the variance of $mrph$ and, hence, the degree of labor misallocation.

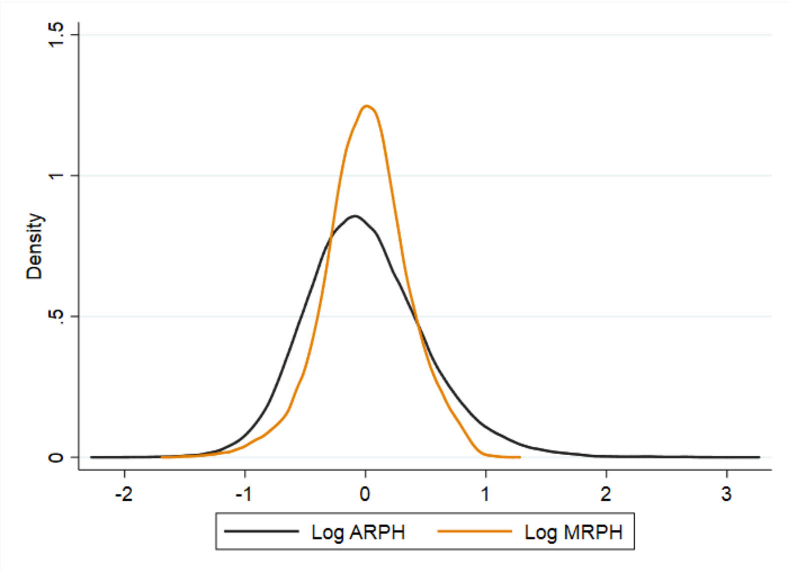

Figure 1: Distribution of the average and marginal revenue product of labor.

Table 5 shows that the variance of $arph$ is over two times larger than the variance of $mrph$. Adjusted for measurement error in both $arph$ and $mrph$, second-to-last column shows that their relative variance is $\frac{V(arph)}{V(mrph)} = \frac{0.18}{0.07} = 2.57$. This is graphically depicted in Figure 1, which plots the de-meaned $mrph$ and $arph$. Intuitively, this mismeasurement

[29] It should be qualified that differences in non-wage amenities across firms can lead to differences in the marginal revenue product of labor that do not imply misallocation. Quantifying the dispersion of marginal revenue products due to amenities is important. See, for example, Lamadon et al. (2019).

stems from the fact that conventional measures of the variance of the marginal revenue product of labor do not account for firms' ability to substitute labor with other inputs in the presence of labor market frictions. In Online Appendix C, I perform a back-of-the-envelope exercise, based on Hsieh and Klenow (2009), to get a sense of the extent to which measured labor misallocation is overstated when one uses the *arph* to approximate the *mrph*. I find that labor misallocation is overstated by over 2.5 times. This finding contributes to recent work showing the importance of markups and markdowns in input misallocation by showing that substitution away from labor in the presence of labor market frictions can mitigate labor misallocation (Edmond et al., 2015; Tortarolo and Zarate, 2018; Berger et al., 2020).

Table 5: Comparing within-sector variation in average and marginal revenue products of labor.

	Mean	Median	25^{th} Pct	75^{th} Pct	Var	Var (i)	Var (ii)
$\log ARPH$	0.00	-0.03	-0.32	0.29	0.23	0.18	0.03
$\log MRPH$	0.00	0.00	-0.18	0.19	0.09	0.07	0.01
Number of firms				130,246			

This table reports the within-sector (two-digit) summary statistics for firms' (log) average and marginal revenue products of labor estimated in my baseline specification: three-input translog production function taking into account input prices, output prices, and markup heterogeneity. Both variables are normalized to have a mean of 0. The column Var (i) reports the variances corrected for measurement error following Krueger and Summers (1988) and Kline et al. (2020), while the column Var (ii) reports the variances for firm-groups.

6.2 Explaining low labor shares among high productivity firms

The decline of the U.S. aggregate labor share of income has attracted significant academic attention. Earlier studies make the case for changes in the aggregate production technology, for example through capital-labor substitution (Karabarbounis and Neiman, 2014). However, recent research shows that the reallocation of sales towards highly productive firms with low labor shares is a key driver, highlighting the importance of understanding heterogeneity in labor shares (Autor et al., 2020; De Loecker et al., 2020; Kehrig and Vincent, 2020). Why do more productive firms have lower labor shares?

I start by looking into the cross-sectional patterns of labor shares. Figure 2 shows how wage markdowns, price-cost markups, and labor elasticities of output vary across deciles of labor shares, where bin 1 denotes the decile of highest labor shares and bin 9 the lowest. Although low labor share firms do not tend to have higher price-cost markups in my estimates, they tend to markdown wages more. Figure 2 also provides a new explanation for high productivity firms' low labor shares: they have a low labor elasticity of output. Therefore, while the aggregate production technology cannot account for the

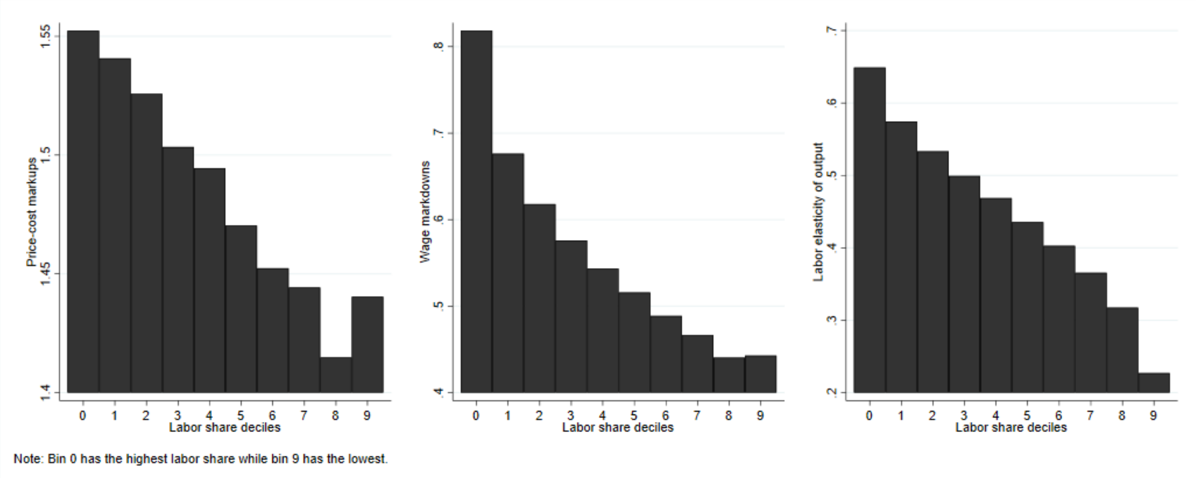

Figure 2: Labor shares and firm characteristics among French firms in 2014.

fact that reallocation of sales towards low labor share firms drives the U.S. labor share decline, at the micro level, production technologies could play an important role.

To get a sense of how much these firm characteristics account for the cross-sectional variation in labor shares, I decompose the variance of (log) labor shares:

$$1 = \underbrace{\frac{CV(ls, wm)}{V(ls)}}_{0.35} - \underbrace{\frac{CV(ls, pm)}{V(ls)}}_{0.03} + \underbrace{\frac{CV(ls, leo)}{V(ls)}}_{0.68}$$

The decomposition suggests that labor elasticities of output account for the bulk of variation in labor shares, followed by wage markdowns and price-cost markups.

Which firm characteristics tend to be associated with changes in firm level labor shares? I decompose changes in firms' labor shares by computing:

$$1 = \underbrace{\frac{CV(\Delta ls, \Delta wm)}{V(\Delta ls)}}_{0.21} - \underbrace{\frac{CV(\Delta ls, \Delta pm)}{V(\Delta ls)}}_{-0.30} + \underbrace{\frac{CV(\Delta ls, \Delta leo)}{V(\Delta ls)}}_{0.49}$$

In ascending order of importance, the decomposition suggests that declines in firms' labor shares reflect larger markdowns of wages below marginal revenue products, higher price-cost markups, and lower labor elasticities of output.

Overall, my findings are consistent with product and labor market power being important determinants of labor shares (De Loecker et al., 2020; Gouin-Bonenfant, 2020), but these findings also highlight that differences in labor elasticities of output are important both for the between-firm and within-firm patterns of labor shares.

6.3 Pass-through of firm productivity to firm wage premia

A key prediction of theories of imperfect labor market competition is that changes in firm productivity transmit into wages. These pass-through estimates are also known as rent-sharing elasticities (Manning, 2011; Card et al., 2018; Chan, Salgado, and Xu, 2021). In models in which workers and firms bargain over wages ex-post matching, the pass-through of productivity to wages reflects rent-sharing. In models in which firms post and commit to paying a certain wage ex-ante matching, this pass-through reflects firms' idiosyncratic changes in labor demand. This section shows that variable markups and labor elasticities of output are important determinants of the degree of pass-through of firm productivity to wage premia.

Suppose one estimates a simple regression of changes in firm wage premia ($\Delta\phi$) on changes in total factor productivity ($\Delta\omega$):

$$\Delta\phi_{g(j,t)t} = \pi_0 \Delta\omega_{g(j,t)t} + \varepsilon_{g(j,t)t} \tag{12}$$

Suppressing the subscripts, the estimated elasticity $\hat{\pi}_0$ can be written as:

$$\underbrace{\frac{CV(\Delta\phi,\Delta\omega)}{V(\Delta\omega)}}_{\hat{\pi}_0} = \underbrace{\frac{CV(\Delta arph,\Delta\omega)}{V(\Delta\omega)}}_{\hat{\pi}_1} + \underbrace{\frac{CV(\Delta wm,\Delta\omega)}{V(\Delta\omega)}}_{\hat{\pi}_2} - \underbrace{\frac{CV(\Delta pm,\Delta\omega)}{V(\Delta\omega)}}_{\hat{\pi}_3} + \underbrace{\frac{CV(\Delta leo,\Delta\omega)}{V(\Delta\omega)}}_{\hat{\pi}_4}$$

The last two components are absent when revenue functions are isoelastic ($\hat{\pi}_3 = \hat{\pi}_4 = 0$). However, suppose that there are sector-level productivity shocks. Then, firm level changes in wages do not necessarily reflect changes in firm-specific labor demand. Changes in wages in the presence of sectoral shocks can occur without labor market frictions, but through changes in aggregate labor demand and the subsequent general equilibrium effects on wages. I therefore also include a set of year, sector, and sector-year fixed effects. I estimate:

$$\Delta\phi_{g(j,t)t} = \pi_0 \Delta\omega_{g(j,t)t} + \text{Sector}_s + \text{Year}_t + \text{Sector}_s \times \text{Year}_t + \varepsilon_{g(j,t)t} \tag{13}$$

where Sector_s represents two-digit sector fixed effects, Year_t represents year fixed effects, and $\text{Sector}_s \times \text{Year}_t$ represents sector-year effects. Similarly, I replace the dependent variable in (13) with $\{\Delta arph_{g(j,t)t}, \Delta wm_{g(j,t)t}, \Delta pm_{g(j,t)t}, \Delta leo_{g(j,t)t}\}$ to obtain $\{\hat{\pi}_1, \hat{\pi}_2, \hat{\pi}_3, \hat{\pi}_4\}$.

Decomposing the pass-through of firm productivity to wage premia, my findings in Table 19 suggest that price-cost markups and labor elasticities of output reduce the productivity-wage premium pass-through. While the estimated elasticity of firm wage premia, average revenue products of labor, and wage markdowns with respect to TFP are positive (0.035, 0.045, and 0.025), the estimated elasticities for *inverse* price-cost markups and labor elasticities of output are -0.008 and -0.027. Further, Table 20 shows that the productivity-wage premium pass-through declines with firm size, measured by total employment. Price-cost markups and labor elasticities of output also help to explain this pattern of declining pass-through by firm size. Non-isoelasticity in revenue functions therefore helps understand the degree of productivity pass-through to wages.

7 Concluding Remarks

This paper investigates the firm characteristics behind a well-known fact: some firms pay higher wages than others for identical workers. To do so, I develop and implement a new structural decomposition of firm wage premia. In workhorse models with isoelastic revenue functions, firms' labor productivity and wage-setting power matter for firm wage premia. This paper allows for a richer notion of firms – non-isoelastic revenue functions – and highlights that differences across firms in product market power and labor elasticities of output also matter. My decomposition suggests that, without considering the role of firms' product market power and labor elasticity of output, workhorse models that generate firm wage premia overestimate the role of labor productivity and wage-setting power. The decomposition also uncovers a negative correlation between labor productivity and the labor elasticity of output underlying the firm wage premium distribution. This generates new implications for the measurement of labor misallocation and for the understanding of low labor shares among high productivity firms. My estimates also suggest that variable price-cost markups and labor elasticities of output are important determinants of incomplete pass-through of firm productivity shocks to wage premia.

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Online Appendix

Understanding High-Wage and Low-Wage Firms

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A Measurement

To estimate production functions using FARE-EAP-DADS (2009-2016) firm balance sheet, output price, and matched employer-employee data from France, I measure the key variables in the following way:

- Sales revenue (PY): measured by the variable CATOTAL in FICUS, and REDI_R310 in FARE.
- Efficiency units of labor ($H = \bar{E}L$): the DADS provides the number of hours worked for each worker under NBHEUR, which enables the researcher to measure total hours (L) at a given firm. The average efficiency of workers ($\bar{E}$) is then measured as the difference between the unconditional mean wage and the firm wage premium, according to the theory.
- Capital (K): measured as total fixed physical assets under variable names IMMO-COR in FICUS, and IMMO_CORP in FARE.
- Materials (M): the French balance sheet data provides a breakdown of intermediate inputs into three components – materials purchased to be used as inputs in production (ACHAMPR in FICUS, REDI_212 in FARE), goods purchased to be resold (ACHAMAR in FICUS, REDI_210 in FARE), and purchase of services (details provided next). I correct for changes in inventory for materials to be used in production (using VARSTMP in FICUS, REDI_213 in FARE) and for goods purchased to be resold (VARSTMA in FICUS, REDI_211 in FARE). I measure M as the sum of these variables, except services.
- Services (O): measured as AUTACHA in FICUS, and REDI_214 in FARE. These variables include the costs of outsourcing and advertising.
- Hourly wages (W): measured by dividing BRUT by NBHEUR in DADS.

- Output prices (P): PRODFRA defines the ten-digit product codes, C_UNITE_VAR gives the quantity and revenue indicator, and VAL_REF gives the values in quantity and revenue terms. These variables are obtained from EAP.
- Market shares: measured within 5-digit sectors.

B K-Means Clustering and AKM Assumptions

B.1 K-means clustering of firms into groups

Specifically, let $g(j) \in \{1, 2, ..., G\}$ denote the cluster of firm j, and G the total number of clusters. The k-means algorithm finds the partition of firms such that the following objective function is minimized:

$$\min_{g(1),...,g(J),H(1),...,H(G)} \sum_{j=1}^{J} N_j \int \left(\hat{F}_j(\ln W_{ij}) - H_{g(j)}(\ln W_{ij})\right)^2 d\gamma(\ln W_{ij})$$

where $H(g)$ denotes the firm-group level cumulative distribution function for log wages at group g, $\hat{F}_j$ is the empirical CDF of log wages at firm j, and N_j is the employment size of firm j. The total number of groups G is the choice of the researcher. I choose sector-specific G such that the variance of log wages between firm-groups captures at least 95% of the total between-firm variance. This choice is motivated by the following consideration: having a coarse classification of firms into fewer groups leads to many more workers who switch between firm-groups, which substantially improves the precision of firm wage premium estimates. However, this comes at the cost of potentially averaging away considerable amounts of multidimensional firm heterogeneity within firm-groups.

B.2 AKM restrictions: conditional exogenous mobility and log-additivity

AKM regressions rely on the assumption that worker mobility is as good as random conditional on observed worker characteristics, worker fixed effects, and firm fixed effects. Formally, $E(\nu_{it}|\chi_{it}, \iota_i, \phi_{g(j(i,t),t)t}) = 0$. This assumption rules out worker mobility based on wage realizations due to the residual component of wages. In theory, this assumption is consistent with the framework outlined in Section 2, which nests frameworks with on-the-job search in which workers move from firm to firm in search of higher wages Burdett and Mortensen (1998). In addition, AKM regressions impose log additivity of the worker and firm components of wages. If these assumptions are reasonable approximations, then one should observe systematic worker mobility up and down the firm wage quartiles. Moreover, workers should experience approximately symmetric wage changes as they move along the firm wage quartiles, given the log additive regression specification. On the other hand, in structural models of worker-firm sorting based on comparative advantage (Eeckhout and Kircher, 2011), worker mobility is based on the match-specific component of wages, which is captured by the residual component of wages in the AKM regression. In this class of models the AKM regression is misspecified in the sense that the wage gains depend on value of the particular worker-firm match, for example, if highly skilled workers have a comparative advantage in high productivity firms. In the event-study exercise show in Figure 3, I compare the changes in mean log wages for workers who move between firms in different quartiles of coworker pay, following Card et al. (2018). Figure 3 shows that workers who move up firm quartiles experience a wage gain similar in magnitude to the wage loss of workers who move down firm quartiles.

An alternative way to assess the AKM regression specification is to compare the changes in residual wages to changes in firm effects, following Sorkin (2018). This is similar to the above method. I run the following regression among all employer-to-employer transitions:

$$w^r_{it} - w^r_{it-1} = \alpha_0 + \alpha_1 \left(\phi_{g(j(i,t))} - \phi_{g(j(i,t-1))}\right) + \epsilon_{it} \;\; \forall\ (i,t),\;\; g(j(i,t)) \neq g(j(i,t-1))$$

where $w^r_{it} = w_{it} - x'_{it}\hat{\beta}$ denotes residualized wages and $\phi_{g(j(i,t))}$ are the firm-group fixed effects. If the AKM regression is not mis-specified, the estimated coefficient $\hat{\alpha_1}$ will equal 1. I find $\hat{\alpha}_1 = 0.857$, with a standard error of 0.007. To see this visually, Figure 4 plots the changes in residual wages and the changes in firm fixed effects in 100 bins of changes in firm fixed effects. In models of assortative matching based on comparative advantage (Lopes de Melo, 2018), worker mobility is strongly driven the residual component of the AKM regression, implying that AKM regressions are mis-specified. As Sorkin (2018) shows, these models predict that worker mobility entails a wage gain, regardless of the direction of worker mobility in terms of the estimated firm effects, as workers move to firms at which they have a comparative advantage: there is a V-shape around zero changes in firm effects. The patterns of wage changes upon changes in firm fixed effects shown in Figure 4 do not resemble a V-shape around zero.

Another way to assess the log additivity of the worker and firm components of wages is to group worker and firm fixed effects into 10 deciles each, generating 100 worker-firm fixed effect deciles, then plot the mean estimated residuals within each worker-firm fixed effect decile. If the firm wage premium depends strongly on the worker's unobserved ability type, log additivity would be severely violated, and one should observe that the estimated residuals systematically varies across worker-firm fixed effect deciles. Figures 5 and 6 show that the mean estimated residuals are approximately zero across worker-firm fixed effect deciles, with the exception of the very top deciles of high-wage workers who are employed at low-wage firms at the very bottom deciles.

As a further robustness check, I follow Bonhomme et al. (2019) and run the BLM regression with worker-firm interactions, but with only 20 firm groups and 6 worker groups to maintain computational tractability. Moving from an additive to an interacted regression model gives a gain in R^2 of 0.01.

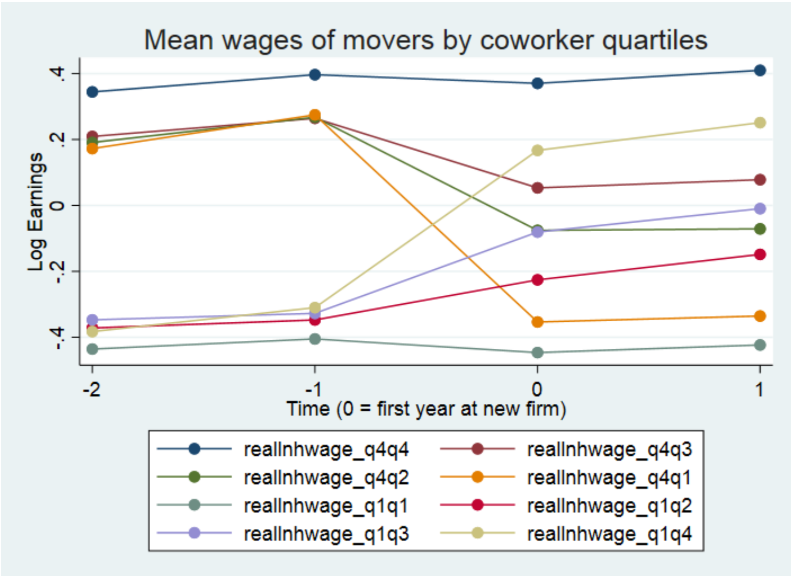

Figure 3: Worker mobility and wage changes by quartiles of coworker effects (2009-2016).

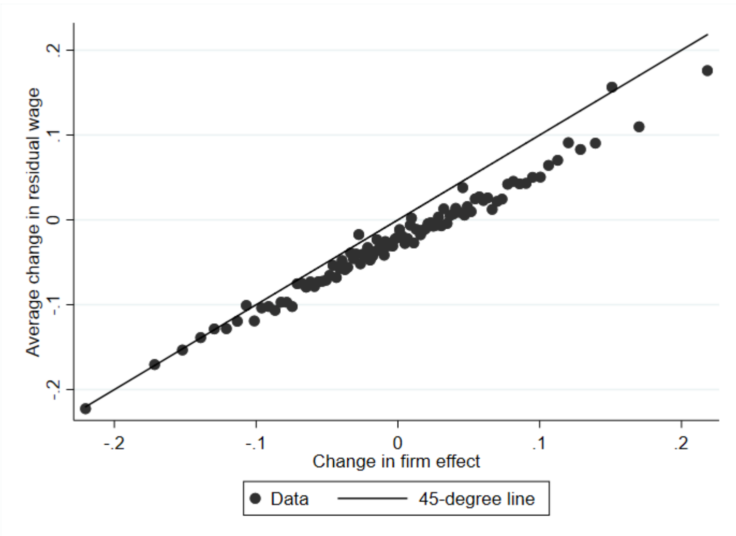

Figure 4: Average wage changes from worker mobility by declines of changes in firm premia (2009-2016).

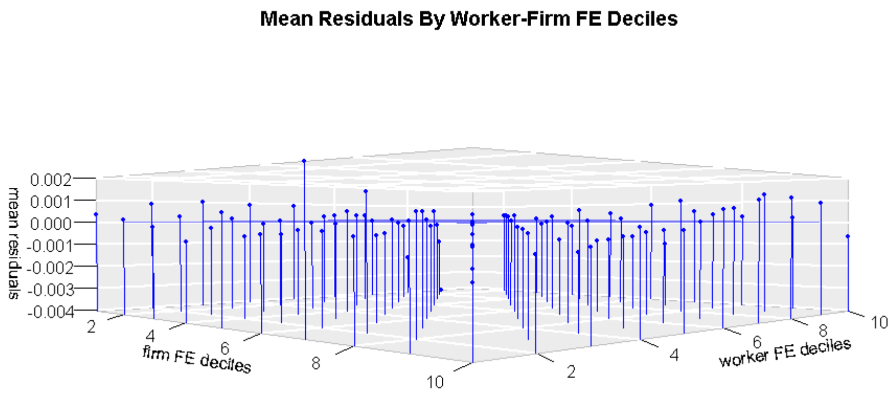

Figure 5: Mean estimated residuals by worker-firm deciles (2014)

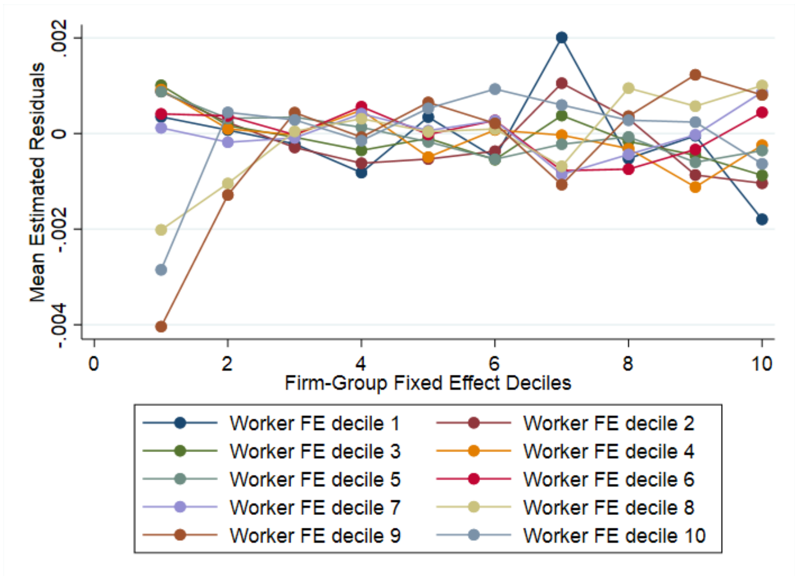

Figure 6: Mean estimated residuals by worker-firm deciles (2016)

C Figures and Tables

	Employees	
Sample size		
People-years	9,233,319	
Firm-years	130,246	
Average number of workers per year	1,154,215	
Average number of firms per year	16,501	
Wage distribution		
Mean log Wage	2.53	
Variance log wage	0.19	
Fraction between-firms	0.44	
Efficiency Units & Firm Premium		
Variance $\bar{e}$	0.03	
Variance ϕ	0.007	
Correlation $(\bar{e}, \phi)$	0.27	
	Employers	
	Mean	Variance
Log production value ('000)	8.31	2.02
Log employment	3.29	1.36
Log capital stock ('000)	7.06	3.17
Log intermediate inputs ('000)	7.22	2.72

Table 6: Summary statistics: manufacturing sector employers and employees (2009-2016).

Table 7: Summary statistics for two-digit French manufacturing sectors.

Sector	# Observations	Sales share	Employment share	Average ϕ	Price-cost markups	Wage markdowns
Textile	5,136	1.9%	2.3%	2.79	1.59	0.66
Apparel	3,256	1.6%	2.1%	2.76	1.73	0.64
Leather	1,468	0.5%	0.8%	2.74	1.68	0.92
Wood products (except furniture)	7,342	2.2%	2.8%	2.75	1.38	0.52
Paper	5,401	5.6%	4.8%	2.82	1.37	0.50
Recorded media	8,229	1.8%	2.6%	2.79	1.78	0.62
Chemicals	6,246	11.4%	7.8%	2.84	1.41	0.45
Pharmaceutical	211	2.5%	1.5%	2.94	1.46	0.29
Rubber & plastics	13,980	12.1%	13.3%	2.81	1.41	0.54
Non-metallic minerals	9,615	7.8%	7.7%	2.79	1.46	0.51
Basic metals	3,615	8.5%	6.0%	2.81	1.38	0.50
Fabricated metals (except machinery)	24,045	9.4%	11.9%	2.80	1.51	0.54
Computers, electronic, & optical	4,669	6.7%	7.1%	2.85	1.55	0.61
Electrical equipment	4,826	3.4%	3.8%	2.83	1.37	0.78
Machinery & equipment	12,923	7.5%	8.3%	2.83	1.30	0.42
Motor vehicles	4,341	7.5%	6.4%	2.83	1.28	0.53
Other transport equipment	88	2.9%	2.4%	2.85	1.47	1.43
Furniture	7,344	2.1%	3.1%	2.78	1.62	0.70
Other manufacturing	3,264	2.4%	2.7%	2.80	1.65	0.73
Repair & installation of machinery	4,238	2.2%	2.5%	2.79	1.65	0.53
Total	130,246	100%	100%	-	-	-

This table reports the summary statistics for manufacturing sectors in my sample (2009-2016). The last two columns report the average price-cost markup and wage markdown in each sector.

Table 8: Summary statistics for estimated wage markdowns in 2016.

Specification	Mean	Median	25^{th} Pct	75^{th} Pct	Var	Var (i)	Var (ii)
(1)	0.65	0.37	0.21	0.69	0.85	0.68	0.19
(2)	0.65	0.37	0.21	0.69	0.85	0.68	0.18
(3)	0.66	0.37	0.21	0.69	0.85	0.68	0.19
(4)	0.65	0.37	0.21	0.69	0.85	0.68	0.18
(5)	0.65	0.37	0.21	0.69	0.84	0.68	0.18
(6)	0.60	0.57	0.45	0.71	0.12	0.08	0.04
(7)	0.60	0.57	0.46	0.70	0.12	0.08	0.04
(8)	0.60	0.57	0.46	0.71	0.12	0.08	0.04
(9)	0.62	0.58	0.46	0.72	0.13	0.09	0.05
(10)	0.60	0.57	0.46	0.71	0.12	0.08	0.04
(11)	0.94	0.55	0.32	1.01	0.83	0.66	0.17
(12)	0.95	0.56	0.32	1.01	0.82	0.66	0.16
(13)	0.94	0.55	0.31	1.01	0.83	0.66	0.17
(14)	0.95	0.55	0.32	1.00	0.82	0.66	0.16
(15)	0.94	0.55	0.32	1.00	0.82	0.66	0.17
(16)	0.84	0.80	0.63	1.00	0.11	0.07	0.03
(17)	0.85	0.80	0.63	1.00	0.11	0.07	0.03
(18)	0.85	0.80	0.63	1.00	0.11	0.07	0.03
(19)	0.85	0.80	0.64	1.00	0.11	0.07	0.03
(20)	0.85	0.80	0.63	1.00	0.12	0.07	0.03

This table reports the summary statistics for the firm characteristics estimated each specification. Variances are reported for the logarithms of the corresponding variable. The column Var (i) reports the variances corrected for measurement error following Krueger and Summers (1988) and Kline et al. (2020), while the column Var (ii) reports the variances for firm-groups.

(1): 3 inputs, Cobb-Douglas, no controls for markups and output prices
(2): 3 inputs, Cobb-Douglas, controls for markups only
(3): 3 inputs, Cobb-Douglas, controls for output prices only
(4): 3 inputs, Cobb-Douglas, controls for markups and output prices
(5): 3 inputs, Cobb-Douglas, controls for markups, output and input prices
(6): 3 inputs, translog, no controls for markups and output prices
(7): 3 inputs, translog, controls for markups only
(8): 3 inputs, translog, controls for output prices only
(9): 3 inputs, translog, controls for markups and output prices
(10): 3 inputs, translog, controls for markups, output and input prices
(11): 4 inputs, Cobb-Douglas, no controls for markups and output prices
(12): 4 inputs, Cobb-Douglas, controls for markups only
(13): 4 inputs, Cobb-Douglas, controls for output prices only
(14): 4 inputs, Cobb-Douglas, controls for markups and output prices
(15): 4 inputs, Cobb-Douglas, controls for markups, output and input prices
(16): 4 inputs, translog, no controls for markups and output prices
(17): 4 inputs, translog, controls for markups only
(18): 4 inputs, translog, controls for output prices only
(19): 4 inputs, translog, controls for markups and output prices
(20): 4 inputs, translog, controls for markups, output and input prices

Table 9: Summary statistics for estimated price-cost markups in 2016.

Specification	Mean	Median	25^{th} Pct	75^{th} Pct	Var	Var (i)	Var (ii)
(1)	1.59	1.15	0.86	1.66	0.32	0.25	0.08
(2)	1.57	1.14	0.85	1.64	0.32	0.25	0.08
(3)	1.60	1.15	0.86	1.66	0.32	0.25	0.08
(4)	1.57	1.14	0.85	1.64	0.32	0.25	0.08
(5)	1.57	1.14	0.85	1.64	0.32	0.25	0.08
(6)	1.51	1.40	1.19	1.71	0.07	0.04	0.02
(7)	1.48	1.42	1.26	1.65	0.04	0.03	0.01
(8)	1.49	1.44	1.27	1.67	0.04	0.03	0.01
(9)	1.50	1.38	1.18	1.70	0.08	0.05	0.02
(10)	1.50	1.38	1.18	1.69	0.08	0.04	0.02
(11)	1.18	0.91	0.68	1.29	0.29	0.24	0.06
(12)	1.19	0.91	0.68	1.28	0.28	0.24	0.06
(13)	1.18	0.91	0.68	1.29	0.29	0.24	0.06
(14)	1.19	0.91	0.68	1.28	0.28	0.24	0.06
(15)	1.19	0.91	0.67	1.29	0.31	0.24	0.07
(16)	1.21	1.18	1.03	1.35	0.04	0.03	0.01
(17)	1.21	1.18	1.03	1.35	0.04	0.03	0.01
(18)	1.21	1.18	1.04	1.35	0.04	0.03	0.01
(19)	1.21	1.18	1.04	1.35	0.04	0.03	0.01
(20)	1.22	1.16	1.01	1.36	0.05	0.03	0.01

This table reports the summary statistics for the firm characteristics estimated each specification. Variances are reported for the logarithms of the corresponding variable. The column Var (i) reports the variances corrected for measurement error following Krueger and Summers (1988) and Kline et al. (2020), while the column Var (ii) reports the variances for firm-groups.
(1): 3 inputs, Cobb-Douglas, no controls for markups and output prices
(2): 3 inputs, Cobb-Douglas, controls for markups only
(3): 3 inputs, Cobb-Douglas, controls for output prices only
(4): 3 inputs, Cobb-Douglas, controls for markups and output prices
(5): 3 inputs, Cobb-Douglas, controls for markups, output and input prices
(6): 3 inputs, translog, no controls for markups and output prices
(7): 3 inputs, translog, controls for markups only
(8): 3 inputs, translog, controls for output prices only
(9): 3 inputs, translog, controls for markups and output prices
(10): 3 inputs, translog, controls for markups, output and input prices
(11): 4 inputs, Cobb-Douglas, no controls for markups and output prices
(12): 4 inputs, Cobb-Douglas, controls for markups only
(13): 4 inputs, Cobb-Douglas, controls for output prices only
(14): 4 inputs, Cobb-Douglas, controls for markups and output prices
(15): 4 inputs, Cobb-Douglas, controls for markups, output and input prices
(16): 4 inputs, translog, no controls for markups and output prices
(17): 4 inputs, translog, controls for markups only
(18): 4 inputs, translog, controls for output prices only
(19): 4 inputs, translog, controls for markups and output prices
(20): 4 inputs, translog, controls for markups, output and input prices

Table 10: Summary statistics for estimated labor elasticities of output in 2016.

Specification	Mean	Median	25^{th} Pct	75^{th} Pct	Var	Var (i)	Var (ii)
(1)	0.52	0.54	0.46	0.55	0.02	0.02	0.03
(2)	0.51	0.52	0.46	0.54	0.02	0.02	0.03
(3)	0.52	0.54	0.46	0.55	0.02	0.02	0.02
(4)	0.51	0.52	0.46	0.54	0.02	0.02	0.03
(5)	0.51	0.51	0.46	0.54	0.02	0.02	0.03
(6)	0.44	0.43	0.34	0.54	0.17	0.14	0.05
(7)	0.44	0.43	0.33	0.53	0.18	0.13	0.06
(8)	0.44	0.43	0.34	0.53	0.17	0.13	0.05
(9)	0.43	0.42	0.33	0.53	0.20	0.15	0.08
(10)	0.43	0.43	0.33	0.53	0.18	0.14	0.06
(11)	0.27	0.29	0.25	0.29	0.03	0.03	0.04
(12)	0.27	0.28	0.25	0.29	0.03	0.03	0.03
(13)	0.28	0.29	0.26	0.29	0.03	0.03	0.03
(14)	0.27	0.28	0.26	0.29	0.03	0.03	0.03
(15)	0.27	0.28	0.26	0.29	0.03	0.03	0.03
(16)	0.26	0.25	0.20	0.32	0.19	0.15	0.06
(17)	0.26	0.25	0.20	0.31	0.19	0.14	0.06
(18)	0.26	0.25	0.20	0.31	0.19	0.15	0.06
(19)	0.26	0.25	0.19	0.31	0.19	0.15	0.06
(20)	0.26	0.25	0.20	0.31	0.19	0.15	0.06

This table reports the summary statistics for the firm characteristics estimated each specification. Variances are reported for the logarithms of the corresponding variable. The column Var (i) reports the variances corrected for measurement error following Krueger and Summers (1988) and Kline et al. (2020), while the column Var (ii) reports the variances for firm-groups.
(1): 3 inputs, Cobb-Douglas, no controls for markups and output prices
(2): 3 inputs, Cobb-Douglas, controls for markups only
(3): 3 inputs, Cobb-Douglas, controls for output prices only
(4): 3 inputs, Cobb-Douglas, controls for markups and output prices
(5): 3 inputs, Cobb-Douglas, controls for markups, output and input prices
(6): 3 inputs, translog, no controls for markups and output prices
(7): 3 inputs, translog, controls for markups only
(8): 3 inputs, translog, controls for output prices only
(9): 3 inputs, translog, controls for markups and output prices
(10): 3 inputs, translog, controls for markups, output and input prices
(11): 4 inputs, Cobb-Douglas, no controls for markups and output prices
(12): 4 inputs, Cobb-Douglas, controls for markups only
(13): 4 inputs, Cobb-Douglas, controls for output prices only
(14): 4 inputs, Cobb-Douglas, controls for markups and output prices
(15): 4 inputs, Cobb-Douglas, controls for markups, output and input prices
(16): 4 inputs, translog, no controls for markups and output prices
(17): 4 inputs, translog, controls for markups only
(18): 4 inputs, translog, controls for output prices only
(19): 4 inputs, translog, controls for markups and output prices
(20): 4 inputs, translog, controls for markups, output and input prices

Table 11: Summary statistics for estimated (log) marginal revenue product of labor in 2016.

Specification	Mean	Median	25^{th} Pct	75^{th} Pct	Var	Var (i)	Var (ii)
(1)	0.00	0.04	-0.57	0.63	0.86	0.71	0.21
(2)	0.00	0.05	-0.56	0.63	0.86	0.71	0.21
(3)	0.00	0.04	-0.57	0.63	0.86	0.71	0.21
(4)	0.00	0.05	-0.56	0.63	0.86	0.71	0.21
(5)	0.00	0.05	-0.56	0.63	0.86	0.71	0.20
(6)	0.00	-0.01	-0.23	0.22	0.12	0.10	0.05
(7)	0.00	-0.01	-0.22	0.21	0.12	0.09	0.05
(8)	0.00	-0.01	-0.23	0.22	0.12	0.09	0.04
(9)	0.00	0.00	-0.22	0.22	0.13	0.10	0.05
(10)	0.00	0.00	-0.23	0.22	0.12	0.10	0.05
(11)	0.00	0.04	-0.56	0.62	0.84	0.68	0.19
(12)	0.00	0.04	-0.55	0.61	0.84	0.67	0.18
(13)	0.00	0.04	-0.56	0.61	0.84	0.68	0.19
(14)	0.00	0.04	-0.55	0.61	0.83	0.67	0.18
(15)	0.00	0.04	-0.55	0.61	0.84	0.67	0.19
(16)	0.00	0.00	-0.23	0.23	0.11	0.08	0.03
(17)	0.00	0.00	-0.22	0.23	0.11	0.08	0.03
(18)	0.00	0.00	-0.22	0.23	0.11	0.08	0.03
(19)	0.00	0.00	-0.22	0.23	0.11	0.07	0.03
(20)	0.00	0.00	-0.23	0.23	0.11	0.08	0.03

This table reports the summary statistics for the firm characteristics estimated each specification. Variances are reported for the logarithms of the corresponding variable. The mean of the logarithm of the marginal revenue product of labor is re-centered at 0. The column Var (i) reports the variances corrected for measurement error following Krueger and Summers (1988) and Kline et al. (2020), while the column Var (ii) reports the variances for firm-groups.

(1): 3 inputs, Cobb-Douglas, no controls for markups and output prices
(2): 3 inputs, Cobb-Douglas, controls for markups only
(3): 3 inputs, Cobb-Douglas, controls for output prices only
(4): 3 inputs, Cobb-Douglas, controls for markups and output prices
(5): 3 inputs, Cobb-Douglas, controls for markups, output and input prices
(6): 3 inputs, translog, no controls for markups and output prices
(7): 3 inputs, translog, controls for markups only
(8): 3 inputs, translog, controls for output prices only
(9): 3 inputs, translog, controls for markups and output prices
(10): 3 inputs, translog, controls for markups, output and input prices
(11): 4 inputs, Cobb-Douglas, no controls for markups and output prices
(12): 4 inputs, Cobb-Douglas, controls for markups only
(13): 4 inputs, Cobb-Douglas, controls for output prices only
(14): 4 inputs, Cobb-Douglas, controls for markups and output prices
(15): 4 inputs, Cobb-Douglas, controls for markups, output and input prices
(16): 4 inputs, translog, no controls for markups and output prices
(17): 4 inputs, translog, controls for markups only
(18): 4 inputs, translog, controls for output prices only
(19): 4 inputs, translog, controls for markups and output prices
(20): 4 inputs, translog, controls for markups, output and input prices

Table 12: Output elasticities and returns to scale in 2016.

Specification	KEO	LEO	MEO	SEO	RTS
(1)	0.045	0.523	0.418	-	0.986
(2)	0.038	0.514	0.412	-	0.964
(3)	0.045	0.522	0.418	-	0.985
(4)	0.038	0.514	0.412	-	0.964
(5)	0.037	0.515	0.412	-	0.964
(6)	0.055	0.439	0.512	-	1.006
(7)	0.050	0.436	0.507	-	0.993
(8)	0.055	0.438	0.512	-	1.005
(9)	0.049	0.431	0.504	-	0.984
(10)	0.051	0.434	0.507	-	0.993
(11)	0.010	0.274	0.326	0.355	0.964
(12)	0.010	0.274	0.326	0.355	0.964
(13)	0.010	0.275	0.326	0.355	0.964
(14)	0.010	0.274	0.325	0.354	0.963
(15)	0.009	0.275	0.325	0.355	0.964
(16)	0.027	0.258	0.419	0.338	1.043
(17)	0.028	0.257	0.420	0.338	1.044
(18)	0.027	0.257	0.420	0.339	1.042
(19)	0.028	0.257	0.420	0.339	1.044
(20)	0.028	0.257	0.419	0.339	1.044

This table reports the estimated returns to scale for each specification of the production function. KEO, LEO, MEO, and SEO represent the capital, labor, material, and service elasticities of output. RTS represents returns-to-scale.
(1): 3 inputs, Cobb-Douglas, no controls for markups and output prices
(2): 3 inputs, Cobb-Douglas, controls for markups only
(3): 3 inputs, Cobb-Douglas, controls for output prices only
(4): 3 inputs, Cobb-Douglas, controls for markups and output prices
(5): 3 inputs, Cobb-Douglas, controls for markups, output and input prices
(6): 3 inputs, translog, no controls for markups and output prices
(7): 3 inputs, translog, controls for markups only
(8): 3 inputs, translog, controls for output prices only
(9): 3 inputs, translog, controls for markups and output prices
(10): 3 inputs, translog, controls for markups, output and input prices
(11): 4 inputs, Cobb-Douglas, no controls for markups and output prices
(12): 4 inputs, Cobb-Douglas, controls for markups only
(13): 4 inputs, Cobb-Douglas, controls for output prices only
(14): 4 inputs, Cobb-Douglas, controls for markups and output prices
(15): 4 inputs, Cobb-Douglas, controls for markups, output and input prices
(16): 4 inputs, translog, no controls for markups and output prices
(17): 4 inputs, translog, controls for markups only
(18): 4 inputs, translog, controls for output prices only
(19): 4 inputs, translog, controls for markups and output prices
(20): 4 inputs, translog, controls for markups, output and input prices

Table 13: Relationship between firm wage premia, firm size, labor productivity, and labor shares.

	Firm wage premium		
	Log firm size	Log ARPH	Labor shares
	(1)	(2)	(3)
Decile 2	0.003	0.021	0.004
	(0.001)	(0.001)	(0.001)
Decile 3	0.007	0.028	0.006
	(0.001)	(0.001)	(0.001)
Decile 4	0.012	0.034	0.006
	(0.001)	(0.001)	(0.001)
Decile 5	0.014	0.040	0.007
	(0.001)	(0.001)	(0.001)
Decile 6	0.017	0.046	0.009
	(0.001)	(0.001)	(0.001)
Decile 7	0.020	0.049	0.009
	(0.001)	(0.001)	(0.001)
Decile 8	0.029	0.056	0.011
	(0.001)	(0.001)	(0.001)
Decile 9	0.039	0.060	0.013
	(0.001)	(0.001)	(0.001)
Decile 10	0.077	0.074	0.020
	(0.001)	(0.001)	(0.001)
Year F.E.	Y	Y	Y
Sector-year F.E.	Y	Y	Y
Sector F.E.	Y	Y	Y
# firms		130,246	

Column (1) reports the estimated relationship between firm wage premia and deciles of firm size, measured as the firm level total employment in a given year. Column (2) reports the estimated relationship between firm wage premia and deciles of labor productivity (in efficiency units). Column (3) reports the estimated relationship between firm wage premia and deciles of labor shares (wage bill share of revenue). Labor share quintiles are ranked from highest to lowest, i.e. decile 1 in column (3) represents the group with the highest labor shares. The reference group is the first decile. Heteroskedascity robust standard errors are reported in parentheses. The sample period is 2009-2016.

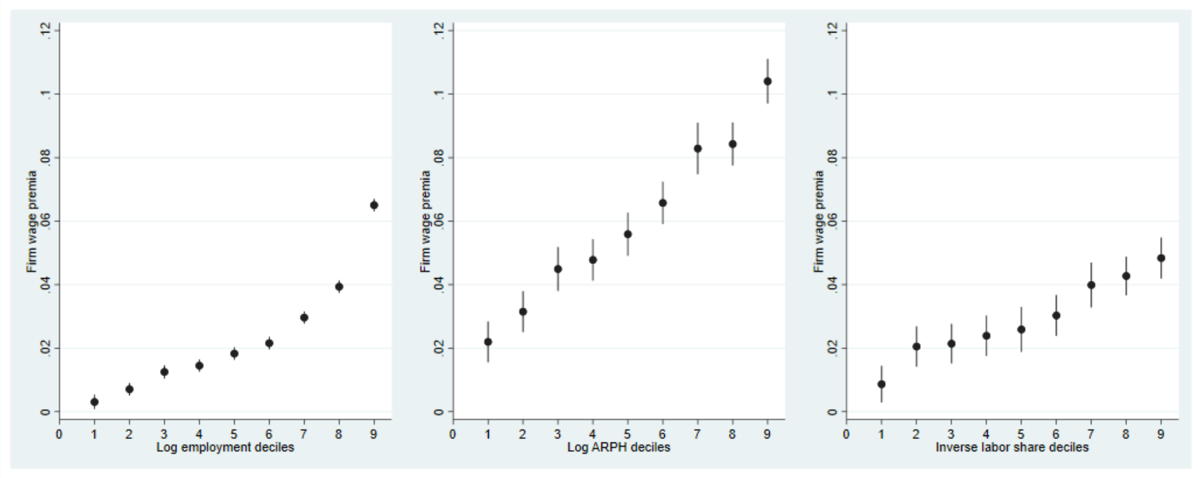

Figure 7: Correlation between firm wage premia and observed firm characteristics (2009-2016).

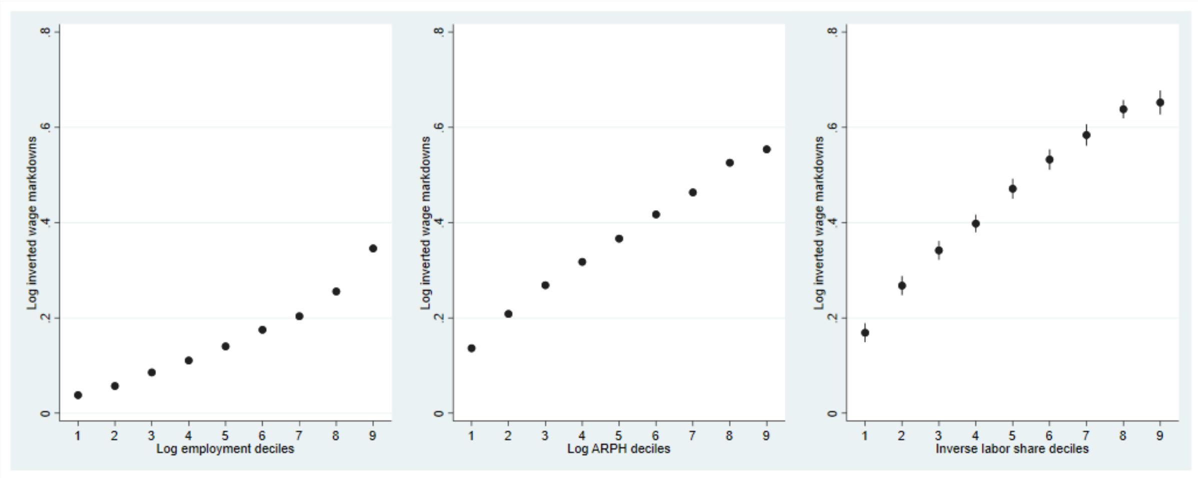

Figure 8: Correlation between wage markdowns and observed firm characteristics (2009-2016).

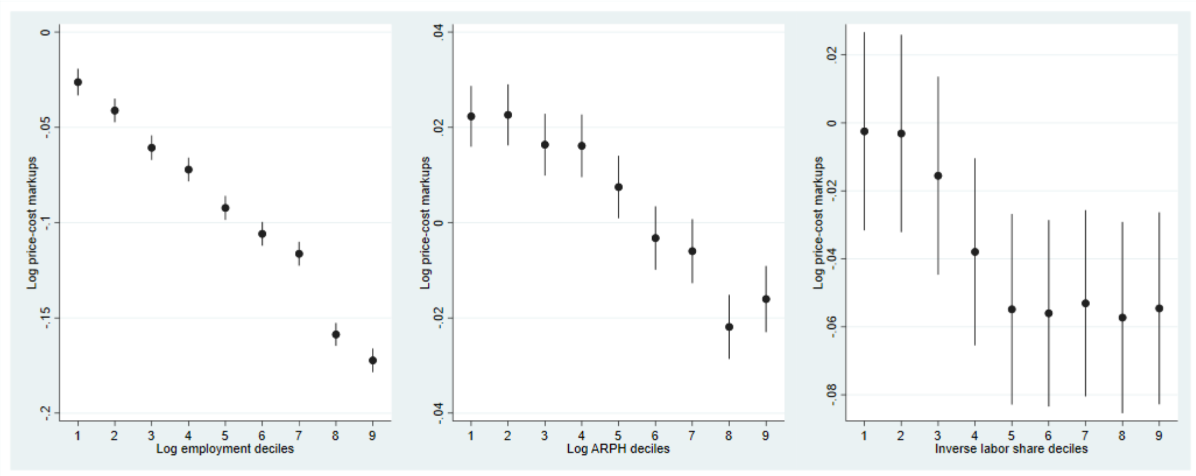

Figure 9: Correlation between price-cost markups and observed firm characteristics (2009-2016).

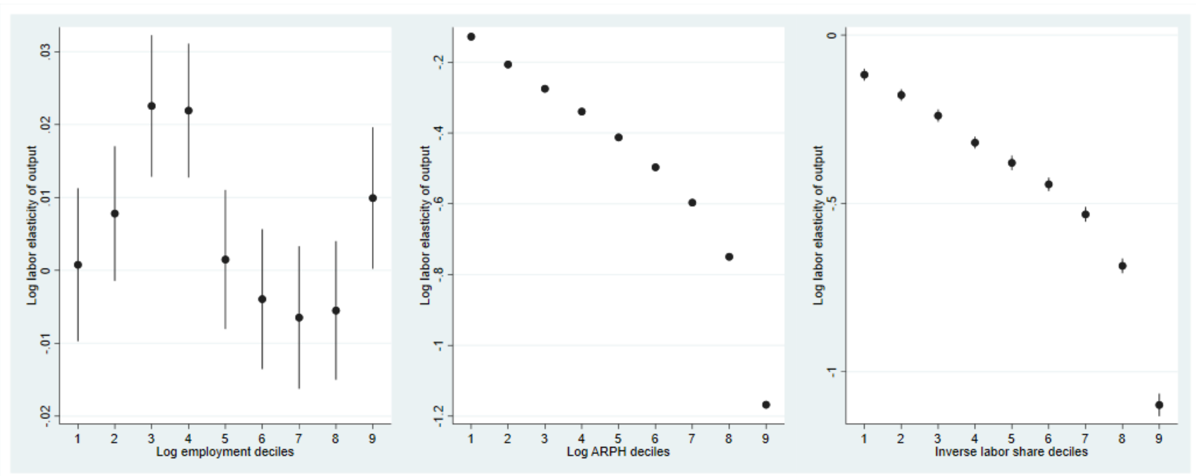

Figure 10: Correlation between labor elasticities of output and observed firm characteristics (2009-2016).

Table 14: Wage markdown correlations across specifications.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1)	1																			
(2)	0.99	1																		
(3)	0.99	0.99	1																	
(4)	0.57	0.57	0.56	1																
(5)	0.99	0.99	0.99	0.58	1															
(6)	0.55	0.55	0.55	0.34	0.56	1														
(7)	0.55	0.55	0.55	0.34	0.56	0.99	1													
(8)	0.55	0.56	0.55	0.34	0.56	0.99	0.99	1												
(9)	0.50	0.50	0.50	0.30	0.51	0.94	0.94	0.94	1											
(10)	0.57	0.57	0.57	0.36	0.57	0.99	0.99	0.99	0.94	1										
(11)	0.97	0.96	0.97	0.52	0.96	0.51	0.50	0.51	0.46	0.53	1									
(12)	0.98	0.97	0.98	0.52	0.96	0.52	0.51	0.51	0.47	0.54	0.99	1								
(13)	0.95	0.94	0.95	0.49	0.94	0.49	0.49	0.49	0.44	0.51	0.99	0.99	1							
(14)	0.97	0.96	0.97	0.52	0.96	0.50	0.49	0.50	0.45	0.51	0.99	0.99	0.98	1						
(15)	0.98	0.97	0.98	0.54	0.97	0.52	0.52	0.52	0.48	0.54	0.99	0.99	0.99	0.99	1					
(16)	0.59	0.58	0.59	0.28	0.57	0.69	0.69	0.69	0.63	0.69	0.61	0.61	0.61	0.60	0.60	1				
(17)	0.59	0.58	0.59	0.28	0.58	0.70	0.70	0.70	0.64	0.70	0.61	0.61	0.61	0.61	0.61	0.99	1			
(18)	0.59	0.58	0.59	0.27	0.57	0.69	0.69	0.69	0.63	0.69	0.61	0.61	0.61	0.60	0.60	0.99	0.99	1		
(19)	0.50	0.50	0.50	0.22	0.49	0.63	0.63	0.63	0.57	0.64	0.50	0.50	0.50	0.50	0.50	0.82	0.82	0.82	1	
(20)	0.98	0.97	0.98	0.54	0.97	0.52	0.52	0.52	0.48	0.54	0.99	0.99	0.99	0.99	0.99	0.61	0.61	0.60	0.50	1

(1): 3 inputs, Cobb-Douglas, no controls for markups and output prices
(2): 3 inputs, Cobb-Douglas, controls for markups only
(3): 3 inputs, Cobb-Douglas, controls for output prices only
(4): 3 inputs, Cobb-Douglas, controls for markups and output prices
(5): 3 inputs, Cobb-Douglas, controls for markups, output and input prices
(6): 3 inputs, translog, no controls for markups and output prices
(7): 3 inputs, translog, controls for markups only
(8): 3 inputs, translog, controls for output prices only
(9): 3 inputs, translog, controls for markups and output prices
(10): 3 inputs, translog, controls for markups, output and input prices
(11): 4 inputs, Cobb-Douglas, no controls for markups and output prices
(12): 4 inputs, Cobb-Douglas, controls for markups only
(13): 4 inputs, Cobb-Douglas, controls for output prices only
(14): 4 inputs, Cobb-Douglas, controls for markups and output prices
(15): 4 inputs, Cobb-Douglas, controls for markups, output and input prices
(16): 4 inputs, translog, no controls for markups and output prices
(17): 4 inputs, translog, controls for markups only
(18): 4 inputs, translog, controls for output prices only
(19): 4 inputs, translog, controls for markups and output prices
(20): 4 inputs, translog, controls for markups, output and input prices

Table 15: Price-cost markups correlations across specifications.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1)	1																			
(2)	0.99	1																		
(3)	0.90	0.90	1																	
(4)	0.90	0.90	0.99	1																
(5)	0.99	0.99	0.99	0.99	1															
(6)	0.67	0.67	0.58	0.58	0.67	1														
(7)	0.66	0.66	0.57	0.58	0.67	0.99	1													
(8)	0.44	0.44	0.68	0.68	0.67	0.64	0.64	1												
(9)	0.44	0.44	0.68	0.67	0.67	0.64	0.64	0.99	1											
(10)	0.68	0.68	0.68	0.68	0.68	0.99	0.99	0.99	0.99	1										
(11)	0.91	0.90	0.94	0.93	0.97	0.57	0.57	0.58	0.58	0.66	1									
(12)	0.91	0.91	0.95	0.94	0.98	0.58	0.58	0.58	0.58	0.66	0.99	1								
(13)	0.87	0.87	0.98	0.97	0.97	0.55	0.55	0.66	0.66	0.66	0.95	0.95	1							
(14)	0.88	0.87	0.98	0.98	0.98	0.53	0.52	0.65	0.65	0.65	0.96	0.96	0.99	1						
(15)	0.98	0.98	0.98	0.98	0.98	0.65	0.65	0.65	0.65	0.66	0.99	0.99	0.99	0.99	1					
(16)	0.66	0.66	0.66	0.65	0.68	0.75	0.75	0.68	0.67	0.81	0.71	0.71	0.67	0.67	0.70	1				
(17)	0.66	0.66	0.66	0.65	0.68	0.75	0.75	0.67	0.67	0.81	0.71	0.72	0.67	0.67	0.70	0.99	1			
(18)	0.56	0.56	0.70	0.69	0.68	0.60	0.60	0.81	0.81	0.82	0.60	0.61	0.71	0.71	0.70	0.81	0.80	1		
(19)	0.55	0.55	0.69	0.68	0.68	0.60	0.60	0.81	0.81	0.81	0.59	0.60	0.70	0.70	0.69	0.80	0.80	0.99	1	
(20)	0.98	0.98	0.98	0.98	0.98	0.65	0.65	0.65	0.65	0.66	0.99	0.99	0.99	0.99	0.99	0.70	0.70	0.70	0.69	1

(1): 3 inputs, Cobb-Douglas, no controls for markups and output prices
(2): 3 inputs, Cobb-Douglas, controls for markups only
(3): 3 inputs, Cobb-Douglas, controls for output prices only
(4): 3 inputs, Cobb-Douglas, controls for markups and output prices
(5): 3 inputs, Cobb-Douglas, controls for markups, output and input prices
(6): 3 inputs, translog, no controls for markups and output prices
(7): 3 inputs, translog, controls for markups only
(8): 3 inputs, translog, controls for output prices only
(9): 3 inputs, translog, controls for markups and output prices
(10): 3 inputs, translog, controls for markups, output and input prices
(11): 4 inputs, Cobb-Douglas, no controls for markups and output prices
(12): 4 inputs, Cobb-Douglas, controls for markups only
(13): 4 inputs, Cobb-Douglas, controls for output prices only
(14): 4 inputs, Cobb-Douglas, controls for markups and output prices
(15): 4 inputs, Cobb-Douglas, controls for markups, output and input prices
(16): 4 inputs, translog, no controls for markups and output prices
(17): 4 inputs, translog, controls for markups only
(18): 4 inputs, translog, controls for output prices only
(19): 4 inputs, translog, controls for markups and output prices
(20): 4 inputs, translog, controls for markups, output and input prices

Table 16: Shapley decomposition of firm wage premia.

Specification	*wm*	*arph*	*pm*	*leo*
(1)	0.24	0.60	0.16	0.00
(2)	0.24	0.60	0.16	0.00
(3)	0.24	0.60	0.16	0.00
(4)	0.23	0.62	0.15	0.00
(5)	0.24	0.60	0.16	0.00
(6)	0.22	0.50	0.11	0.17
(7)	0.22	0.50	0.11	0.17
(8)	0.22	0.50	0.11	0.17
(9)	0.24	0.48	0.11	0.17
(10)	0.24	0.48	0.11	0.17
(11)	0.25	0.59	0.16	0.00
(12)	0.25	0.59	0.16	0.00
(13)	0.25	0.59	0.16	0.00
(14)	0.25	0.59	0.16	0.00
(15)	0.25	0.59	0.16	0.00
(16)	0.28	0.44	0.08	0.21
(17)	0.28	0.44	0.08	0.21
(18)	0.28	0.44	0.08	0.21
(19)	0.27	0.45	0.09	0.20
(20)	0.28	0.44	0.08	0.20

This table reports the results of a Shapley decomposition of the variance of firm wage premia within two-digit sectors. All lowercase letters denote the natural logarithm of the corresponding variables. *wm* denotes wage markdowns. *arph* denotes the average revenue product of labor. *pm* denotes price-cost markups. *leo* denotes labor elasticities of output.

(1): 3 inputs, Cobb-Douglas, no controls for markups and output prices
(2): 3 inputs, Cobb-Douglas, controls for markups only
(3): 3 inputs, Cobb-Douglas, controls for output prices only
(4): 3 inputs, Cobb-Douglas, controls for markups and output prices
(5): 3 inputs, Cobb-Douglas, controls for markups, output and input prices
(6): 3 inputs, translog, no controls for markups and output prices
(7): 3 inputs, translog, controls for markups only
(8): 3 inputs, translog, controls for output prices only
(9): 3 inputs, translog, controls for markups and output prices
(10): 3 inputs, translog, controls for markups, output and input prices
(11): 4 inputs, Cobb-Douglas, no controls for markups and output prices
(12): 4 inputs, Cobb-Douglas, controls for markups only
(13): 4 inputs, Cobb-Douglas, controls for output prices only
(14): 4 inputs, Cobb-Douglas, controls for markups and output prices
(15): 4 inputs, Cobb-Douglas, controls for markups, output and input prices
(16): 4 inputs, translog, no controls for markups and output prices
(17): 4 inputs, translog, controls for markups only
(18): 4 inputs, translog, controls for output prices only
(19): 4 inputs, translog, controls for markups and output prices
(20): 4 inputs, translog, controls for markups, output and input prices

Table 17: Ensemble decomposition of firm wage premia.

Specification	*wm*	*arph*	*pm*	*leo*
(1)	-0.36	1.39	-0.04	0.00
(2)	-0.36	1.40	-0.04	0.00
(3)	-0.35	1.39	-0.04	0.00
(4)	-0.39	1.42	-0.03	0.00
(5)	-0.36	1.39	-0.04	0.00
(6)	0.35	1.33	-0.27	-0.41
(7)	0.38	1.33	-0.26	-0.46
(8)	0.36	1.33	-0.27	-0.42
(9)	0.41	1.33	-0.26	-0.47
(10)	0.39	1.33	-0.26	-0.46
(11)	-0.37	1.39	-0.02	0.00
(12)	-0.36	1.39	-0.03	0.00
(13)	-0.36	1.38	-0.02	0.00
(14)	-0.34	1.38	-0.04	0.00
(15)	-0.36	1.39	-0.03	0.00
(16)	0.59	1.36	-0.15	-0.80
(17)	0.59	1.36	-0.15	-0.80
(18)	0.59	1.36	-0.15	-0.80
(19)	0.60	1.35	-0.17	-0.79
(20)	0.59	1.35	-0.15	-0.80

This table reports the results of an ensemble decomposition of the variance of firm wage premia within two-digit sectors. All lowercase letters denote the natural logarithm of the corresponding variables. *wm* denotes wage markdowns. *arph* denotes the average revenue product of labor. *pm* denotes price-cost markups. *leo* denotes labor elasticities of output.

(1): 3 inputs, Cobb-Douglas, no controls for markups and output prices
(2): 3 inputs, Cobb-Douglas, controls for markups only
(3): 3 inputs, Cobb-Douglas, controls for output prices only
(4): 3 inputs, Cobb-Douglas, controls for markups and output prices
(5): 3 inputs, Cobb-Douglas, controls for markups, output and input prices
(6): 3 inputs, translog, no controls for markups and output prices
(7): 3 inputs, translog, controls for markups only
(8): 3 inputs, translog, controls for output prices only
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(10): 3 inputs, translog, controls for markups, output and input prices
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(13): 4 inputs, Cobb-Douglas, controls for output prices only
(14): 4 inputs, Cobb-Douglas, controls for markups and output prices
(15): 4 inputs, Cobb-Douglas, controls for markups, output and input prices
(16): 4 inputs, translog, no controls for markups and output prices
(17): 4 inputs, translog, controls for markups only
(18): 4 inputs, translog, controls for output prices only
(19): 4 inputs, translog, controls for markups and output prices
(20): 4 inputs, translog, controls for markups, output and input prices

Table 18: Standard variance decomposition of firm wage premia.

	$\frac{V(wm)}{V(\phi)}$	$\frac{V(arph)}{V(\phi)}$	$\frac{V(pm)}{V(\phi)}$	$\frac{V(leo)}{V(\phi)}$	$2\frac{CV(wm,arph)}{V(\phi)}$	$2\frac{CV(wm,pm)}{V(\phi)}$	$2\frac{CV(wm,leo)}{V(\phi)}$	$-2\frac{CV(arph,pm)}{V(\phi)}$	$2\frac{CV(arph,leo)}{V(\phi)}$	$-2\frac{CV(pm,leo)}{V(\phi)}$
(1)	12.27	5.34	5.27	0.00	-11.27	-13.99	0.00	3.38	0.00	0.00
(2)	12.23	5.36	5.24	0.00	-11.28	-13.91	0.00	3.35	0.00	0.00
(3)	12.27	5.35	5.26	0.00	-11.28	-13.98	0.00	3.37	0.00	0.00
(4)	12.14	5.07	5.32	0.00	-10.85	-14.23	0.00	3.54	0.00	0.00
(5)	12.22	5.35	5.23	0.00	-11.26	-13.89	0.00	3.34	0.00	0.00
(6)	1.62	4.62	0.82	2.13	-1.63	-1.17	0.26	0.31	-4.65	-0.69
(7)	1.54	4.65	0.82	2.31	-1.42	-1.11	0.23	0.25	-4.98	-0.78
(8)	1.58	4.69	0.80	2.15	-1.61	-1.14	0.30	0.34	-4.77	-0.67
(9)	1.58	4.70	0.86	2.34	-1.43	-1.21	0.30	0.22	-5.11	-0.82
(10)	2.67	4.30	0.95	2.87	-2.20	-1.93	0.30	0.84	-5.07	-1.13
(11)	12.44	5.40	5.26	0.00	-11.54	-14.07	0.00	3.51	0.00	0.00
(12)	12.61	5.47	5.33	0.00	-11.69	-14.26	0.00	3.53	0.00	0.00
(13)	12.52	5.38	5.32	0.00	-11.54	-14.23	0.00	3.54	0.00	0.00
(14)	12.53	5.39	5.32	0.00	-11.51	-14.24	0.00	3.51	0.00	0.00
(15)	12.64	5.46	5.35	0.00	-11.69	-14.31	0.00	3.55	0.00	0.00
(16)	1.79	4.76	0.59	3.23	-0.46	-1.31	-0.62	0.45	-6.79	-0.64
(17)	1.80	4.74	0.63	3.24	-0.51	-1.29	-0.61	0.46	-6.73	-0.74
(18)	1.76	4.74	0.58	3.20	-0.44	-1.27	-0.64	0.42	-6.74	-0.62
(19)	1.93	4.76	0.62	3.35	-0.56	-1.27	-0.82	0.45	-6.70	-0.76
(20)	1.78	4.71	0.63	3.27	-0.50	-1.23	-0.65	0.48	-6.68	-0.80

This table reports the results of a standard variance decomposition of firm wage premia within two-digit sectors. All lowercase letters denote the natural logarithm of the corresponding variables. wm denotes wage markdowns. $arph$ denotes the average revenue product of labor. pm denotes price-cost markups. leo denotes labor elasticities of output.
(1): 3 inputs, Cobb-Douglas, no controls for markups and output prices
(2): 3 inputs, Cobb-Douglas, controls for markups only
(3): 3 inputs, Cobb-Douglas, controls for output prices only
(4): 3 inputs, Cobb-Douglas, controls for markups and output prices
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(7): 3 inputs, translog, controls for markups only
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(17): 4 inputs, translog, controls for markups only
(18): 4 inputs, translog, controls for output prices only
(19): 4 inputs, translog, controls for markups and output prices
(20): 4 inputs, translog, controls for markups, output and input prices

Table 19: Pass-through of firm productivity to firm wage premia.

Panel A	$\Delta\phi$	$\Delta arph$	Δwm	Δpm	Δleo
$\Delta\omega$	0.036	0.047	0.027	0.010	-0.029
	(0.001)	(0.003)	(0.003)	(0.002)	(0.003)
Year F.E.	Yes	Yes	Yes	Yes	Yes
Sector F.E.	Yes	Yes	Yes	Yes	Yes
Sector-Year F.E.	No	No	No	No	No
# firms			103,468		

Panel B	$\Delta\phi$	$\Delta arph$	Δwm	Δpm	Δleo
$\Delta\omega$	0.035	0.045	0.025	0.008	-0.027
	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)
Year F.E.	Yes	Yes	Yes	Yes	Yes
Sector F.E.	Yes	Yes	Yes	Yes	Yes
Sector-Year F.E.	Yes	Yes	Yes	Yes	Yes
# firms			103,468		

This table reports the estimates of the pass-through of firms' total factor productivity (ω) to firm wage premia (ϕ). Average revenue products of labor are denoted as $arph$, wage markdowns are denoted as wm, price-cost markups are denoted as pm, and labor elasticities of output denoted as leo. All lowercase letters are in natural logs.

Table 20: Pass-through of firm productivity to firm wage premia by firm size.

Panel A $\Delta\omega$	$\Delta\phi$	$\Delta arph$	Δwm	Δpm	Δleo
<50 employees	0.040	0.054	0.021	0.011	-0.024
	(0.001)	(0.003)	(0.003)	(0.002)	(0.003)
$50-100$ employees	0.035	0.038	0.010	0.012	-0.002
	(0.004)	(0.007)	(0.008)	(0.005)	(0.009)
$100-500$ employees	0.021	0.022	0.039	0.001	-0.040
	(0.004)	(0.003)	(0.005)	(0.004)	(0.007)
$500-1000$ employees	0.015	0.022	0.038	0.001	-0.044
	(0.001)	(0.007)	(0.016)	(0.006)	(0.019)
>1000 employees	0.002	0.024	0.143	0.013	-0.152
	(0.008)	(0.003)	(0.041)	(0.014)	(0.036)
Year F.E.	Yes	Yes	Yes	Yes	Yes
Sector F.E.	Yes	Yes	Yes	Yes	Yes
Sector-Year F.E.	No	No	No	No	No
# firms			103,468		

Panel B $\Delta\omega$	$\Delta\phi$	$\Delta arph$	Δwm	Δpm	Δleo
<50 employees	0.039	0.051	0.019	0.009	-0.023
	(0.001)	(0.003)	(0.003)	(0.002)	(0.003)
$50-100$ employees	0.039	0.042	0.006	0.014	0.005
	(0.004)	(0.003)	(0.008)	(0.004)	(0.008)
$100-500$ employees	0.021	0.022	0.041	0.002	-0.041
	(0.004)	(0.006)	(0.005)	(0.003)	(0.007)
$500-1000$ employees	0.014	0.020	0.044	0.003	-0.047
	(0.006)	(0.007)	(0.012)	(0.006)	(0.015)
>1000 employees	0.004	0.030	0.146	0.017	-0.155
	(0.008)	(0.030)	(0.039)	(0.015)	(0.036)
Year F.E.	Yes	Yes	Yes	Yes	Yes
Sector F.E.	Yes	Yes	Yes	Yes	Yes
Sector-Year F.E.	Yes	Yes	Yes	Yes	Yes
# firms			103,468		

This table reports the estimates of the pass-through of firms' total factor productivity (ω) to firm wage premia (ϕ) by different firm size categories. Firm size is defined by employment. Average revenue products of labor are denoted as *arph*, wage markdowns are denoted as *wm*, price-cost markups are denoted as *pm*, and labor elasticities of output denoted as *leo*. All lowercase letters are in natural logs.

C.1 Results using hiring wages only

A caveat for the results presented in Section 5 is that firm wage premia and wage markdowns are estimated for all workers – new hires and incumbent workers. As discussed in Section 2, it may be important to allow the wages of incumbent workers to be determined separately from those of new hires. In this section, I estimated and implement a decomposition of firm wage premia using hiring wages only, following Di Addario et al. (2020). I do not take a stance on the wage-setting protocol for incumbent workers. The tables below show that the main qualitative takeaways of the decompositions in Section 5 remain true.

To repeat the main decomposition exercises of this paper, I first k-means cluster firms into groups using only hiring wages (W^n) and estimate firm wage premia (ϕ^n). To estimate production functions taking into account differences in worker ability composition across firms, I then compute the average worker ability at the firm level using the following relationship: $W^n_{jt} = \bar{E}^n_{jt}\Phi^n_{jt}$. The rest of the estimation routine is as described in Section 3.

Once production functions and price-cost markups are estimated, wage markdowns are measured as follows:

$$WM^n_{jt} = \frac{W^n_{jt}L_{jt}}{P_{jt}Y_{jt}} \cdot PM_{jt} \cdot LEO^{-1}_{jt}$$

WM^n represents wage markdowns for new hires. Then, firm wage premia can be decomposed using a slightly modified version of equation (4):

$$\phi^n_{jt} = wm^n_{jt} + arph_{jt} - pm_{jt} + leo_{jt}$$

Note that the estimation of labor elasticities of output, price-cost markups, and average revenue products of labor are the same as in the main body of the paper.

Table 21: Summary statistics for estimated firm wage premia and wage markdowns in 2016 (using hiring wages only).

	Mean	Median	25^{th} Pct	75^{th} Pct	Var	Var (i)	Var (ii)
ϕ	2.58	2.58	2.52	2.63	0.01	0.01	0.01
WM	0.45	0.40	0.30	0.53	0.20	0.05	0.06
PM	1.49	1.38	1.18	1.68	0.07	0.04	0.02
LEO	0.42	0.42	0.31	0.52	0.21	0.14	0.07
$\log ARPH$	0.00	-0.04	-0.39	0.35	0.20	0.16	0.13
$\log MRPH$	0.00	0.00	-0.28	0.28	0.20	0.06	0.07
# firms				12,826			

This table reports the summary statistics for estimated firm wage premia and wage markdowns using hiring wages only (Di Addario et al., 2020). Variances for wage markdowns, price-cost markups, and labor elasticities of output are reported for the logarithms of those variables ($\log WM$, $\log PM$, and $\log LEO$). The log of average and marginal revenue products of labor ($\log ARPH$ and $\log MRPH$) are normalized to have a mean of 0. The column Var (i) reports the variances corrected for measurement error following Krueger and Summers (1988) and Kline et al. (2020), while the column Var (ii) reports the variances for firm-groups. The distribution of joint market power ($\log \frac{WM}{PM}$) is trimmed by 1% on either side.

Table 22: Shapley and ensemble decomposition of firm wage premia estimated using hiring wages only.

Specification	wm	$arph$	pm	leo
Shapley	0.20	0.42	0.16	0.22
Ensemble	0.84	3.30	-0.30	-1.16

This table reports the results of a Shapley and ensemble decomposition of the variance of firm wage premia within two-digit sectors. Firm wage premia here are estimated using hiring wages only: when clustering firms into groups following Bonhomme et al. (2019), I use only hiring wages (Di Addario et al., 2020). Firm characteristics are estimated under my preferred specificiation. All lowercase letters denote the natural logarithm of the corresponding variables. wm denotes wage markdowns. $arph$ denotes the average revenue product of labor. pm denotes price-cost markups. leo denotes labor elasticities of output.

Table 23: Standard variance decomposition of firm wage premia estimated using hiring wages only.

Variance component	Value
$V(wm)/V(\phi)$	15.51
$V(arph)/V(\phi)$	34.08
$V(pm)/V(\phi)$	6.79
$V(leo)/V(\phi)$	14.61
$2CV(wm, arph)/V(\phi)$	26.44
$2CV(wm, pm)/V(\phi)$	8.65
$2CV(wm, leo)/V(\phi)$	-2.39
$-2CV(arph, pm)/V(\phi)$	-3.35
$2CV(arph, leo)/V(\phi)$	-31.76
$-2CV(pm, leo)/V(\phi)$	-2.18

This table reports the results of a standard variance decomposition of firm wage premia within two-digit sectors. Firm wage premia here are estimated using hiring wages only: when clustering firms into groups following Bonhomme et al. (2019), I use only hiring wages (Di Addario et al., 2020). Firm characteristics are estimated under my preferred specificiation. All lowercase letters denote the natural logarithm of the corresponding variables. *wm* denotes wage markdowns. *arph* denotes the average revenue product of labor. *pm* denotes price-cost markups. *leo* denotes labor elasticities of output.

D Derivations

D.1 Shapley decomposition

Recall the firm wage premium equation, written in natural logs:

$$\phi = wm + arph - pm + leo$$

To assess the relative importance of each channel of firm heterogeneity for firm wage premia, I implement the Shapley decomposition of the variance of firm wage premia (Shorrocks, 1982, 2013).

The decomposition borrows ideas from cooperative game theory – the Shapley value is the unique solution to distributing the total surplus generated by a coalition of players. The idea is to view each variable (firm characteristic) as a player in a coalition and the variance of firm wage premia as the total surplus. The Shapley decomposition then applies the Shapley value to partition the total variance based on each variable's marginal contribution. The Shapley value is derived under the following axioms:

- Efficiency: the entire surplus is distributed.
- Symmetry: any two players (variables) with same marginal contribution to the total surplus obtains the same share.
- Monotonicity: the total surplus is non-decreasing in the number of players.
- Null player: the null player does not obtain a share of the surplus.

In practice, to implement this decomposition, I regress firm wage premia on the four firm characteristics and decompose the R^2 of the regression. Since the firm characteristics are exactly identified in estimation approach (see Section 3), the R^2 sums to one. The result of the Shapley decomposition is four partial R^2's. Let $\Xi = \{wm, arph, pm, leo\}$, then the partial R^2 of each variable is:

$$R^2(\Xi(i)) = \sum_{T \subseteq \tau \setminus \{\Xi(i)\}} \frac{m! \cdot (n-m-1)!}{n!} \big(R^2(T \cup \{\Xi\}) - R^2(T)\big)$$

where n denotes the number of variables, which is equal to four in this case; T is a regression with m number of variables, and τ is the set of all combinations of regressor variables excluding $\Xi(i)$ of element i.

D.2 The misallocation effects of market power on sectoral TFP

Section 6 shows that the variance of the marginal revenue product of labor is overstated when approximated by the average revenue product of labor, as is conventionally done to measure labor misallocation. To get a sense of the extent to which aggregate efficiency gains from removing labor market frictions could potentially be overstated, I perform a Hsieh and Klenow (2009) type exercise to compare the implied efficiency gains from using the conventional measure and my estimated measure of $MRPH$ dispersion. Let s denote the sector. As in Hsieh and Klenow (2009), assume that the sector-specific CES aggregator over firm level output is $Y_s = \left(Y_{sj}^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}}$. To derive closed-form solutions for aggregate sectoral efficiency (TFP_s), I impose the assumption that firms operate sector-specific Cobb-Douglas constant returns-to-scale production functions $Y_{sj} = \Omega_{sj} K_{sj}^{\alpha_s^K} H_{sj}^{\alpha_s^H} M_{sj}^{\alpha_s^M}$. As in Section 2, firms face firm-specific labor supply curves. I assume that labor market frictions are the only distortions present. Below, I show that under these assumptions the sectoral TFP gains from removing labor market frictions is given by:

$$\ln TFP_s^* - \ln TFP_s = \frac{\rho}{2} V_s \left(\ln(MRPH_{sj}^{\alpha_s^H})\right)$$

where TFP^* denotes the sectoral efficiency (total factor productivity) in a world without labor market frictions. Let $M\tilde{R}PH$ denote the measure of the marginal revenue product of labor that does not account for the negative correlation between $ARPH$ and LEO, while $M\hat{R}PH$ denotes the measure that does. Then, the average relative sectoral efficiency gains from removing labor market frictions is:

$$E\left[\frac{\ln T\tilde{F}P_s^* - \ln TFP_s}{\ln T\hat{F}P_s^* - \ln TFP_s}\right] = E\left[\frac{V_s\left(\ln(M\tilde{R}PH_{sj})\right)}{V_s\left(\ln(M\hat{R}PH_{sj})\right)}\right]$$

In 2016, on average the relative sectoral efficiency gains ratio is 2.57. This implies that the conventional measure of labor misallocation on average overstates the efficiency gains of removing labor market frictions by over 2.5 times, relative to the measure of labor misallocation that takes the negative correlation between $ARPH$ and LEO into account.

Derivations. Let s be a sector identifier. The sector-specific CES aggregator over firm level output is $Y_s = \left(Y_{sj}^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}}$. To derive closed-form solutions for sectoral TFP, I impose the assumption that firms operate sector-specific Cobb-Douglas constant returns-to-scale production functions $Y_{sj} = \Omega_{sj} K_{sj}^{\alpha_s^K} H_{sj}^{\alpha_s^H} M_{sj}^{\alpha_s^M}$. Firms face firm-specific product demand and labor supply curves, as in Section 2. The firm-specific price is then a markup

(PM_{sj}) over marginal costs:

$$P_{sj} = PM_{sj}\frac{1}{\Omega_{sj}}\left(\frac{R^K}{\alpha_s^K}\right)^{\alpha_s^K}\left(\frac{WM_{sj}^{-1}\Phi_{sj}}{\alpha_s^H}\right)^{\alpha_s^H}\left(\frac{P^M}{\alpha_s^M}\right)^{\alpha_s^M}$$

where WM_{sj}^{-1} denotes the inverted wage markdowns. The firm-specific revenue TFP can then be written as:

$$TFPR_{sj} = P_{sj}\Omega_{sj} \propto PM_{sj}\cdot(WM_{sj}^{-1}\Phi_{sj})^{\alpha_s^H}$$

Note that when markups are constant, this can be written as: $TFPR_{sj} \propto MRPH_{sj}^{\alpha_s^H}$. Following Hsieh and Klenow (2009), the expression sectoral TFP can be derived as:

$$TFP_s = \left[\sum_{j\in s}\left(\Omega_{sj}\frac{\overline{TFPR_s}}{TFPR_s}\right)^{\rho-1}\right]^{\frac{1}{\rho-1}}$$

where $\overline{TFPR}_s$ denotes the mean revenue TFP within sector s. Finally, as shown in Hsieh and Klenow (2009), under the assumption that quantity TFP (Ω_{sj}) and revenue TFP $(TFPR_{sj})$ are jointly log-normally distributed, I obtain an analytical expression for sector-specific TFP:

$$\ln TFP_s = \frac{1}{\rho-1}\log\left(\sum_{j\in s}\Omega_{sj}^{\rho-1}\right) - \frac{\rho}{2}V_s\left(\ln(PM_{sj}\cdot(WM_{sj}^{-1}\Phi_{sj})^{\alpha_s^H})\right)$$

As Section 5.3 shows, the variance of firm wage premia is modest. I therefore assume that $\Phi_j \approx \Phi\ \forall j$. Therefore, approximately,

$$\ln TFP_s \approx \frac{1}{\rho-1}\log\left(\sum_{j\in s}\Omega_{sj}^{\rho-1}\right) - \frac{\rho}{2}V_s\left(\ln(PM_{sj}\cdot WM_{sj}^{-\alpha_s^H})\right)$$

Denote TFP_s^* as aggregate sectoral TFP when there are no labor market frictions. Then, the potential gains to aggregate sectoral productivity from removing labor market frictions is:

$$\ln TFP_s^* - \ln TFP_s \approx \frac{\rho}{2}V_s\left(\ln(PM_{sj}\cdot WM_{sj}^{-\alpha_s^H})\right) - \frac{\rho}{2}V_s\left(\ln(PM_{sj})\right)$$

when labor market power is the only source of distortion, we have:

$$\ln TFP_s^* - \ln TFP_s \approx \frac{\rho}{2}V_s\left(WM_{sj}^{-\alpha_s^H})\right) = \frac{\rho}{2}V_s\left(\ln(MRPH_{sj}^{\alpha_s^H})\right)$$

D.3 Random Search Wage-Bargaining Framework

The structural framework presented in Section 2 does not take a stance on the micro-foundations that generate upward-sloping labor supply curves. I present here a model in which labor markets are characterized by search frictions and wages are set via bargaining over the match surplus. I derive the firm wage premium equation from this model and discuss the interpretation of wage markdowns. I draw on the multiworker-firm random search models of Mortensen (2010), Elsby et al. (2018), and Schaal (2017) in which workers search on-the-job. I assume that there are no aggregate shocks.

Matching in the labor market is governed by a matching function $\Upsilon_t = \Upsilon(\bar{U}_t + \xi(\bar{H}_t - \bar{U}_t), \bar{V}_t)$, where $\bar{H}$ and $\bar{U}$ denote total skill-adjusted population of workers and unemployed workers, and $\bar{V}$ denotes aggregate vacancies. The search intensity of employed workers is ξ. Labor market tightness is the ratio of vacancies to jobseekers $\theta_t \equiv \frac{\bar{V}_t}{\bar{U}_t + \xi(\bar{H}_t - \bar{U}_t)}$. The vacancy contact rate is then $q(\theta_t) = \Upsilon(\theta_t^{-1})$, and the unemployed and employed worker job finding rates are $f(\theta_t)$ and $\xi f(\theta_t)$.

On the firm side, the hiring rate for a firm providing a value V^e_{jt} to its workers is:

$$\upsilon(V^e_{jt}) = q(\theta_t)\left[\frac{\bar{U}_t}{\bar{U}_t + \xi(\bar{H}_t - \bar{U}_t)} + \frac{\xi(\bar{H}_t - \bar{U}_t)}{\bar{U}_t + \xi(\bar{H}_t - \bar{U}_t)} G_E(V^e_{jt})\right]$$

where $G_E(.)$ denotes the cumulative distribution function of the realized value of employment across employed workers. Similarly, the separation rate of this firm is:

$$s(V^e_{jt}) = \delta_s + (1-\delta_s)\xi f(\theta_t)\left(1 - F_V(V^e_{jt})\right)$$

where δ_s is an exogenous separation rate, and $F_V(.)$ is the cumulative distribution function of the offered value of employment to workers among vacancies.

The unemployed worker's value function is:

$$U_t = b + \beta[(1 - f(\theta_{t+1}))U_{t+1} + f(\theta_{t+1})E_t(V^e_{t+1})]$$

which is a function of the flow value of unemployment b and the expected utility next period. Since there are no aggregate shocks, $U_t = U_{t+1}$. The employed worker's value function is:

$$\begin{aligned} V^e_{jt} = \Phi_{jt} + \beta\{&\delta_s U_{t+1} + (1-\delta_s)E_t[(1 - \xi f(\theta_{t+1}))V^e_{jt+1} \\ &+ \xi f(\theta_{t+1})F(V^e_{jt+1})V^e_{jt+1} + \xi f(\theta_{t+1})(1 - F(V^e_{jt+1}))E_t(V^e_{t+1} | V^e_{t+1} \geq V^e_{jt+1})]\} \end{aligned}$$

which depends on the wage Φ_{jt} this period, the expected utility next period if the worker is exogenously separated from the firm, and the expected utility if the worker is not exogenously separated. The last component depends on the expected utility of being employed at the same firm, and the expected utility of moving to a new employer conditional on the new employer offering a higher utility. Therefore, the value of unemployment and employment is proportional to worker efficiency. A worker with time-invariant efficiency E_i obtains a value of $E_i U_t$ while unemployed and $E_i V_{jt}^e$ while employed.

The firm's profit maximization problem can be written as:

$$\Pi_{jt} = \max_{P_{jt}, K_{jt}, M_{jt}, V_{jt}} P_{jt} Y_{jt} - P_t^K K_{jt} - P_t^M M_{jt} - \Phi(H_{jt}) H_{jt} - c_t(V_{jt}) V_{jt} + \beta E_t[\Pi_{jt+1}]$$

subject to the law of motion for employment:

$$H_{jt} = (1 - s(V_{jt}^e)) H_{jt-1} + \upsilon(V_{jt}^e) V_{jt} \tag{14}$$

The average skill of workers at firm j is denoted as $\bar{E}_j$. The vacancy posting cost function $c_t(V_{jt})$ is assumed to be twice differentiable, monotonically increasing in vacancies $c_t'(V_{jt}) > 0$, and the marginal cost of vacancies is increasing $c_t''(V_{jt}) > 0$.

Wages are determined via Stole and Zwiebel (1996) bargaining between the firm and the marginal worker over the marginal match surplus. This generalizes the Nash bargaining protocol in models with constant marginal returns to labor to the case of diminishing marginal returns to labor. Employers do not make counteroffers. The bargained wage $\Phi(H_{jt})$ is a function of the firm's size, since diminishing marginal returns to labor implies that, all else equal, the marginal revenue product of labor and total match surplus are decreasing in firm size. The marginal surplus to be bargained over is:

$$\kappa_j J_{jt} = (1 - \kappa_j)(V_{jt}^e - U_t)$$

where κ_j is the worker's relative bargaining weight, which is allowed to differ across firms, and $J_{jt} \equiv \frac{\partial \Pi_{jt}}{\partial H_{jt}}$ is the firm's marginal surplus from an additional skill-adjusted worker. I obtain the following familiar equation for the firm's wage (premium):

$$\Phi_{jt} = \kappa_j (MRPH_{jt} - \frac{\partial \Phi_{jt}}{\partial H_{jt}} H_{jt} + \beta E_t[(1 - s(\Phi_{jt+1})) J_{jt+1}]) + (1 - \kappa_j) W_{jt}^r$$

This equation shows that the firm's wage is a weighted average of the value of the worker to the firm and the worker's reservation wage (W^r).

Combining the wage bargaining protocol with the first-order condition with respect to vacancies, I rearrange the above firm wage equation to obtain the firm wage premium equation (5), in which the firm's wage markdown component can be written as:

$$WM_{jt} = \frac{\left(\frac{\kappa_j}{1-\kappa_j}\right)\left(1+\frac{W^r_{jt}}{\Phi_{jt}-W^r_{jt}}\right)}{1+(1-|\frac{\partial \Phi_{jt}}{\partial H_{jt}}\frac{H_{jt}}{\Phi_{jt}}|)\left(\frac{\kappa_j}{1-\kappa_j}\right)\left(1+\frac{W^r_{jt}}{\Phi_{jt}-W^r_{jt}}\right)-\beta E_t\left(\frac{(1-s(\Phi_{jt+1}))J_{jt+1}}{c'_t(V_{jt})V_{jt}+c(V_{jt})}\right)\upsilon(\Phi_{jt})}$$

Note that $\frac{\partial \Phi_{jt}}{\partial H_{jt}}\frac{H_{jt}}{W_{jt}} < 0$ is no longer the inverse labor supply elasticity. It takes a negative value. This is because with multilateral bargaining the firm bargains with all of its worker over the marginal surplus of a match. With diminishing marginal returns to labor, if the firm and worker do not agree on a wage, the match is not formed and the marginal revenue product of labor is higher for the remaining workers. This is an additional channel on top of workers' bargaining weight from which workers extract rents from the match.

The numerator of the wage markdown shows that the firm's wage markdown depends on its workers' relative bargaining power (κ_j) and the reservation wage (W^r_{jt}). The higher the workers' bargaining power or reservation wage, the higher the fraction of marginal revenue product of labor workers obtain (higher wage markdown). The denominator shows that the wage markdown is also increasing in the expected future value of the worker to the firm.

D.4 Random Search Wage-Posting Framework

I now replace the wage-setting protocol of the random search framework above with wage-posting and discuss the determinants of the wage markdown. This model provides one microfoundation for the wage markdown derived from the structural framework presented in Section 2.

The firm's profit maximization problem is:

$$\Pi_{jt} = \max_{P_{jt},K_{jt},M_{jt},V_{jt},\Phi_{jt}} P_{jt}Y_{jt} - P^K_t K_{jt} - P^M_t M_{jt} - \Phi_{jt}H_{jt} - c_t(V_{jt})V_{jt} + \beta E_t[\Pi_{jt+1}]$$

subject to the law of motion for employment:

$$H_{jt} = (1 - s(\Phi_{jt}))H_{jt-1} + \upsilon(\Phi_{jt})V_{jt} \tag{15}$$

The wage markdown in this model is as follows:

$$WM_{jt} = \frac{\epsilon^H_{jt}}{1+\epsilon^H_{jt}-\beta E_t\left(\frac{(1-s(\Phi_{jt+1}))J_{jt+1}}{c'_t(V_{jt})V_{jt}+c(V_{jt})}\right)\upsilon(\Phi_{jt})}$$

where the firm-specific labor supply elasticity (ϵ^H_{jt}) can be written as:

$$\epsilon^H_{jt} = \frac{\upsilon(\Phi_{jt})V_{jt}}{H_{jt}}\epsilon^{\upsilon}_{\Phi,jt} - \frac{s(\Phi_{jt})H_{jt-1}}{H_{jt}}\epsilon^{s}_{\Phi,jt} > 0$$

which depends on the elasticity of the firm's hiring rate with respect to the firm's wage ($\epsilon^{\upsilon}_{\Phi,jt} > 0$) weighted by the share of new hires among its workforce, minus the elasticity of the firm's separation rate with respect to the firm's wage ($\epsilon^{s}_{\Phi,jt} < 0$) weighted by the share of workers who separate from the firm among its workforce.

D.5 Directed Search Wage-Posting Framework

The random search model assumes that workers have no information about wages when they search for a job. An alternative assumption is that workers observe the full menu of wages in the economy when searching for jobs – directed or competitive search (Moen, 1997) and Kaas and Kircher (2015). I now replace random search with directed search in the otherwise identical wage-posting model. I show in this environment that the firm wage premium equation can be obtained and the wage markdown is identical as the model with random search.[30] The following timing assumption applies. First, idiosyncratic firm productivity and worker efficiency shocks are realized. Next, firms post wages and workers decide on where to search. Then, matching and separations take place. Finally, production begins.

In this model, workers can choose the firm or market at which she searches for a job by trading off offered utility and job-finding probability. The worker observes the offered utility V^e_{jt} at each firm j, before matching takes place. The pre-matching value to the unemployed worker is:

$$U^{bm}_t = \max_{V^e_{jt}}(1 - f(\theta(V^e_{jt})))U_t + f(\theta(V^e_{jt}))V^e_{jt}$$

and the pre-matching value to a worker employed at firm j is:

$$V^{e,bm}_{jt} = \max_{V^e_{kt}} \delta_s U_t + (1-\delta_s)\left[(1 - sf(\theta(V^e_{kt})))\, V^e_{jt} + sf(\theta(V^e_{kt}))V^e_{kt}\right]$$

where the offered utility $V(W_{jt})$ at any firm j depends on the offered wages. As I show in the next subsection, no two workers with different utility V^e will search for employment at the same firm. Relative to a worker with lower utility, the worker with a higher utility will search for employment at a firm that offers an even higher utility, at the cost of a

[30]For a comprehensive discussion of the theory and applications of directed search, see Wright, Kircher, Julien, and Guerrieri (2018).

lower probability of this employment relationship materializing.

Firms post wages taking into account its effect on both recruitment and retention. Each firm recruits from other firms who offer a lower utility to their employees. From the employed worker's value function above, given the value of employment at a firm that offers $\underline{V}^e_t$, this worker optimally searches for employment at firm j, where $V^e_{jt} > \underline{V}^e_t$. Denote this unique solution as $V^e_{jt} = v(\underline{V}^e_t)$. Therefore, firm j recruits workers from this market. Similarly, firm j loses workers due to quits to a higher utility firm who pays $\overline{V}^e_t$. The optimal search strategy of a worker employed at firm j is then $\overline{V}^e_t = v(V^e_{jt})$. Next, note that the firm-specific separation rate is now $s_{jt} = \delta_s + (1-\delta_s)sf(\theta(\overline{V}^e_t))$. Using the law of motion for employment, the firm-specific "labor supply" curve is then:

$$\begin{aligned} H_{jt} &= (1 - s(\overline{V}^e_t))H_{jt-1} + q(\underline{V}^e_t)V_{jt} \\ &= (1 - s(V^e_{jt}))H_{jt-1} + q(V^e_{jt})V_{jt} \end{aligned}$$

The second line obtains by inverting the employed worker's optimal search function $v(.)$, which is monotonically increasing in its argument. Solving for the firm wage premium equation gives the same wage markdown expression as the random search wage-posting model above.

D.6 Workplace-Differentiation Monopsonistic Framework

This section presents a static monopsonistic model based on the imperfect substitutability of firm-specific non-wage amenities (Card et al., 2018). Worker i's indirect utility when employed at firm j is:

$$u_{ijt} = \gamma \ln(W_{ijt}) + \varphi_{jt} + \eta_{ijt}$$

where $W_{ijt} = E_{it}\Phi_{jt}$ is the wage obtained by worker i with efficiency E_{it} earning a wage premium Φ_{jt}. The common value of the firm-specific non-wage amenity φ_{jt}. Worker's preferences over non-wage amenities are subject to idiosyncratic shocks η_{ijt}, which is identically and independently drawn from a type I extreme value distribution.

Each worker i maximizes utility by choosing where to work:

$$j = \arg\max_j u_{ijt}$$

The firm-specific labor supply curve is then:

$$\frac{H_{jt}}{\bar{H}_t} = \frac{exp(\gamma \ln(\Phi_{jt}) + \varphi_{jt})}{\sum_{k=1}^{J} exp(\gamma \ln(\Phi_{kt}) + \varphi_{kt})}$$

Firm j's profit-maximization problem is:

$$\Pi_{jt} = \max_{K_{jt}, M_{jt}, \Phi_{jt}} P_{jt}Y_{jt} - R_t^K K_{jt} - P_t^m M_{jt} - \Phi(H_{jt})H_{jt} + \beta E_t[\Pi_{jt+1}]$$

subject to the firm-specific labor supply curve. This model gives the firm wage premium equation and the following expression for the wage markdown:

$$WM_{jt} = \frac{\epsilon_{jt}^h}{1 + \epsilon_{jt}^h}$$

where the labor supply elasticity $\epsilon_{jt}^h = \gamma$ is constant when firms are monopsonistic (atomistic) and it depends on the labor market share of firm j, i.e. $\epsilon_{jt}^h = \gamma(1 - \frac{H_{jt}}{H_t})$ when firms are oligopsonistic (granular). This equation shows that the wage markdown is decreasing in the firm's labor market share, as firm's with a high market share face a low labor supply elasticity. This expression provides a mapping between labor market shares, labor market concentration, and wages (Azar, Marinescu, and Steinbaum, 2020; Benmelech, Bergman, and Kim, 2020).

E Extension with Differentially Skilled Occupations

As discussed in Section 2.3, one limitation of the current analysis is that workers enter the production function in efficiency units. To relax this assumption, I extend the analysis in Section 5 to a setting with a high-skilled and a low-skilled occupation. The main findings of this extension are similar to that of Section 5.

Defining high-skilled and low-skilled occupations. I use the one-digit occupation classifications in the DADS matched employer-employee data set to define low-skilled occupations as blue-collar occupations (e.g. maintenance workers and welders) and administrative support occupations (e.g. clerical workers and secretaries); I define high-skilled occupations as senior staff in top management positions (e.g. head of logistics or human resources), employees in supervisory roles (e.g. accounting and sales managers), and technical workers (e.g. IT and quality control technicians).

Structural firm wage premium equation by skill group. Let the subscript $a = \{h, l\}$ denote high and low-skilled labor. The firm wage premium equation is:

$$\phi_{j,a} = wm_{j,a} - pm_j + leo_{j,a} + arph_{j,a}$$

where the wage markdown, labor elasticity of output, and average revenue product of labor are now firm-skill-group-specific. The average revenue product of labor for a given skill group in this case is (log) total revenue divided by the total efficiency units of that skill group.

Estimating firm wage premia. The estimation procedure is as described in Section 3.2. However, firm-group effects are now occupation-specific:

$$\ln W_{it} = \iota_i + \phi_{g(j(i,t))} + \mathrm{Occ}_{a(i,t)} \times \phi_{g(j(i,t))} + \chi_{it}'\beta + \nu_{it}$$

where i denotes the individual, j denotes the firm, $g(j)$ denotes the group of firm j at time t, $a(i,t)$ denotes worker i's occupational group at time t, a_i are worker fixed effects, $\phi_{g(j(i,t))}$ are firm-group fixed effects, and χ_{it} is a vector of time-varying worker characteristics.

Estimating firm characteristics. The production function now looks as follows:

$$y = f(h, l, k, m) + \omega$$

I approximate $f(.)$ with a translog functional form, where k denotes capital and m denotes materials. With a slight abuse of notation, $h = \bar{e}_h + n_h$ and $l = \bar{e}_l + n_l$ now denote high-skilled and low-skilled labor in efficiency units, where $\bar{e}_h$ and $\bar{e}_l$ denote the average ability of each skill group, and n_h and n_l denote total hours in each skill group. Skill-group-specific average ability can be measured as the difference between the skill-group-specific average wage at a firm j and the corresponding firm wage premium, $\bar{w}_{j,a} = \bar{e}_{j,a} + \phi_{g(j),a}$ where $a = \{h, l\}$. All lowercase letters are in logs.

The procedure to back out price-cost markups and skill-group-specific wage markdowns are identical to the one described in Section 3.3. Table 24 reports the summary statistics for wage markdowns among high-skilled and low-skilled workers. high-skilled workers typically incur a smaller markdown of wages below marginal revenue products compared to low-skilled workers.

	Partial R^2	
	Low-skill (l)	High-skill (h)
Wage markdown	0.23	0.35
Average revenue product of labor	0.43	0.22
Price-cost markup	0.11	0.21
Labor elasticity of output	0.24	0.21

Number of firms	90,999

Table 25: Shapley decomposition of firm wage premia by skill groups.

Shapley decomposition of firm wage premia. Table 25 shows that the overarching message of the Shapley decomposition by skill groups remains the same – price-cost markups and labor elasticities of output matter for firm wage premia.

Cross-sectional correlations of firm characteristics. Table 26 shows that the negative correlation between labor productivity and the labor elasticity of output documented in the main body of the paper also holds when disaggregating by skill group, with a somewhat larger coefficient among low-skilled occupations than high-skilled ones. One difference between high-skilled and low-skilled occupations is that wage markdowns increase more strongly with labor productivity among low-skilled occupations than among high-skilled ones.

	Low-skill (l)					High-skill (h)			
	wm_l	$arph_l$	$-pm$	leo_l		wm_h	$arph_h$	$-pm$	leo_h
wm_l	1				wm_h	1			
$arph_l$	-0.82	1			$arph_h$	-0.62	1		
$-pm$	-0.65	-0.45	1		$-pm$	-0.24	-0.28	1	
leo_l	0.58	-0.89	0.52	1	leo_h	0.68	-0.85	0.05	1

Table 26: Correlation matrix of estimated firm characteristics by skill group.

Table 24: Summary statistics for estimated firm wage premia and wage markdowns by skill group in 2016.

Panel A	Mean	Median	25^{th} Pct	75^{th} Pct	Var
ϕ	2.87	2.88	2.81	2.92	0.01
WM	0.55	0.48	0.38	0.64	0.12
LEO	0.23	0.22	0.15	0.30	0.38
$\log ARPH$	0.00	-0.04	-0.45	0.42	0.41
$\log MRPH$	0.00	0.04	-0.22	0.25	0.13

Panel B	Mean	Median	25^{th} Pct	75^{th} Pct	Var
ϕ	2.26	2.26	2.21	2.32	0.01
WM	0.99	0.82	0.51	0.31	0.12
LEO	0.21	0.21	0.15	0.27	0.25
$\log ARPH$	0.00	-0.09	-0.54	0.44	0.54
$\log MRPH$	0.00	0.00	-0.39	0.38	0.30

This table reports the summary statistics for estimated firm wage premia and wage markdowns using by skill group. Panel A reports the summary statistics for the high-skill group and Panel B the low-skill group. Variances for wage markdowns, price-cost markups, and labor elasticities of output are reported for the logarithms of those variables ($\log WM$, $\log PM$, and $\log LEO$). The log of average and marginal revenue products of labor ($\log ARPH$ and $\log MRPH$) are normalized to have a mean of 0.