Understanding High-Wage Firms*

Horng Chern Wong†

March 2023

Abstract

Some firms pay higher wages than others for identical workers. I explore the role of product market power in accounting for this fact. I document new empirical relationships between wages and firms' product market power that are inconsistent with existing models. To explain these patterns, I build a model in which firms produce vertically differentiated goods and share product market rents with their employees. The model shows that product appeal/quality is as important as productivity and amenities for wage dispersion. Further, markups may widen wage dispersion through rent-sharing, but quantitatively dampen it as high-wage firms reduce output, suppressing wage levels overall.

Keywords: wage inequality, firm heterogeneity, market power, rent-sharing, misallocation
JEL codes: D24, D33, E2, J3, J42

*First version: August 2019. Previously circulated as "Understanding High-Wage and Low-Wage Firms". Special thanks to Thijs van Rens, Roland Rathelot, and Dennis Novy for their invaluable guidance and support. I am very grateful to Jan Eeckhout, Lawrence Katz, Paul Klein, Francis Kramarz, Jay Euijung Lee, Attila Lindner, Isabelle Mejean, Aviv Nevo, Andrew Oswald, Vincent Sterk, John Van Reenen, and anonymous reviewers for excellent comments. For insightful conversations, I thank Jesper Bagger, Dan Bernhardt, Christine Braun, Danilo Cascaldi-Garcia, Dita Eckardt, Basile Grassi, Daniel Habermacher, Alice Kuegler, Thomas Le Barbanchon, Tim Sang Yoon Lee, Timo Leidecker, Norman Loayza, Roberto Pancrazi, Ayush Pant, Carlo Perroni, Josep Pijoan-Mas, Camilla Roncoroni, Nina Roussille, Alessandro Ruggieri, Marta Santamaria, Jesse Shapiro, Ben Smith, Douglas Staiger, Anna Stansbury, Liliana Varela, Marija Vukotic, Jonathan Yeo, and the many seminar and conference participants. I gratefully acknowledge financial support from the ESRC, the ERC TRADENET grant (714597), and the Tore Browaldh Foundation, and data access from DARES, DGFiP, INSEE, and CASD.

†Stockholm University, Department of Economics. Email: horngchernwong@gmail.com

1 Introduction

Some firms pay higher wages than others for identical workers (Slichter, 1950; Abowd, Kramarz, and Margolis, 1999). Firm-specific wage premia are systematically related to measures of firm productivity and profitability (Van Reenen, 1996; Card, Cardoso, Heining, and Kline, 2018). Recent decades have seen the rise of highly profitable firms that dominate product markets and charge high markups (De Loecker, Eeckhout, and Unger, 2020). How such firms may impact labor markets is a growing concern (Song, Price, Guvenen, Bloom, and Von Wachter, 2019; Autor, Dorn, Katz, Patterson, and Van Reenen, 2020).

Do firms' product market power matter for firm wage premia? I address this question in three steps. First, I set up a structural framework to interpret standard regression-based estimates of firm wage premia. Existing research on firm wage premia often assumes that firms produce a homogenous good and operate in perfectly competitive product markets. In my model, firms produce horizontally and vertically differentiated products that afford them product market power. Differences in product appeal/quality allow some firms to charge higher prices per unit of goods sold. Wage premia, then, are the outcome of bargaining between workers and firms over rents generated by labor and product market power. Second, guided by the model, I propose a new approach to estimate firms' labor and product market power, and workers' bargaining power. I do so using detailed French administrative datasets on workers and firms containing information on wages and output prices. Third, I use these estimates to calibrate my structural model and quantify the role of product market power for firm wage premia.

I report three main findings that point to product market power as a key driver of firm wage premia. First, I show that a model without firm product market power and worker bargaining power cannot jointly explain the new empirical patterns I document: high-wage firms charge higher output prices, higher markups, and pay wages that are closer to labor's full marginal revenue productivity than low-wage firms do. Second, the passthrough of firm heterogeneity to wages depends on the substitutability of product varieties. The more differentiated the product varieties are, the more consumers care about appeal rather than prices, implying a lower passthrough of productivity and higher passthrough of appeal to wages. Quantitatively, productivity and appeal are both important for firm wage premia. Third, markups determine both wage dispersion and wage levels. In the model, markups may amplify wage dispersion as firms share product market rents with workers. However, firms also exploit product market power by restricting output and labor demand, dampening wage dispersion. Quantitatively, the latter dominates: if markups were equalized across firms, wage dispersion rises by 31%, accompanied by a 15% increase in average wage levels. The model suggests that raising workers' bargaining power can deliver a similar increase in wage levels, but with a smaller increase in wage dispersion.

In Section 2, I set up a flexible partial equilibrium framework to interpret statistical estimates of firm wage premia. In the model, both product and labor markets are imperfectly competitive. The model remains agnostic about the specific microfoundation for product demand and labor supply curves.[1] Firms differ in productivity, product appeal, and amenities. Wages are determined through bargaining between workers and firms, taking into account rents generated by imperfect product and labor market competition. Workers at each firm bargain over wages collectively with their employer, a key feature of French wage-setting institutions and a source of tractability for the model. In equilibrium, the firm-level wage is the marginal revenue product of labor times a *labor wedge*.

The model provides four main insights. First, the model nests monopsony in the labor market as a special case: when workers have no bargaining power, wages are marked down below marginal revenue products of labor, with markdowns being a function of labor supply elasticities. The *labor wedge* is then the *monopsony wage markdown*. Second, wages include product market rents due to *rent-sharing*: when workers have some bargaining power, the *labor wedge* also depends on, and is increasing in, *price-cost markups*. Third, markups reduce labor demand, as firms with product market power *restrict output*. Markups can therefore affect firm wage premia positively through rent-sharing but also negatively through reduced output. Fourth, the model implies that markups and labor wedges can be empirically disentangled by noting that the former is a common distortion on all input demands, but the latter is only a direct distortion on labor demand.

In Section 3, I rely on the model's fourth insight to estimate markups and labor wedges. My approach to estimating labor wedges builds on the production-based markup estimation approach of De Loecker and Warzynski (2012) and panel data methods widely used in labor economics to estimate wage premia (Abowd et al., 1999; Bonhomme, Lamadon, and Manresa, 2019). This approach has the advantage that it does not require the researcher to commit to a specific market structure in a wide array of product and labor markets. To separately estimate production function parameters from productivity, I adopt 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. I then disentangle labor wedges from markups using the fact that the former distorts labor demand, while the latter distorts all input demands.

Next, I estimate workers' bargaining power using a different insight of the model: workers' bargaining power governs the passthrough of markups to labor wedges. An identification challenge is that the labor wedges also depend on firm-specific labor supply elasticities. The labor supply elasticities are functions of firms' employment sizes and amenities. The latter are not observed in the data. Drawing on the model, I use a control function approach: firms' wage-bill and employment jointly control for differences

[1] These may arise for reasons such as search frictions or product/workplace differentiation (Burdett and Mortensen, 1998; Melitz, 2003; Manning, 2011; Gourio and Rudanko, 2014; Card et al., 2018)

in amenities. Intuitively, more desirable amenities allow firms to employ more workers for a given wage. At this stage, the estimation approach does not produce estimates for product appeal or amenities, which require further assumptions on product demand and labor supply. I return to this point in Section 6.

The estimation procedure requires detailed information about workers and firms, discussed in Section 4. I use large administrative datasets from France that covers the population of employers and employees. I estimate firm wage premia using matched employer-employee panel data, which includes information on hourly wages. I estimate the relevant firm characteristics using firm balance sheet panel data, which contains information such as revenue, materials, and capital. I complement the balance sheet data with survey data on firm-product level prices for manufacturing firms. The survey is exhaustive for firms with at least 20 employees or sales exceeding 5 million Euros. The key advantage of the survey 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; De Loecker, Goldberg, Khandelwal, and Pavcnik, 2016). This is particularly important in the context of markup estimation. As Bond, Hashemi, Kaplan, and Zoch (2021) show, when output prices are unobserved, the production approach systematically biases markup estimates towards 1. Output price information in the survey further makes it possible to measure quantity TFP (TFPQ) rather than revenue TFP (TFPR). I therefore focus my empirical analysis on the manufacturing sector.

In Section 5, I report two novel empirical relations between firm wage premia and firms' labor and product market power. First, I find that high-wage firms tend to charge higher markups and output prices. These patterns remain true conditional on TFPQ and focusing on variation within narrow industries, suggesting that differences in product appeal drive these patterns. Second, I compare firms in terms of their labor market power (captured by the *labor wedge*) and find that high-wage firms tend to have higher labor wedges: they pay closer to labor's full marginal revenue productivity. This finding is inconsistent with existing models of monopsony where workers have no bargaining power (Manning, 2011; Card et al., 2018). In such models, labor wedges are equal to monopsony wage markdowns, which are either constant or lower for high-wage firms. My model explains this finding through positive worker bargaining power, allowing workers to capture some of the product market rents.

I find workers' bargaining power to be low, obtaining between 5% to 11% of total economic rents. These numbers fall within the typical range summarized in Jäger, Schoefer, Young, and Zweimüller (2020). Combining the estimated labor wedges, markups, and worker bargaining power, I back out the implied monopsony wage markdowns. Consistent with models with variable wage markdowns (Berger, Herkenhoff, and Mongey, 2020), I find that high-wage firms have lower markdowns (that is, they mark down wages more).

In Section 6, I use these estimates to quantify my structural framework to decompose firm wage premia. I take a specific stance on market structures in product and labor markets, and extend the model in Section 2 to a general equilibrium setting. I model product and labor markets as oligopolistically and oligopsonistically competitive with nested-CES structures (Edmond, Midrigan, and Xu, 2018; Berger et al., 2020). The model implies that markups and wage markdowns are functions of firms' market shares in product and labor markets. I use the empirical counterpart of these structural relationships to calibrate the underlying preference parameters. I measure product appeal (amenities) using the model-implied relationship between sales (wage-bill) market shares and output (employment) market shares. I allow non-labor input prices to vary across firms as a residual wedge, such that the model reproduces the empirical firm wage premium and firm size distributions. The quantified model shows that high-wage firms tend to have higher TFPQ, product appeal, and amenities. Amenities therefore partially offset wage premia driven by TFPQ and product appeal.

In Section 7, the quantitative model shows that firms' product market power matters for firm wage premia in two main ways. First, the passthrough of firm heterogeneity to wage premia depends on the substitutability of product varieties. When product varieties are close substitutes, consumers are price sensitive, giving more weight to prices (hence, TFPQ) than appeal. I simulate the passthrough of a 1% increase in firm productivity and find an elasticity of wage premia to TFPQ of 1.10. In contrast, I find an elasticity of wage premia to product appeal of 0.20. Nevertheless, appeal is a source of sizable wage dispersion: in an exercise where firms differ *only in appeal*, the model generates a variance for wage premia that is 104 times that of the data. The corresponding numbers when *only TFPQ* or *only amenities* vary are 155 times and 23 times.

Second, variable markups shape wage levels and wage dispersion, with implications for allocative efficiency. Markups affect average wage levels in two ways: (i) as a uniform tax on aggregate labor demand, and (ii) as a source of misallocation due to markup dispersion (relative to a social planner's choice). Markup dispersion also affects the wage premium distribution in two opposing ways: (a) through rent-sharing, and (b) by reducing output at some firms more than others (misallocation). In a counterfactual equilibrium in which firms behave monopolistically in product markets, charging uniform markups, average wage levels rise by 15%, accompanied by a 31% increase in the variance of wage premia. The increase in wage levels come from shutting down misallocation. The increase in wage dispersion shows that the output reduction effect (b) dominates the rent-sharing effect (a). Can strengthening workers' bargaining power raise wages and improve labor market allocations? A counterfactual in which workers' bargaining power rises from 6% to 16% achieves a similar increase in average wages, but with only a 3% increase in the variance of wage premia. The rise of workers' bargaining power redistributes product and labor market rents from firms to workers, partially correcting the role of markups (and markdowns) both as a tax on aggregate labor demand and as a source of misallocation. Nevertheless, because markups also distort the market allocation of non-labor inputs, even full worker bargaining power cannot fully restore the social planner's allocation.

Section 8 concludes.

Contributions to related literature. A large literature 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 widely replicated.[2] Existing research provides structural approaches to evaluate firm productivity and amenities as drivers of firm wage premia.[3] Bagger, Christensen, and Mortensen (2014) estimate TFPR and show that firm productivity is important. Sorkin (2018) shows that amenities account for a substantial share of wage premia. Lamadon, Mogstad, and Setzler (2019) show that having both productivity and amenities are crucial for rationalizing the wage distribution. My contribution is to show that firms' product market power is also quantitatively important for wage premia. My model is motivated by new empirical patterns that relate wage premia to firms' measured labor and product market power. My findings show that product appeal generates levels of dispersion in wage premia comparable to productivity and amenities. In addition, the combination of variable markups and wage bargaining delivers a new result: markups may widen wage dispersion through rent-sharing, but quantitatively dampens it through misallocation.

My paper also speaks to a large body of work providing evidence for rent-sharing.[4] The literature shows that shocks to measured firm productivity or profitability passes through to wages (Card et al., 2018). Van Reenen (1996) shows that innovation raises the firms' profits and the wages they pay. Kline, Petkova, Williams, and Zidar (2019) study how valuable patents affect firm performance and wages. Innovation can improve process efficiency (TFPQ) and/or product quality (appeal), allowing firms to make greater product market rents. My paper shows that the passthrough of TFPQ and appeal shocks to wages differ depending on the degree of product differentiation. My model also shows that the resulting increase in product market rents affects wages through two opposing effects: rent-sharing and misallocation.

A growing number of researchers study the causes and consequences of product market power, showing that profitable firms have grown even more profitable over time. Barkai (2020) and De Loecker et al. (2020) make the case for growing product market power among US firms. Edmond et al. (2018) evaluate the welfare costs of markups. Since these papers abstract from imperfect labor market competition, firms pay the same wage premium. My paper contributes by showing that markups also matter for firm wage premia, and by studying how workers' bargaining power can affect wage levels and wage

[2]See Card, Heining, and Kline (2013), Alvarez, Benguria, Engbom, and Moser (2018), Song et al. (2019), and Bonhomme et al. (2019).

[3]See Postel-Vinay and Robin (2002), Cahuc, Postel-Vinay, and Robin (2006), Barlevy (2008), Manning (2011), Card et al. (2018), and Haanwinckel (2020).

[4]See Faggio, Salvanes, and Van Reenen (2007), Barth, Bryson, Davis, and Freeman (2016), Garin and Silverio (2019) and Chan, Salgado, and Xu (2021).

dispersion when firms have product market power.

My work also relates to a literature on firms' monopsony power in labor markets (Manning, 2011).[5] Dube, Jacobs, Naidu, and Suri (2018) provide evidence for monopsony and Azar, Marinescu, Steinbaum, and Taska (2020) show that US labor markets are highly concentrated. Recent papers study the effects of labor market power on wages and labor shares.[6] Berger et al. (2020) provide a quantitative oligopsonistic labor markets model to assess the aggregate welfare and productivity impacts. Azkarate-Askasua and Zerecero (2020) do so in a model where firms bargain with unions. My model draws on their work by incorporating labor market power and wage bargaining. However, my focus is on how product market power affects firm wage premia and the role that wage bargaining plays in such a setting. My empirical approach is closely related to those of Dobbelaere and Mairesse (2013), Mertens (2020), and Chen, Hershbein, and Macaluso (2022) who directly estimate monopsony wage markdowns as labor wedges using a production approach. I show that in the presence of wage bargaining, the labor wedge is generally not the same as the monopsony markdown, but a weighted average of markups and markdowns which nests monopsony as a special case. I jointly estimate bargaining power and markdowns, showing that monopsony power is greater than the labor wedges imply.

While existing work on imperfect competition often focus separately on product or labor markets, several papers analyze them jointly. Kroft, Luo, Mogstad, and Setzler (2021) quantify product and labor market rents in the US construction industry. MacKenzie (2019) studies the gains from trade when firms are granular in both markets. Deb, Eeckhout, Patel, and Warren (2022) study how product and labor market structure affects wage levels and skill premia. I study the impact of firms' price-setting power on firm wage premia and wage levels in a framework where workers and firms bargain over wages.

2 A Framework to Interpret Firm Wage Premia

I now set up a heterogeneous-firms model of the labor market. The model features both labor and product market power, which generate economic rents that are shared with workers through wage bargaining. The model serves two main purposes: (i) to structurally interpret regression-based estimates of firm wage premia; (ii) to guide how equilibrium objects of interest may be estimated in the data in Section 3, so that their equilibrium relationships with firm wage premia can be documented empirically. For these purposes, I remain agnostic about certain primitives of the model – the underlying distributions of firm heterogeneity and the sources of labor and product market power – as much as is feasible. In Section 6, I make assumptions about the market structure in labor and product markets and calibrate model primitives for quantitative exercises.

[5]A closely related literature studies the effects of workers' outside options on wages. See, for example, Caldwell and Danieli (2019), Caldwell and Harmon (2019), and Schubert, Stansbury, and Taska (2019).

[6]See Gouin-Bonenfant (2020) and Jarosch, Nimczik, and Sorkin (2021).

2.1 Model environment

Labor supply. Let Φ_j be the piece-rate wage per efficiency unit of labor paid by firm j. A worker i with efficiency E_i obtains a wage $W_i = E_i\Phi_j$. Taking logs, this wage equation has a log-additive structure reminiscent of the "AKM" regression due to Abowd et al. (1999): $w_j = e_j + \phi_j$, where lowercase letters denote variables in logs. The piece-rate wage (ϕ) is the *firm-specific wage (premium)*.

Efficiency units of labor in the firm can be written as $H_j = \bar{E}_j L_j$, where $\bar{E}_j$ denotes average efficiency and L_j denotes amount of labor. Let the upward-sloping labor supply curve facing each firm be $H_j = \mathcal{H}(\Phi_j, A_j)$. The firm-specific labor supply shifter A_j captures firms' non-wage amenities and is taken as given by the firm. I assume that the labor supply function is twice differentiable and monotonically increasing in Φ_j and A_j.

Product demand. Let the downward-sloping demand curve for firm j's output be $Y_j = \mathcal{G}(P_j, D_j)$. The price charged by firm j is P_j. Firms take as given the demand shifter for its goods D_j, capturing its product appeal. I assume that the goods demand function is twice differentiable and monotonically decreasing in P_j and increasing in D_j.

Production technology. Firms operate a general production function with diminishing marginal returns to each input $Y_j = \Omega_j F(K_j, M_j, H_j)$. Ω_j is the Hicks-neutral productivity term, K_j are physical capital, M_j are material inputs, and H_j are units of effective labor. I assume that this production function is twice differentiable. The market for capital and material inputs are perfectly competitive with prices P_k and P_m.

Wage determination. Workers bargain collectively with their employer j. This assumption is consistent with an important feature of wage bargaining in France: annually, firms with at least 50 employees are legally required to bargain with their employees, who are represented by labor union representatives.[7,8,9] Let Π_j be the firm's profit. Let workers' indirect utilities be linear in wages: $V_j = \Phi_j H_j$.

Bargaining is efficient in the sense that workers and firms jointly decide on wages, prices, materials, and capital to maximize total rents, taking into account the product demand curve and labor supply curve.[10] Workers' bargaining power is κ. In the event that an agreement is not reached between firms and their employees, I assume that firms do not produce and have an outside option of zero profits; workers do not supply labor

[7] See Appendix A for a description of French wage-setting institutions.

[8] In Appendix C, I make specific functional form assumptions on revenue functions under a Stole and Zwiebel (1996) bargaining protocol, where firms bargain with individual workers, and show that a similar firm wage premium equation can be obtained.

[9] See also Card, Devicienti, and Maida (2014), Card et al. (2018), and Azkarate-Askasua and Zerecero (2020), for models of wage bargaining between firms and groups of workers.

[10] When capital is a production input and capital investments are sunk, an important concern is whether workers can holdup its employers and extract rents. However, recent evidence suggests that such holdup problems tend to be small (see Card et al. (2014) and the references therein).

and have an outside option of zero wages.[11] Workers and firms maximize the following Nash product:

$$\max_{\Phi_j, P_j, M_j, K_j} \Big(\Phi_j H_j\Big)^{\kappa} \Big(\Pi_j\Big)^{1-\kappa}$$

subject to $H_j = \mathcal{H}(\Phi_j, A_j)$, $Y_j = \mathcal{G}(P_j, D_j)$, and $Y_j = \Omega_j F(K_j, M_j, H_j)$. The firm's profit is $\Pi_j = P_j Y_j - \Phi_j H_j - P_m M_j - P_k K_j$.

Firm wage premia. The solution to this bargaining problem gives the following firm-specific wage (premium):

$$\Phi_j = \kappa \underbrace{\left(\frac{P_j Y_j - P_m M_j - P_k K_j}{H_j} \right)}_{\text{Rents}} + (1-\kappa) \underbrace{\lambda_j MRPH_j}_{\substack{\text{Markdown of labor's} \\ \text{marginal revenue product}}} \tag{1}$$

where the marginal revenue product of effective labor is $MRPH_j = \mu_j^{-1} \alpha_{h,j} \frac{P_j Y_j}{H_j}$. Revenue per effective labor is $\frac{P_j Y_j}{H_j}$. The *price-cost markup* μ_j is a function of the price elasticities of demand $\upsilon_j = \upsilon(P_j, D_j)$, with $\mu_j = \frac{\upsilon_j}{\upsilon_j - 1}$. The output elasticity with respect to labor inputs is $\alpha_{h,j}$. Finally, $\lambda_j = \frac{\xi_j}{1+\xi_j}$ is a monopsonistic *wage markdown* below the $MRPH$, where $\xi_j = \xi(\Phi_j, A_j)$ are labor supply elasticities. The specific functional form for labor supply elasticities depends on the microfoundation for the labor supply curve.

Equation (1) shows that the firm wage premium is a weighted average of two common wage-setting mechanisms: a pure bargaining outcome and a pure monopsony outcome. When workers have no bargaining power ($\kappa = 0$), wages converge to the standard monopsonistic outcome – wages are marked down below marginal revenue products of labor. When workers have full bargaining power ($\kappa = 1$), the rents are fully captured by workers. A higher worker bargaining power therefore redistributes rents generated by imperfect product and labor market competition from firms to workers.

Labor wedges and labor demand. To see how variable markups and markdowns affect labor demand in the presence of wage bargaining, equation (1) can be written as:[12]

$$\Phi_j = \Lambda_j MRPH_j = \Lambda_j \mu_j^{-1} MPH_j \tag{2}$$

where there is a *labor wedge* Λ_j between wages and the $MRPH$. There is also a markup wedge (μ_j^{-1}) between the $MRPH$ and the marginal product of labor ($MPH_j = \alpha_{h,j} \frac{P_j Y_j}{H_j}$), capturing the idea that monopolists *reduce output*, and hence labor demand. When

[11] This assumption is consistent with the lack of wage response from large increases in unemployment insurance levels (Jäger et al., 2020), and the lack of response of reservation wages to changes in the potential unemployment benefit duration (Le Barbanchon, Rathelot, and Roulet, 2019). This assumption does not alter the results in this section. In Appendix C.1, I derive firm wage premia when firms have positive outside options and discuss the implications for the empirical results presented in Section 5.

[12] To get from equation (1) to equation (2), I used the optimal material demand $P_m = \mu_j^{-1} \alpha_{m,j} \frac{P_j Y_j}{M_j}$ and capital demand $P_k = \mu_j^{-1} \alpha_{k,j} \frac{P_j Y_j}{K_j}$.

markups and markdowns are variable, they can distort input demand and lead to misallocation (Edmond et al., 2018; Berger et al., 2020). In Section 6 and Appendix C.3, I derive the market and the social planner's labor allocation under specific labor and product market structure assumptions. The *labor wedge* can be expressed as:

$$\Lambda_j = \kappa\left(1 - \frac{\alpha_{m,j} + \alpha_{k,j}}{\mu_j}\right)\frac{\mu_j}{\alpha_{h,j}} + (1-\kappa)\lambda_j \tag{3}$$

where the first term represents the rents (per unit of MRPH) captured by workers – *rent-sharing*. When workers have no bargaining power ($\kappa = 0$), the labor wedge is the monopsony markdown $\Lambda_j = \lambda_j$ and workers capture no product market rents. The model therefore nests monopsony as a special case. Equation (2) then converges to a familiar form: $\Phi_j = \lambda_j \mu_j^{-1} \alpha_{h,j} \frac{P_j Y_j}{H_j}$, in which markups and markdowns fully distort labor demand away from the marginal product of labor.

When workers have full bargaining power ($\kappa = 1$), the labor wedge becomes $\Lambda_j = \left(1 - \frac{\alpha_{m,j}+\alpha_{k,j}}{\mu_j}\right)\frac{\mu_j}{\alpha_{h,j}}$ and workers capture all of the rents generated by markups and markdowns and firms make no profits. In this case, equation (2) converges to $\Phi_j = \left(1 - \frac{\alpha_{m,j}+\alpha_{k,j}}{\mu_j}\right)\frac{P_j Y_j}{H_j}$. Wage markdowns ($\lambda_j$) are no longer a distortion. The remaining wedge $\left(1 - \frac{\alpha_{m,j}+\alpha_{k,j}}{\mu_j}\right)$ reflects the fact that markups also generate rents by distorting capital and material demand away from their marginal products. Since workers capture these rents, the remaining wedge is increasing in markups. Consider a special case in which the production process requires only labor inputs ($\alpha_{m,j} = \alpha_{k,j} = 0,\ \alpha_{h,j} = 1$), so that markups only distort labor demand: with $\kappa = 1$, we arrive at $\Phi_j = \frac{P_j Y_j}{H_j}$, where wages are equal to MPL. Alternatively, consider when the goods market is perfectly competitive ($\mu_j = 1$) and the production function has constant returns-to-scale ($\alpha_{h,j} + \alpha_{m,j} + \alpha_{k,j} = 1$), we have again that wages are equal to MPL: $\Phi_j = \alpha_{h,j} \frac{P Y_j}{H_j}$.

3 Estimating Firm Wage Premia and Market Power

3.1 Empirical approach

I now take the model to the data to learn about the characteristics of high-wage and low-wage firms. I first estimate firm wage premia (ϕ), then estimate TFPQ (Ω), labor wedges (Λ), and markups (μ). Finally, I estimate workers' bargaining power (κ) and firms' monopsony markdowns (λ). A common approach to measuring markups is the cost share approach, which measures markups using sales to total variable cost ratios. However, a key assumption required to implement the cost share approach is that all input markets are perfectly competitive, which precludes the estimation of labor wedges.

To overcome this challenge, 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 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' labor wedges. Once output elasticities are obtained, I show that markups and labor wedges can be disentangled by exploiting the fact that markups distort each input demand, while labor wedges distort only labor demand.

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, as I explain in the next subsection, measuring firms' efficiency units of labor over time requires allowing wage premia to 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).[13]

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, 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, $j(i,t)$ denotes the firm that employs i at time t, $g(j,t)$ denotes the group of firm j at time t, ι_i are worker fixed effects, $\phi_{g(j(i,t),t)}$ are firm-group effects that vary by t, and χ_{it} includes age polynomials and part-time status. When there are as many firm-groups as there are firms, this regression converges to the AKM regression. The firm-group fixed effects are 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, enabling wage premia to be more precisely estimated.[14]

To classify firms with similar 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 log additive wage structure, firms with similar firm effects and worker effects should have similar internal wage distributions. If two firms have internal wage distributions of very

[13] 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.

[14] See Bonhomme, Holzheu, Lamadon, Manresa, Mogstad, and Setzler (2020) for a systematic assessment of the importance of clustering firms before estimating firm effects.

similar shapes, but their average wages differ significantly, then 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 wage premia to vary over time.[15] Online Appendix B provides more detail on how I cluster firms and addresses the main restrictions underlying the AKM regression.

3.3 Estimating labor wedges and price-cost markups

Estimation approach in theory. Having estimated firm wage premia, I now discuss a three-step approach to estimating TFP, labor wedges, and markups. First, I compute labor in efficiency units $H_{jt} = \bar{E}_{jt} L_{jt}$. The model-consistent average efficiency of workers per hour as the ratio of the firm's average wage to the firm wage premium, $\bar{E}_{jt} = \frac{\bar{W}_{jt}}{\Phi_{jt}}$, where $\log \bar{E}_{jt}$ 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: $y_{jt} = f_s(k_{jt}, m_{jt}, h_{jt}; \beta) + \omega_{jt}$. 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, intermediate inputs, and effective labor: $\alpha_{k,jt} := \frac{\partial y_{jt}}{\partial k_{jt}}$, $\alpha_{m,jt} := \frac{\partial y_{jt}}{\partial m_{jt}}$, and $\alpha_{h,jt} := \frac{\partial y_{jt}}{\partial h_{jt}}$.

In the third step, I separately disentagle firms' markups from their labor wedges. I use the fact that markups are common distortions to the demand of each input while labor wedges distort only labor demand to separately identify markups and labor wedges. Under the assumption that intermediate inputs are flexible 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 markups as a function of the intermediate input expenditure share and intermediate input elasticity of output:

$$\mu_{jt} = \alpha_{m,jt} \frac{P_{jt} Y_{jt}}{P_{m,t} M_{jt}}$$

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

$$\Lambda_{jt} = \frac{\Phi_{jt} H_{jt}}{P_{m,t} M_{jt}} \cdot \frac{\alpha_{m,jt}}{\alpha_{h,jt}} = \frac{\bar{W}_{jt} L_{jt}}{P_{m,t} M_{jt}} \cdot \frac{\alpha_{m,jt}}{\alpha_{h,jt}} \tag{4}$$

Since the 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

[15] Engbom, Moser, and Sauermann (2022) and Chan et al. (2021) also estimate time-varying firm effects. They do so within the connected set of firm-years, rather than the connected set of firms.

flexible inputs, the only remaining distortion is the labor wedge.

Estimation approach in practice. There are a few common practical considerations when estimating production functions: (i) Unobserved firm productivity, (ii) unobserved output prices, and (iii) unobserved input prices. I now address them in turn.

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.

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).[16] In practice, the estimated production function often becomes:

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

where $p_{jt} + \omega_{jt}$ is 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. Further, as Bond et al. (2021) show, when firms have product market power, this output price bias implies that estimated markups will be biased towards 1 (no markups).[17] To address this issue, I measure firm level prices p_{jt} directly using French administrative data on firm-product-year level prices for manufacturing firms and compute firm-year level output y_{jt} as revenue divided by prices.[18] The estimated firm productivity is then TFPQ rather than TFPR. I provide further 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:

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

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

[17] Chen et al. (2022) show that the Bond et al. (2021) critique does not affect the production approach to estimating labor wedges.

[18] 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.

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 these input markets (De Loecker and 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 et al. (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 and total wage bills to control for labor market power in $\mathbf{Z}_{jt}$.[19] The function $B(.)$ can then be written as:

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

[19] This is because firms' labor market power affect their marginal costs when labor markets are imperfectly competitive. Recall that firms' monopsony markdowns are a function of wage premia and amenities $\lambda(\Phi_{jt}, A_{jt})$. Φ_{jt} alone does not fully control for markdown variation due to A_{jt}. However, under the model's assumption that labor supply H_{jt} is monotonically increasing in A_{jt}, amenities can be written as a function of wage premia and wage bills, $A_{jt} = \mathcal{A}(\Phi_{jt}, \Phi_{jt}H_{jt})$.

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 $f(.)$.[20]

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 first-order conditions for intermediate inputs:

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

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:

$$\omega_{jt} = \omega_s(h_{jt}, \tilde{k}_{jt}, \tilde{m}_{jt}, \mu_{jt}, p_{jt}, \mathbf{Z}_{jt}) \tag{5}$$

The control function points to an important challenge in production function estimation when goods markets are imperfectly competitive – it includes markups $\mu_{jt} = \mu(P_{jt}, D_{jt})$, which are unobserved. As Bond et al. (2021) explain, when prices and markups are unobserved, the intermediate input demand function cannot generally be inverted, unless all variation in prices and markups are driven only by unobserved TFP ω_{jt}. In the French data, I observe output prices. If firm heterogeneity in markups is driven by differences in 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, Midrigan, and Xu (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 heterogeneity 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 Table 11 in Appendix B.4, I compare the markup and labor wedge estimates across various specifications that

[20] 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 $B(.)$ as lone variables is that the control function for input prices is built only from the consumer demand side.

(i) include additional controls for demand shifters, (ii) address output and input price biases. I find the estimates to be similar across specifications, consistent with the findings of De Ridder et al. (2021) and Chen et al. (2022).

The production function can then be estimated following the two-step GMM approach described in Ackerberg et al. (2015). I do so for each 2-digit manufacturing sector. To allow output elasticities to vary across firms, I estimate translog production functions. Further details about the implementation is in Appendix B.

3.4 Estimating workers' bargaining power and wage markdowns

Having estimated the labor wedges, markups, and output elasticities, this subsection estimates workers' bargaining power (κ) and measures wage markdowns (λ). Recall from the framework in Section 2 that the labor wedges are: $\Lambda_{js} = \kappa\tilde{\mu}_{js} + (1-\kappa)\lambda_{js}$, where $\tilde{\mu}_{js} \equiv \left(1 - \frac{\alpha_{m,js}}{\mu_{js}}\right)\frac{\mu_{js}}{\alpha_{h,js}}$ are product market rents. One could then use the passthrough of markups to labor wedges to estimate bargaining power, conditional on markdowns $\lambda_{js} = \lambda(\Phi_{js}, A_{js})$.[21] However, markdowns depend on amenities A_{js}, which I do not observe in the data. Heterogeneous amenities can drive a correlation between markups and markdowns.

I therefore propose a control function approach to address unobserved variation in amenities.[22] I assume that labor supply to the firm $H_{js} = \mathcal{H}(\Phi_{js}, A_{js})$ is monotonically increasing in the value of its amenities A_{js}, conditional on Φ_{js}. Under this assumption, I write the control function for amenities as $A_{js} = \mathcal{A}(\Phi_{js}, \Phi_{js}H_{js})$.[23] The estimating equation becomes:

$$\Lambda_{jst} = \kappa\tilde{\mu}_{jst} + (1-\kappa)\lambda(\Phi_{jst}, \mathcal{A}(\Phi_{jst}, \Phi_{jst}H_{jst})) + \tilde{\epsilon}_{jst}$$

where $\tilde{\epsilon}$ is a residual capturing measurement error in labor wedges. I approximate the wage markdown function $\lambda(.)$ with a 4^{th}-order polynomial in wage premia and wage bills. The estimated κ is potentially downward-biased due to measurement error on markups. To address this issue, I additionally estimate a specification that uses only variation across the firm-groups computed prior to estimating wage premia. Finally, I compute wage markdowns using the estimated bargaining parameter: $\lambda_{jst} = \frac{1}{1-\hat{\kappa}}\left(\Lambda_{jst} - \hat{\kappa}\tilde{\mu}_{jst} - \hat{\tilde{\epsilon}}_{jst}\right)$.

[21] Equivalently, markdowns can be written as a function of firm size H_{js} and amenities.

[22] Here I focus on the case where workers have a null outside option $\Phi^o = 0$, consistent with empirical findings from Austria and France that wages and reservation wages are insensitive to changes in unemployment benefit policies (Le Barbanchon et al., 2019; Jäger et al., 2020). In Appendix C.1, I estimate κ when $\Phi^o > 0$. I find similar estimates for worker bargaining power, but larger markdowns.

[23] In models where markdowns are constant, this control function approach is not needed. In recent oligopsonistic competition labor market models such as Berger et al. (2020) and Azkarate-Askasua and Zerecero (2020), wage-bill or employment market shares are sufficient controls for markdown variation.

3.5 Discussion

The structural framework described in Section 2 allows for a rich firm side by introducing firm-specific downward-sloping product demand schedules. Firm wage premia can therefore be driven by differences across firms in product appeal and markups, in addition to productivity and amenities. However, it is important to note the environments in which my analysis does not immediately extend to.

First, the presence of downward-sloping product demand curves imply that firms face diminishing returns to labor. In models where labor markets are characterized by search frictions and on-the-job search (e.g. Burdett and Mortensen (1998)), diminishing returns to labor can result in an equilibrium where all firms pay the same wage.[24,25] My estimates of firm wage premia and labor wedges do not readily extend to these settings. In Section 6, I decompose wage premia using a model of oligopsonistic labor markets where jobs at different firms are imperfect substitutes.

Second, my structural framework and estimation approach allows for within-firm wage dispersion due to differences in worker skills, but does not extend to settings in which workers have different outside options or wage contracts within firms. An important example is the sequential auctions mechanism (Postel-Vinay and Robin, 2002), where wages within firms can differ between two identical workers because one worker received an outside offer that induces the incumbent employer to engage in wage competition. Further, incumbent workers and new hires who are otherwise identical may be paid differently. In such cases, equation (2) is misspecified. In Appendix B, I show that my empirical findings are robust to considering only hiring wages following Di Addario, Kline, Saggio, and Solvsten (2020), allowing incumbents to be paid differently.

Third, 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

[24] An example is when workers and firms bargain over wages and hiring costs per worker are constant. In this environment, firms will hire until marginal products of labor equal hiring costs. Since marginal products are equalized in this case, so are wages.

[25] For recent developments in modeling firm dynamics with diminishing returns to labor, search frictions, and on-the-job search, I refer readers to Bilal, Engbom, Mongey, and Violante (2019) and Elsby and Gottfries (2021).

regression is misspecified – an interaction term between the worker and firm effect needs to be present (see, for example, Lamadon et al. (2019)). 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 Appendix E. I find that the results of this extension are similar to those reported in Section 5.

4 Data Description

4.1 Administrative datasets from France

Implementing the estimation 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. Labor wedges, markups, and TFPQ 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 Appendix A.

To obtain output price data at the firm level, I use the *Enquête Annuelle de Production* (EAP), available from 2009 to 2019. This dataset contains firm-product-level sales and output for all manufacturing firms with at least 20 employees or with sales exceeding 5 million Euros, and 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 sales-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 worker level, such as age, gender, earnings, hours, and occupational category. One advantage of the DADS is that work hours are observed, allowing researchers to construct 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.[26] Because workers are followed over time and their employer identifiers are observed, I use this dataset to estimate firm wage premia. 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 translog production functions, as this procedure would be demanding on small samples 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 (jobs in which workers are paid for at least 30 days of work and at least 120 hours of work that year). I use only years 2009-2016, since INSEE reports that wages are recorded with errors in 2017 and 2018. I keep workers in almost all 1-digit occupational categories, except farm workers. The included occupational categories are top management, senior executives and technical professions, middle management, non-supervisory white-collar workers, and blue-collar workers. Occupation codes are harmonized and updated to the latest version (PCE-ESE 2003). Workers whose wages fall outside 3 standard deviations of the mean are excluded.

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

Firm wage premia in the wage 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 126,836 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 9 in Appendix A.

5 The Characteristics of High and Low-Wage Firms

5.1 The distributions of estimated firm characteristics

In this subsection, I report the distribution of estimated firm wage premia and firm heterogeneity. I show that estimated dispersion TFPQ is large and substantially larger than the dispersion of TFPR, highlighting the importance of distinguishing between the two measures when quantifying the importance of TFPQ for firm wage premia. I then show that the median French manufacturing firm charges high markups and pays wages that are significantly below the marginal revenue product of labor.

Table 1 reports statistics about firm wage premia in 2016. The variance of firm wage premia is modest, 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 average 30% more than a firm at the 10th percentile. This difference amounts to approximately 4 Euros per hour or 25% of the hourly wage of the median French worker in 2016. The interquartile range is 15%, similar in magnitude to the typical estimate for the costs of job displacement (Schmieder, Von Wachter, and Heining, 2018). This gap is also approximately three times as large as the gender wage gap in France. Among manufacturing firms, the 90-10 wage premium difference is slightly smaller at 23%.

The first and second rows of Table 2 report the summary statistics for TFPQ and TFPR. The large dispersion of firm productivity is well-documented (Syverson, 2011).

Table 1: Dispersion of firm wage premia.

	BLM		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%
$Var(\phi)$	0.008	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

This table reports the summary statistics for firm wage premia in 2016. Columns labeled 'MN' are estimates for manufacturing firms in my estimation sample. Columns labeled 'Overall' are estimates for all firms in the private sector. The first and second columns report statistics for firm effects estimated at the firm-group level following BLM. The columns under AKM report the firm effects without grouping firms. The columns under KSS report firm effects corrected for limited mobility bias following the Kline et al. (2020) leave-out approach.

However, the table shows that dispersion in TFPQ is much larger than dispersion in TFPR. The interquartile range of TFPR is similar to those found by Blackwood, Foster, Grim, Haltiwanger, and Wolf (2021) for US manufacturing firms. To quantify the contribution of TFPQ for firm wage premia in a structural model in Section 6, it is therefore important to estimate TFPQ separately from TFPR. Using TFPR in place of TFPQ would understate the contribution of heterogeneous TFPQ to wage dispersion.

Table 2: Summary statistics for estimated firm characteristics.

	Mean	Median	25^{th} Pct	75^{th} Pct	Var	Var (i)	Var (ii)
Log TFPQ (ω)	0.00	-0.05	-0.60	0.58	1.18	1.11	0.06
Log TFPR ($p+\omega$)	0.00	-0.02	-0.14	0.12	0.04	0.04	0.02
Labor wedge (Λ)	0.63	0.59	0.47	0.76	0.13	0.09	0.03
Markups (μ)	1.48	1.36	1.15	1.67	0.08	0.05	0.01
Number of firms				15,934			

This table reports the summary statistics in 2016 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 are reported for log labor wedges, log price-cost markups, log TFPQ, and log TFPR. Log TFPQ and Log TFPR 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. Markups and labor wedges are winsorized by 2%.

The third row of Table 2 describes the distribution of labor wedges (Λ), which captures the wage-setting power of employers relative to their employees. Most French manufacturers appear to have significant wage-setting power. France has one of the highest national minimum wages.[27] Nevertheless, half of the firms in my sample pay less than 60% of the marginal revenue product of labor as wages. I also find substantial dispersion of labor wedges across firms. Firms at the 75^{th} percentile of the labor wedge distribution pay a wage that is 76% of the marginal revenue product of labor. At the 25^{th} percentile, workers obtain less than half of their marginal revenue productivity. The minimum wage forces firms to pay wages closer to workers' full marginal revenue productivity, to the extent that it is binding.

The set of direct estimates of labor wedges is small. I start by comparing my estimates to those of Chen et al. (2022) and Mertens (2020), whose estimates are methodologically the closest to mine.[28] 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 corresponding number is 0.59. Kroft et al. (2021) find a markdown of 20% below marginal product in the US construction sector.

The fourth row of Table 2 reports that price-cost markups (μ) are heterogeneous across firms. The median markup among French manufacturers is 1.36. De Loecker and Warzynski (2012) estimate markups using Slovenian manufacturing 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 economy, while my estimates for French manufacturing is 1.67 in 2016. Edmond et al. (2018) report an interquartile range for markups of 1.31-0.97=0.34. The interquartile range for my estimates is 0.52.

5.2 Labor wedges, markups, and prices among high-wage firms

I now compare high-wage and low-wage firms. I first show that high-wage firms have higher TFPQ than low-wage firms. I then present new empirical patterns: conditional on TFPQ, high-wage firms charge higher output prices and price-cost markups, and pay a larger fraction of their marginal revenue product of labor as wages. I reason that these empirical patterns cannot be readily explained by existing monopsony models of the labor market where: (i) firms produce homogenous goods and do not have price-setting power, (ii) workers have no bargaining power.

I start by investigating whether high-wage and low-wage firms differ in TFPQ. I regress TFPQ (ω_{jt}) on deciles of firm wage premia (ϕ_{jt}), controlling for year and five-digit sector fixed effects. Figure 1 shows how TFPQ varies by bins of firm wage premia. On average, firms at the top decile of the firm wage premium distribution are approximately 8% more

[27] In 2016, about 15% of French workers are earning at or close to the minimum wage. In manufacturing, the corresponding number is 10%. See Appendix A for a description of French wage-setting institutions.

[28] However, the interpretation of these labor wedges differ between my paper and those in Chen et al. (2022) and Mertens (2020). In the aforementioned papers, labor wedges are interpreted as monopsonistic (oligopsonistic) wage markdowns, corresponding to the case where workers do not have bargaining power ($\kappa = 0$) in my framework in Section 2. Allowing $\kappa > 0$ also helps rationalize that about 7% of firms have a labor wedge greater than 1. Indeed, firms with $\Lambda > 1$ tend to have much higher markups.

productive than firms at the bottom decile.

I next explore the differences between high-wage and low-wage firms in the estimated price-setting and wage-setting characteristics. I run the same regression for log output prices (p_{jt}), markups ($\log \mu_{jt}$), and labor wedges ($\log \Lambda_{jt}$) on deciles of firm wage premia (ϕ_{jt}), additionally controlling for heterogeneity in TFPQ. The estimated coefficients are shown in Figure 2. When I do not control for differences in TFPQ, I find similar patterns across deciles of firm wage premia (see Figure 9).

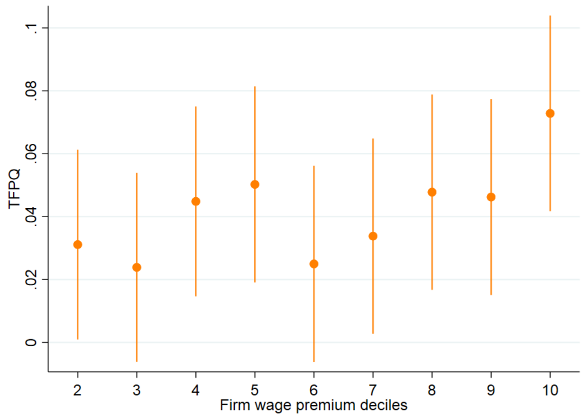

Figure 1: TFPQ by high-wage status.

Notes: This figure shows how quantity TFP vary by deciles of firm wage premia relative to firms in the first decile, controlling for year fixed effects and 5-digit sector fixed effects. Decile 10 represents high-wage firms. Confidence intervals at the 95% level are plotted.

Figure 2 shows that high-wage firms tend to charge higher output prices and higher markups. In theory, firms with higher productivity charge higher markups (Atkeson and Burstein, 2008) and pay higher wages (Card et al., 2018) – the positive relationship between markups and wage premia can be explained with productivity differences between firms. However, if TFPQ were the only driver of wage premia and markups, then one would expect that high-wage firms charge lower output prices, contrary to the data. Indeed, Figure 2 shows that the positive correlation between output prices, markups, and wage premia remains conditional on TFPQ. These empirical patterns are consistent with heterogeneity in product appeal as a driver wage premia.

Figure 2 also shows that high-wage firms pay a larger fraction of marginal revenue products of labor as wages. This empirical pattern cannot be readily explained by a purely monopsonistic labor market model where workers have no bargaining power. In such an environment, the estimated labor wedge (Λ) would be a monopsonistic wage markdown (λ), which are often constant or decreasing in wages (Burdett and Mortensen, 1998; Card et al., 2018; Berger et al., 2020).[29] That is, in such models high-wage firms

[29]In theory, the oligopsonistic labor markets model in Berger et al. (2020) allows markdowns to increase with wages if jobs across labor markets are closer substitutes than jobs within the same labor market.

would pay a smaller fraction of $MRPH$ as wages. However, notice from equation (3) that if workers have bargaining power ($\kappa > 0$), the labor wedge is increasing in markups. The positive correlation between markups and labor wedges is consistent with workers being able to extract product market rents through bargaining.

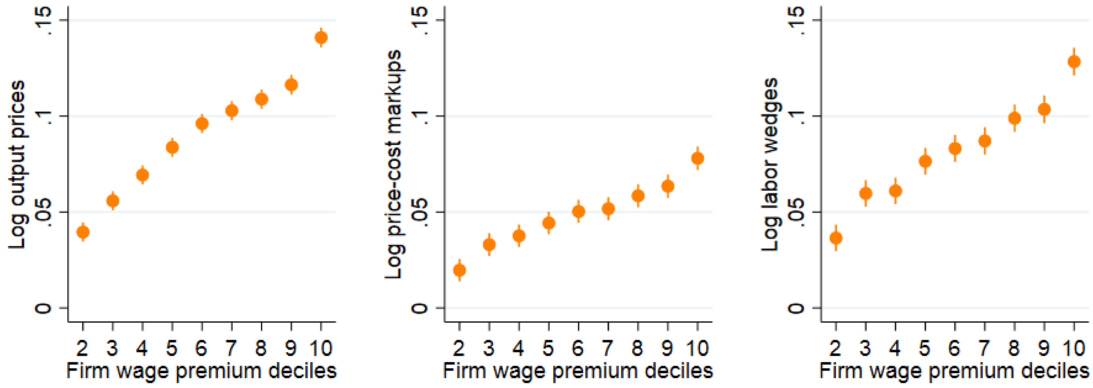

Figure 2: Prices, markups, and labor wedges by high-wage status, conditional on TFPQ.

Notes: This figure shows how output prices, price-cost markups, and labor wedges vary by deciles of firm wage premia relative to firms in the first decile, controlling for TFPQ, year fixed effects and 5-digit sector fixed effects. Decile 10 represents high-wage firms. Confidence intervals at the 95% level are plotted.

5.3 Monopsony markdowns & workers' bargaining power

I now report my estimates for workers' bargaining power and wage markdowns.[30] My estimates suggest that workers' bargaining power is low but not zero. Table 3 shows that across various specifications workers obtain less 10% of the economic rents. Comparing columns (1) and (2) with columns (3) and (4) suggests the presence of some attenuation bias on the estimated bargaining parameter, although these estimates are not dissimilar to estimates from the rent-sharing literature, which generally finds values between 0.05 and 0.15 (Card et al., 2018; Jäger et al., 2020).

I next compute the implied monopsonistic/oligopsonistic wage markdowns taking specification (4) in Table 3 as my baseline specification. Table 4 reports the estimated markdowns. I find markdowns to be substantial – at the median, the markdown is 54% of the marginal revenue product of labor. The implied firm-specific labor supply elasticities are 0.89, 1.17, 1.63 at the 25^{th}, 50^{th}, and 75^{th} percentiles. This is similar to 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.

[30] In Appendix C.1, I estimate bargaining power when $\Phi^o > 0$. I find similar estimates for worker bargaining power, but larger markdowns.

Table 3: Estimated workers' bargaining power.

Labor wedge (Λ_{jst})	(1)	(2)	(3)	(4)
Product market	0.083	0.055	0.111	0.062
rents ($\tilde{\mu}_{jst}$)	(0.005)	(0.003)	(0.007)	(0.005)
Year fixed effects	Yes	Yes	Yes	Yes
Sector fixed effects	No	Yes	No	Yes
Variation	firms	firms	firm-groups	firm-groups
Number of firms	126,836			

This table reports the estimated workers' bargaining power parameter. In column (2), sector fixed effects are at the 5-digit level. In column (4), sector fixed effects are at the 2-digit level, since firm-groups are constructed within 2-digit sectors. Robust standard errors are reported in parentheses.

Table 4: Comparing monopsony markdowns across high-wage and low-wage firms.

Summary statistics	Mean	Median	25^{th} Pct	75^{th} Pct	Var	Var (i)	Var (ii)
Markdowns (λ_{jst})	0.55	0.54	0.47	0.62	0.04	0.03	0.03

This table reports the summary statistics in 2016 for the estimated monopsonistic/oligopsonistic markdowns. Markdowns are computed using the estimated bargaining parameter κ from specification (4) in Table 3. The variance is for $\log\lambda$. 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. Each variable is winsorized by 2%.

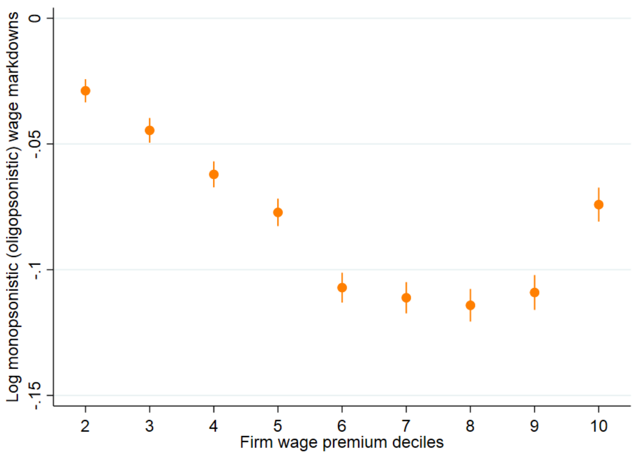

Figure 3: Monopsony markdowns by high-wage status.

Notes: This figure shows how monopsony markdowns vary by deciles of firm wage premia relative to firms in the first decile, controlling for year fixed effects and 5-digit sector fixed effects. Decile 10 represents high-wage firms. Confidence intervals at the 95% level are plotted.

Do high-wage firms have higher or lower markdowns (λ)? I regress markdowns ($\log\lambda$) on deciles of wage premia, controlling for year and five-digit sector fixed effects. Figure 3 shows that firms in the top decile of the firm wage premium distribution mark down wages more than those at the bottom decile, although the cross-sectional relationship is not monotonic. The differences between deciles are small and disappears for above-median firms. The inverse relationship between markdowns and wage premia is consistent with the predictions of monopsonistic or oligopsonistic labor market models in which markdowns vary endogenously, such as Gouin-Bonenfant (2020) and Berger et al. (2020).

6 A Framework to Decompose Firm Wage Premia

Having compared the equilibrium characteristics of high- and low-wage firms. This section proposes a specific general equilibrium model that is nested within the setup of Section 2. I use the model to quantify the importance of firm heterogeneity, firms' price-setting power, and workers' bargaining power in shaping wage dispersion and wage levels. Compared to Section 2, I now make specific market structure assumptions about product and labor markets: product markets are oligopolistic (Atkeson and Burstein, 2008) and labor markets are oligopsonistic (Berger et al., 2020).

6.1 Environment

There is a continuum of sectors $s \in [0, \mathcal{S}]$. In what follows, I assume that each sector is both a product market and a labor market. Each sector contains an exogenously given finite number of firms n_s. Each firm j belongs to one sector.

Labor supply. The representative household maximizes utility by choosing the amount of numeraire final goods to consume C and effective labor H_{js} to supply to each firm:

$$U = \max_{\{C, H_{js}\}} C - \frac{H^{1+\varphi}}{1+\varphi}$$

subject to the budget constraint $C = \Phi H + \Pi$, where Φ is the aggregate wage index and Π are aggregate profits. Jobs across and within sectors are imperfect substitutes. Aggregate labor supply H is a composite of sector-level labor supply H_s, with a constant elasticity of substitution ν. Labor supply to each sector is a composite of labor supply to each firm in that market, with a constant elasticity of substitution η. The aggregate and sectoral labor supply aggregators are:

$$H = \left[\int_0^{\mathcal{S}} \tilde{A}_s^{-\frac{1}{\nu}} H_s^{\frac{\nu+1}{\nu}} \, ds \right]^{\frac{\nu}{\nu+1}} \qquad \text{and} \qquad H_s = \left[\sum_{j=1}^{n_s} \tilde{A}_{js}^{-\frac{1}{\eta}} H_{js}^{\frac{\eta+1}{\eta}} \right]^{\frac{\eta}{\eta+1}}$$

where $\tilde{A}_s$ are sectoral labor supply shifters such that $\int_s \tilde{A}_s \, ds = 1$, and $\{\tilde{A}_{js}\}$ are firm-specific labor supply shifters such that $\sum_{j=1}^{n_s} \tilde{A}_{js} = 1$. When $\eta \geq \nu$, jobs within sectors are closer substitutes than jobs across sectors. When $\eta \to \infty$ ($\nu \to \infty$), there is no job differentiation within (between) sectors. Firms face the following labor supply curve:

$$H_{js} = \tilde{A}_{js}\tilde{A}_s \Phi_{js}^{\eta} \Phi_s^{\nu-\eta} \Phi^{-\nu} H \tag{6}$$

I refer to $A_{js} \equiv \tilde{A}_{js}\tilde{A}_s$ as amenities.

Product demand. The competitive final good producer produces good Y by combining the output of firms in each sector. The CES goods aggregator across sectors and within sectors are:

$$Y = \left[\int_0^1 \tilde{D}_s^{\frac{1}{\theta}} Y_s^{\frac{\theta-1}{\theta}} \, ds \right]^{\frac{\theta}{\theta-1}} \qquad \text{and} \qquad Y_s = \left[\sum_{j=1}^{n_s} \tilde{D}_{js}^{\frac{1}{\sigma}} Y_{js}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

where $\tilde{D}_s$ are sectoral demand shifters such that $\int_s \tilde{D}_s \, ds = 1$, and $\{\tilde{D}_{js}\}$ are firm-specific demand shifters such that $\sum_{j=1}^{n_s} \tilde{D}_{js} = 1$. The within-sector and between-sector elasticities of substitution between goods are σ and θ. When $\sigma \geq \theta$, goods within a sector are more substitutable than goods across sectors. When $\sigma \to \infty$ ($\theta \to \infty$), there is no product differentiation within (between) sectors. Firms face the following inverse goods demand curve:

$$Y_{js} = \tilde{D}_{js}\tilde{D}_s P_{js}^{-\sigma} P_s^{\sigma-\theta} Y \tag{7}$$

where I refer to $D_{js} \equiv \tilde{D}_{js}\tilde{D}_s$ as product appeal.

Resource constraint. Final goods can be consumed by the representative household or used as factor inputs – capital and material – such that $Y = C + K + M$, where $K = \int_s \sum_j^{n_s} e^{\tau_{js}} K_{js} \, ds$ and $M = \int_s \sum_j^{n_s} M_{js} \, ds$ are aggregate capital and material use.

Wage bargaining. Wage-setting is as described in Section 2. Workers and firms jointly decide wages, output, capital, and materials to maximize the following Nash product:

$$\max_{\Phi_j, Y_j, K_j, M_j} \left(\Phi_{js} H_{js} \right)^{\kappa} \left(\Pi_{js} \right)^{1-\kappa}$$

subject to the labor supply curve (6), product demand curve (7), and production function $Y_j = \Omega_j K_j^{\alpha_k} M_j^{\alpha_m} H_j^{\alpha_h}$. Profits are $\Pi_{js} = P_{js}Y_{js} - \Phi_{js}H_{js} - P_{k,js}K_{js} - P_m M_{js}$. Since final goods are used as material and capital inputs, we have $P_m = 1$ and $P_{k,js} = e^{\tau_{js}}$, where the wedge τ_{js} denotes heterogeneity in capital input prices that may arise due, for example, to differences in capital quality.[31]

Equilibrium. Given a set of firms that each belong to a single sector $s \in [0, \mathcal{S}]$, an equilibrium is: (i) An aggregate output Y, consumption C, labor supply H, price index $P = 1$, wage index Φ, capital inputs K, materials M; (ii) A sequence of sectoral aggregates: output Y_s, labor supply H_s, price index P_s, wage index Φ_s; (iii) A sequence

[31] The capital wedges help the model to match the empirical firm size distribution.

of firm-level prices and allocations: output Y_{js}, labor H_{js}, capital inputs K_{js}, materials M_{js}, output prices P_{js}, wages Φ_{js} that maximize household utility, the worker-firm Nash product, and clear all goods and labor markets. In Appendix C.3, I compare the market allocation to a social planner's allocation.

6.2 Calibrating the model

I now describe my calibration approach. The calibrated parameter values are reported in Table 5. I first calibrate parameters that govern price-cost markups and oligopsonistic markdowns, then measure product appeal (D_{js}) and amenities (A_{js}).

Parameters related to markups. The relationship between markups and product market shares in this model can be written as:

$$\upsilon_{js}^{-1} = \frac{\mu_{js} - 1}{\mu_{js}} = \frac{1}{\sigma} + \left(\frac{1}{\theta} - \frac{1}{\sigma}\right)\Gamma_g \frac{P_{js}Y_{js}}{\sum_{j'}^{n_s} P_{j's}Y_{j's}}$$

where Γ_g is a goods market competitive conduct parameter, equal to 1 under oligopolistic competition and 0 under monopolistic competition. In my calibration, I assume that $\Gamma_g = 1$, but conduct counterfactual exercises with $\Gamma_g = 0$ later. The elasticity of substitution between varieties across sectors θ and within sectors σ are calibrated to match the level of estimated markups μ_{js} and their correlation with market shares. I measure market shares as the share of sales within 5-digit sectors.

Parameters related to markdowns. The relationship between oligopsonistic markdowns and wage bill shares in this model can be written as:

$$\xi_{js} = \frac{\lambda_{js}}{1 - \lambda_{js}} = \eta + (\nu - \eta)\Gamma_h \frac{\Phi_{js}H_{js}}{\sum_{j'}^{n_s} \Phi_{j's}H_{j's}}$$

where Γ_h is a labor market competitive conduct parameter, equal to 1 under oligopsonistic competition and 0 under monopsonistic competition. In my calibration, I assume that $\Gamma_h = 1$. The elasticity of substitution between jobs across sectors ν and within sectors η are calibrated to match the level of estimated oligopsonistic markdowns λ_{js} and their correlation with wage bill shares. I measure wage bill shares at the 5-digit sector level.

Calibrating heterogeneous TFPQ, appeal, and amenities. TFPQ is estimated directly from the data in Section 3. Given the parameters governing product demand and labor supply curves, I back out firm heterogeneity in product appeal and amenities. The product and labor market shares of a given firm are:

$$\frac{P_{js}Y_{js}}{P_sY_s} = D_{js}\left(\frac{P_{js}}{P_s}\right)^{1-\sigma} \qquad \text{and} \qquad \frac{\Phi_{js}H_{js}}{\Phi_sH_s} = A_{js}\left(\frac{\Phi_{js}}{\Phi_s}\right)^{1+\eta}$$

Table 5: Calibrated parameters.

Parameter		Value
Frisch labor supply elasticity	φ	0.25
Between-market elasticity of subs. (labor)	ν	0.93
Within-market elasticity of subs. (labor)	η	1.14
Between-market elasticity of subs. (goods)	θ	2.10
Within-market elasticity of subs. (goods)	σ	6.54
Union bargaining power	κ	0.06
Number of firms within markets	n_s	FARE data
Labor elasticity of output	α_h	Average of estimates
Material elasticity of output	α_m	Average of estimates
Capital elasticity of output	α_k	$1-\alpha_h-\alpha_m$
TFPQ	Ω_{js}	Production function estimates
Product appeal	D_{js}	Sales shares
Non-wage amenities	A_{js}	Wage bill shares
Capital wedges	τ_{js}	Firm size distribution (eff. labor)

I use the data to measure firms' product and labor market shares, as well as output prices and wages. I use these equations to compute D_{js} such that $\sum_j^{n_s} D_{js} = 1$ and A_{js} such that $\sum_j^{n_s} A_{js} = 1$. Similarly, the sectoral goods demand and labor supply shifters (D_s and A_s) are measured using the relative size of sectors: $\frac{P_s Y_s}{PY} = D_s \left(\frac{P_s}{P}\right)^{1-\theta}$ and $\frac{\Phi_s H_s}{\Phi H} = A_s \left(\frac{\Phi_s}{\Phi}\right)^{1+\nu}$.

Other parameters. The parameter value for the Frisch labor supply elasticity is obtained from Chetty (2012). I calibrate workers' bargaining power to 0.06 using my estimates in Table 3 from specification (4). The number of firms within each 5-digit sector is obtained from the FARE firm balance sheet data. The production function parameters are calibrated as the average of my production function estimates. Finally, capital price heterogeneity τ_{js} is calibrated to match the distribution of efficiency units of labor. They absorb unmodelled differences in capital quality, adjustment costs, materials quality, and other unmodelled determinants of the firm size distribution. Combined with the calibrated values of non-wage amenities, the model exactly reproduces the empirical firm wage premium distribution.

7 Decomposing Firm Wage Premia

In this subsection I use the calibrated model for four main exercises. First, I report how the measured product appeal and amenities vary across high-wage and low-wage firms. Second, I study the passthrough of firm heterogeneity to wage premia and assess its determinants. Third, I quantify the importance of labor and product market structure for wage premia and wage levels. Fourth, I show how worker bargaining power interacts with product market competition to determine wages.

7.1 Product appeal and amenities among high-wage firms

Analogously to Section 5, I compare the product appeal and amenities across deciles of firm wage premia, controlling for year and 5-digit sector fixed effects.[32] Figure 4 reports the estimated coefficients of the wage premium deciles. It shows that the differences between high-wage and low-wage firms in appeal and amenities are considerably larger than the difference in TFPQ. While firms in the top decile of the wage premium distribution are on average 8% more productive than firms at the bottom decile, they have 125% greater appeal and 15% higher amenity on average. That is, for a given price, firms in the top decile can sell 125% more goods than firms in the bottom decile. Similarly, for a given wage, firms in the top decile can employ 15% more labor than firms in the bottom decile. That high-wage firms have better amenities is consistent with the findings of Lamadon et al. (2019) for US firms.

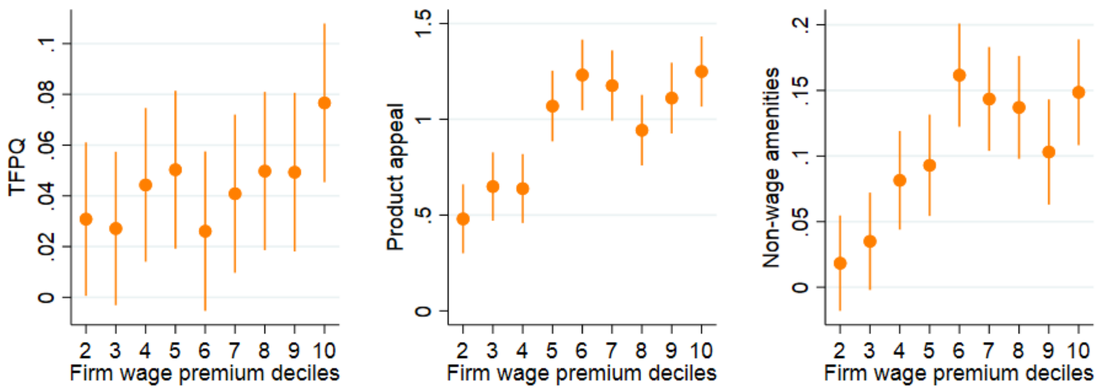

Figure 4: Measured firm heterogeneity by high-wage status.

Notes: This figure shows how measured TFPQ, product appeal, and non-wage amenities vary by deciles of firm wage premia relative to firms in the first decile (low-wage firms), controlling for year fixed effects and 5-digit sector fixed effects. Decile 10 represents high-wage firms. Confidence intervals at the 95% level are plotted.

7.2 Understanding the passthrough of heterogeneity to wages

I now assess the passthrough of firm heterogeneity to wages and report two main findings. First, the degree of product differentiation governs the passthrough of TFPQ compared to product appeal. When there is little product differentiation, the passthrough of TFPQ becomes larger than the passthrough of appeal. Second, firm size dampens the passthrough of TFPQ. As a result, passthrough is smaller among high-wage firms.

[32] Table 17 in Appendix D reports the unconditional correlations between sources of firm heterogeneity. The last column shows that firms with high TFPQ or high product appeal on average have better amenities. However, firms with high TFPQ tend to have lower product appeal, consistent with the findings in Eslava, Haltiwanger, and Urdaneta (2023).

Before interpreting the quantitative results, I first write firm wage premia from the model of Section 6 as a function of the sources of firm heterogeneity:

$$
\begin{aligned}
\phi_{js} = {} & \underbrace{\frac{(\sigma-1)}{1+\eta+\alpha_h(\sigma-1)}\omega_{js} + \frac{1}{1+\eta+\alpha_h(\sigma-1)}\big(d_{js}-a_{js}\big) - \frac{\alpha_k(\sigma-1)}{1+\eta+\alpha_h(\sigma-1)}\tau_{js}}_{\text{direct effect}} \\
& + \underbrace{\frac{1+\alpha_h(\sigma-1)}{1+\eta+\alpha_h(\sigma-1)}\overbrace{\log\Lambda_{js}}^{\text{labor wedge}} - \frac{\sigma}{1+\eta+\alpha_h(\sigma-1)}\overbrace{\log\mu_{js}}^{\text{variable markup}}}_{\text{variable market power effect}} + \underbrace{\bar{\alpha}}_{\text{constant}} \\
& + \underbrace{\frac{\sigma-\theta}{1+\eta+\alpha_h(\sigma-1)}p_s + \frac{\eta-\nu}{1+\eta+\alpha_h(\sigma-1)}\phi_s}_{\text{granularity effect}} + \underbrace{\frac{1}{1+\eta+\alpha_h(\sigma-1)}\log\big(\Phi^{\nu}\frac{Y}{H}\big)}_{\text{general equilibrium effect}}
\end{aligned} \tag{8}
$$

where $\bar{\alpha}$ is a constant. The first line of equation (8) shows the *direct effect* of firm heterogeneity on wage premia. The direct effect is present even when firms are atomistic and markups and markdowns are constant. A higher labor elasticity of output α_h reduces the passthrough of TFPQ, product appeal, and amenities, since a smaller increase in employment can now achieve a given increase in output. When jobs within markets are closer substitutes (higher η), the passthough of firm heterogeneity becomes smaller, because a smaller wage increase is sufficient to achieve a given increase in employment.

The substitutability of product varieties (σ) affects the passthrough of TFPQ and product appeal in opposite ways. TFPQ passthrough increases when σ is higher, while the passthrough of product appeal decreases. Intuitively, when σ is higher, product varieties become closer substitutes, leading consumers to become more price-sensitive, magnifying the importance of TFPQ differences across firms for labor demand and wages. As a result, TFPQ becomes a more important determinant of wage premia when σ is high.

The second line shows that endogenously variable labor wedges and markups affect wage premia. I refer to this term the *variable market power effect.* A higher markup can raise wage premia through *rent-sharing* – by raising the labor wedge. However, it can also reduce wage premia by inducing the firm to *restrict output* and labor demand. Labor wedges also depend on variable wage markdowns. Larger markdowns reduce wages and labor demand.

The third line shows that firm wage premia depend on sectoral price and wage indices. I refer to this term the *granularity effect* since individual firms can only affect the sectoral price and wage index when they are large relative to the product and labor markets they belong – they are granular as opposed to atomistic. They can also indirectly affect the price and wage index by influencing their competitor's price and wage-setting decision. For example, if a granular firm reduces prices, it lowers the market-level price index, forcing its competitors to also reduce prices. Since $\sigma > \theta$, a lower sectoral price index induces firms to produce and hire less, reducing wages. Similarly, given that $\eta > \theta$, a higher sectoral wage index forces firms to pay higher wages.

Passthrough of TFPQ, product appeal, and amenities. I now present quantitative findings that point to firms' price-setting power as an important determinant of passthrough. The passthrough is defined as the elasticity of firm wage premia with respect to a shock. To compute the passthrough of a shock, I randomly select one firm from each sector and assign it a 1% positive shock, while holding general equilibrium aggregates constant. I then compute the average elasticity of wages to the shock across shocked firms. Panel (A) of Table 6 shows the passthrough of a 1% TFPQ shock, product appeal shock, and amenity shock.[33]

The passthrough of a TFPQ shock is 1.10, over five times larger than the passthrough of a product appeal shock, as the last column of Panel (A) shows. To see why, columns one through five breaks down the total passthrough into various channels. The *direct* channel accounts for most of the difference between TFPQ and product appeal passthrough. As equation (8) shows, the direct component of TFPQ passthrough is increasing in the within-market goods substitutability σ, while for product appeal passthrough it is decreasing in σ. Given the relatively high calibrated σ of 6.54, the direct effect is larger for TFPQ passthrough. However, for sufficiently low σ, the passthrough of product appeal can be higher than the passthrough of TFPQ, as Table 16 in Appendix C shows. On the other hand, as η increases, the passthrough of each shock becomes smaller.

The *variable market power* channel also plays a role in the passthrough of TFPQ. The first row of columns two and three in Table 6 shows how variable markups and markdowns contribute to the passthrough of TFPQ. A higher TFPQ leads to higher markups, leading to an increase in rent-sharing (higher labor wedges) but also a stronger incentive to restrict output. Overall, the output restriction effect dominates, implying that endogenously higher markups dampen the passthrough of TFPQ.

The *granularity* channel further dampens the passthrough of TFPQ. A positive TFPQ shock reduces a firm's output price, which directly reduces the sectoral price index if the firm is large relative to the sector. Moreover, when σ is higher so consumers are more price-sensitive, the firm's competitors reduce prices more aggressively in response to the price reduction of the shocked firm, further reducing the price index. Given the relatively high calibrated σ, the reduction in sectoral output prices is large, offsetting the shocked firm's wage increase by -0.17. Granularity in the labor market also means that its wage directly affects the sectoral wage index and induces competitors to raise wages. Given the relatively low substitutability of jobs within sectors η, the response of the sectoral wage index to a firm-specific TFPQ shock is muted and does not affect the TFPQ passthrough.

[33] These passthrough simulations show how wage premia change in response to shocks at the firm-level, but they do not show how wages at the worker-level would respond. The latter will require accounting for job mobility, as workers may be induced to switch firms, e.g. due to a negative shock. Chan et al. (2021) show that job mobility is an important determinant of passthrough in response to negative shocks.

Table 6: Passthrough of firm heterogeneity to firm wage premia.

Panel (A)	Channels					Total
	Direct	Var. market power		Granularity		passthrough
		$\Delta \log \Lambda$	$-\Delta \log \mu$	Δp_s	$\Delta \phi_s$	
Δ TFPQ	1.33	0.01	-0.06	-0.17	0.00	1.10
Δ Product appeal	0.25	0.00	-0.01	-0.04	0.00	0.20
Δ Amenity	-0.25	0.00	-0.01	-0.04	0.00	-0.30

Panel (B)	Firm wage premium distribution		
	10^{th} pct.	50^{th} pct.	90^{th} pct.
Δ TFPQ	1.32	1.31	0.85
Δ Product appeal	0.24	0.24	0.16
Δ Amenity	-0.25	-0.25	-0.35

This table reports the passthrough of firm heterogeneity to firm wage premia. The passthrough measures are with respect to a positive 1% shock. Panel (A) decomposes the total passthrough into different effects. The first column shows the *direct effect* of a shock on wage premia, which is present even when firms are atomistic (see equation (8)). The second and third columns show the effects coming from variable labor wedges and markups, capturing *rent-sharing* and *output restriction* motives. The fourth and fifth columns present the effects coming from firms being *granular*. The final column presents the total passthrough, which is the sum of columns 1 through 5. Panel (B) looks at the passthrough at different percentiles of the firm wage premium distribution.

The total passthrough of an amenity shock is larger than that of a product appeal shock. Table 6 shows that the direct effect of an amenity shock is the mirror image of a product appeal shock (-0.25 compared to 0.25). However, while variable markups and sectoral price indices dampen the passthrough of positive product appeal shocks, they amplify the passthrough of positive amenity shocks. This is because an increase in the value of amenities allows the firm to hire workers at a lower wage, effectively acting as a negative shock to production costs and expanding the size of the firm.

Given the above discussion on the role of variable markups and sectoral price indices in determining wage passthrough, a shock of a given size should have a different passthrough at different points in the wage premium distribution. Panel (B) of Table 6 shows that TFPQ and appeal passthrough is substiantially smaller for firms in the 90^{th} percentile, while the amenity passthrough is larger. In comparison, firms in the 10^{th} and 50^{th} percentiles have a passthrough that is well-approximated by the direct effect only.

7.3 Decomposing the dispersion of firm wage premia

I now decompose firm wage premia and present two main findings. First, TFPQ is the most important driver of wage premium dispersion, closely followed by product appeal, and then by amenities. Second, if markups were constant instead of variable, wage premium dispersion increases substantially, driven by high-wage firms. The increase in wage premium dispersion is paired with a large increase in wages overall.

Which sources of firm heterogeneity are most important for firm wage premia? I introduce *one* source of firm heterogeneity at a time into the model. I then compare the generated variance of wage premia to that of the full model, which exactly reproduces the wage premium distribution in the data. Panel (A) of Table 7 shows the contribution of TFPQ, product appeal, and amenities to wage premia, in descending order of importance. When only TFPQ varies, the model generates a variance of wage premia that is 155 times that of the full model. The corresponding numbers for product appeal and amenities are 104 times and 23 times. TFPQ is thus a larger contributor to wage premium dispersion than product appeal and amenities. Nevertheless, product appeal and amenities play an important role in driving firm wage premia.

Table 7: Importance of firm heterogeneity for firm wage premia.

Panel (A)	Counterfactual		
	Vary only TFPQ	Vary only appeal	Vary only amenity
$\frac{V(\phi^{\text{counterfactual}})}{V(\phi^{\text{full}})}$	155.14	104.26	22.74

Panel (B)	Counterfactual		
	Constant markups	Constant markdowns	Both constant
$\frac{V(\phi^{\text{counterfactual}})}{V(\phi^{\text{full}})}$	1.31	1.01	1.37
Δ 99-90 ratio (p.p.)	0.05	0.00	0.06
Δ 90-50 ratio (p.p.)	0.03	0.00	0.03
Δ 50-10 ratio (p.p.)	0.01	0.00	0.01
Agg. wage index (%Δ)	15	1	17

This table reports the variance of firm wage premia under different counterfactual experiments. ϕ^{full} refers to firm wage premia in the full model, which has heterogeneity in TFPQ, product appeal, amenities, and capital wedges, as well as variable markups and markdowns. Note that the variance of ϕ^{full} is the same as the variance of ϕ^{data}. Panel (A) compares the wage premium distribution when there is only one dimension of heterogeneity to that of the baseline model. Panel (B) compares the counterfactual when markups (μ) and/or markdowns (λ) are constant to the full model.

How important are price-cost markups and wage markdowns for firm wage premia? I now turn to the role of endogenously variable markups and markdowns in determining firm wage premia. To go from variable markups to constant markups, I switch the goods market conduct parameter from $\Gamma_g = 1$ to $\Gamma_g = 0$ (i.e. from oligopolistic competition to monopolistic competition). When going from variable markdowns to constant markdowns, I do the same with the labor market conduct parameter (Γ_h).

Firms' markups are important determinants of wage premia. Panel (B) of Table 7 shows how the variance of firm wage premia changes when markups and markdowns are constant. When firms charge constant markups, wage premia are 31% more dispersed. The increase in wage dispersion comes primarily from the top end of the wage premium distribution: the 99-90 ratio increases by 5 percentage points (p.p.) while the 50-10 ratio increases by 1 p.p. This is because markups at high-wage firms fall the most, leading to higher output and labor demand at these firms. The fall in markups also leads to a decline in goods market rents shared with workers, which tends to reduce wages. Overall, the output restriction effect dominates the rent-sharing effect, leading to higher wages.

The increase in wage dispersion is slightly larger when markups *and* markdowns both become constant, compared to when *only* markups become constant. In the latter, the expansion of high-wage firms also increases their labor market share, allowing them to mark down wages more, which partially erases the wage gains from lower markups. However, given the similarity of the calibrated within-market and across-market substitutability of jobs (η and ν), the increase in firms' labor market power is relatively small.

Aggregate wage gains. The last row in Table 7 shows that moving from variable to constant markups delivers substantial aggregate wage gains. The aggregate wage index (Φ) is 15% higher with constant markups than with variable markups. The wage gains are slightly larger when wage markdowns are also constant (17%). This finding suggests that the wage gains from greater product market competition are sizable and larger than the wage gains from greater labor market competition. Moreover, while greater product market competition leads to greater labor market power among high-wage firms when markdowns are variable, this offsetting effect of variable markdowns is small.

7.4 How do worker bargaining power and product market competition interact to shape wage levels and dispersion?

I show that in this model the impact of removing markup dispersion wage levels and wage premium dispersion depends on the level of workers' bargaining power. I also show that raising workers' bargaining power can generate comparable wage increases to removing markup dispersion, but with a smaller increase in wage premium dispersion.

Panel (A) of Table 8 compares the effects of removing markup dispersion under different levels of workers' bargaining power. When bargaining power is low, removing markup dispersion leads to a 15% increase in the aggregate wage index, but also a 31% increase in wage premium dispersion. When bargaining power is high, the wage gains and increase in wage premium dispersion become significantly smaller.

Why do the effects of equalizing markups depend on the level of workers' bargaining power? In Appendix C.3 I compare the market allocation to the social planner's allocation and show that workers' bargaining power simultaneously (i) transfers economic rents from firms to workers, (ii) reduces the effects of product and labor market power as a uniform tax on labor demand, and (iii) reduces the effects of markup and markdown dispersion in distorting the allocation of labor across firms. Equalizing markups across firms removes the misallocation effect of variable markups. When worker bargaining power is low, bargaining does little to affect the allocation of labor, so the market allocation of labor is far from the social planner's allocation. Therefore, the effects of equalizing markups on wage levels and dispersion is large. When worker bargaining power is high, bargaining does more to improve the allocation of workers to firms, forcing high-markup (high-wage) firms to share more rents as wages and employ more workers. Therefore, the market allocation of labor is closer to the social planner's allocation and the wage gains from removing markup dispersion is smaller.

Panel (B) of Table 8 shows that in this model increasing worker bargaining power (from a baseline of 0.06 to 0.16) achieves a comparable aggregate wage gain as equalizing markup dispersion, with a smaller increase in wage dispersion. To see why, I start by looking at the effects of raising bargaining power when both markups and markdowns are *constant* (second row in Panel (B)). The results show that higher bargaining power raises wage levels without increasing wage dispersion. Intuitively, when markups and markdowns are constant, they only act as a uniform tax on labor demand, but do not induce misallocation of labor. In this case, increasing bargaining power acts like a reduction in the uniform markup/markdown tax and redistributes profits from firms to workers, thereby raising labor demand and wages across all firms.

I now compare this case to the case when both markups and markdowns are variable (first row in Panel (B)). This comparison shows the extent of wage gains from higher bargaining power due to the improved allocation of workers to firms: a 2 p.p. higher wage gain and a 3 p.p. higher wage dispersion. This exercise suggests that the main source of wage gains from higher worker bargaining power comes from redistribution and a reduction in the uniform tax, although it also improves the allocation of labor across firms.

Table 8: Effects of wage bargaining power and product market competition on wage levels and wage dispersion.

Panel (A)	Counterfactual: constant markups	
Bargaining power (ρ)	Aggregate wage index (%Δ)	Variance of ϕ (%Δ)
Low ($\rho = 0.1$)	15	31
Med. ($\rho = 0.5$)	7	16
High ($\rho = 0.9$)	4	8

Panel (B)	Counterfactual: raise bargaining power (0.06 to 0.16)	
Markups & markdowns are ...	Aggregate wage index (%Δ)	Variance of ϕ (%Δ)
Both variable	16	3
Both constant	14	0

This table shows the percentage changes in the aggregate wage index and the variance of firm wage premia under two counterfactual exercises. Panel (A) equalizes markups across firms and compares its effects under different levels of worker bargaining power. Markdowns remain variable in these exercises. Panel (B) raises worker bargaining power by 10 p.p. above the baseline value.

8 Conclusion

This paper investigates the role of product market power in explaining why some firms pay higher wages than others. Using French administrative data, I estimate firm wage premia and firms' market power in labor and product markets. I then document novel empirical relationships that are inconsistent with existing monopsony models of the labor market. I account for these empirical patterns in a structural model where firms produce differentiated product varieties and share product market rents with workers.

Quantitatively, the model suggests four main reasons why product differentiation and product market power matter for wages. First, it shows that heterogeneity in product appeal is an important source of heterogeneity in wage premia. Second, the substitutability of product varieties affect the passthrough of productivity and product appeal in opposite directions. To the extent that process innovation raises productivity and product innovation raises product appeal, this finding suggests that these two types of innovation can have different wage passthrough effects. Third, although product market rents are partially shared with workers, variable markups dampen wage dispersion as they induce high-wage firms to restrict output. Fourth, workers' bargaining power redistributes product market rents from firms to workers and reduces the misallocation effects of variable markups. These findings suggest a potentially important role for profit-sharing schemes in redistributing rents and addressing inefficiencies from product market power. Such schemes are present in many countries, although their coverage and efficacy remains an open question (Batut and Rachiq, 2021).

Bibliography

Abowd, J., F. Kramarz, and D. Margolis (1999). High Wage Workers and High Wage Firms. *Econometrica 67*(2), 251–333.

Ackerberg, D., K. Frazer, and G. Caves (2015). Identification Properties of Recent Production Function Estimators. *Econometrica 83*(6), 2411–2451.

Alvarez, J., F. Benguria, N. Engbom, and C. Moser (2018). Firms and the Decline in Earnings Inequality in Brazil. *American Economic Journal: Macroeconomics 10*(1), 149–189.

Atkeson, A. and A. Burstein (2008). Pricing-to-Market, Trade Costs, and International Relative Prices. *American Economic Review 98*(5), 1998–2031.

Autor, D., D. Dorn, L. Katz, C. Patterson, and J. Van Reenen (2020). The Fall of the Labor Share and the Rise of Superstar Firms. *Quarterly Journal of Economics 135*(2), 645–709.

Azar, J., I. Marinescu, M. Steinbaum, and B. Taska (2020). Concentration in US Labor Markets: Evidence from Online Vacancy Data. *Labour Economics 66*, 1018–86.

Azkarate-Askasua, M. and M. Zerecero (2020). The Aggregate Effects of Labor Market Concentration. *Working paper*.

Bagger, J., B. Christensen, and D. Mortensen (2014). Productivity and Wage Dispersion: Heterogeneity or Misallocation. *Working paper*.

Barkai, S. (2020). Declining Labor and Capital Shares. *Journal of Finance 75*(5), 2421–2463.

Barlevy, G. (2008). Identification of Search Models using Record Statistics. *Review of Economic Studies 75*(1), 29–64.

Barth, E., A. Bryson, J. Davis, and R. Freeman (2016). It's Where You Work: Increases in Earnings Dispersion Across Establishments and Individuals in the US. *Journal of Labor Economics 34*(52), 67–97.

Batut, C. and C. Rachiq (2021). Employee Financial Participation Schemes in France and Europe. *Direction générale du Trésor, Report No. 286*.

Berger, D., K. Herkenhoff, and S. Mongey (2020). Labor Market Power. *Working paper*.

Bilal, A., N. Engbom, S. Mongey, and G. Violante (2019). Firm and Worker Dynamics in a Frictional Labor Market. *Working paper*.

Blackwood, G., L. Foster, C. Grim, J. Haltiwanger, and Z. Wolf (2021). Macro and Micro Dynamics of Productivity: From Devilish Details to Insights. *American Economic Journal: Macroeconomics 13*(3), 142–172.

Bond, S., A. Hashemi, G. Kaplan, and P. Zoch (2021). Some Unpleasant Markup Arithmetic: Production Function Elasticities and their Estimation from Production Data. *Journal of Monetary Economics 121*, 1–14.

Bonhomme, S., K. Holzheu, T. Lamadon, E. Manresa, M. Mogstad, and B. Setzler (2020). How Much Should We Trust Estimates of Firm Effects and Worker Sorting. *Working paper*.

Bonhomme, S., T. Lamadon, and E. Manresa (2019). A Distributional Framework for Matched Employer-Employee Data. *Econometrica 87*(3), 699–738.

Burdett, K. and D. Mortensen (1998). Wage Differentials, Employer Size, and Unemployment. *International Economic Review 39*(2), 257–273.

Cahuc, P., F. Postel-Vinay, and J. Robin (2006). Wage Bargaining with On-the-Job Search: Theory and Evidence. *Econometrica 74*(2), 323–364.

Caldwell, S. and O. Danieli (2019). Outside Options in the Labor Market. *Working paper*.

Caldwell, S. and N. Harmon (2019). Outside Options, Bargaining, and Wages: Evidence from Coworker Networks. *Working paper*.

Card, D., A. Cardoso, J. Heining, and P. Kline (2018). Firms and Labor Market Inequality: Evidence and Some Theory. *Journal of Labor Economics 36*(1), 13–70.

Card, D., F. Devicienti, and A. Maida (2014). Rent-sharing, Holdup, and Wages: Evidence from Matched Panel Data. *Review of Economic Studies 81*(1), 84–111.

Card, D., J. Heining, and P. Kline (2013). Workplace Heterogeneity and the Rise of West German Wage Inequality. *Quarterly Journal of Economics 128*(3), 967–1015.

Chan, M., S. Salgado, and M. Xu (2021). Heterogeneous Passthrough from TFP to Wages. *Working paper*.

Chen, Y., B. Hershbein, and Macaluso (2022). Monopsony in the US Labor Market. *American Economic Review 112*(7), 2099–2138.

Chetty, R. (2012). Bounds on Elasticities with Optimization Frictions: Synthesis of Micro and Macro: Evidence on labor Supply. *Econometrica 80*(3), 969–1018.

De Loecker, J., J. Eeckhout, and G. Unger (2020). The Rise of Market Power and the Macroeconomic Implications. *Quarterly Journal of Economics 135*(2), 561–644.

De Loecker, J. and P. Goldberg (2014). Firm Performance in a Global Market. *Annual Review of Economics 6*, 201–227.

De Loecker, J., P. Goldberg, A. Khandelwal, and N. Pavcnik (2016). Prices, Markups, and Trade Reform. *Econometrica 84*(2), 445–510.

De Loecker, J. and P. Scott (2016). Estimating Market Power: Evidence from the US Brewery Industry. *Working paper*.

De Loecker, J. and C. Syverson (2021). An Industrial Organization Perspective on Productivity. *Handbook of Industrial Organization IV*.

De Loecker, J. and F. Warzynski (2012). Markups and Firm-Level Export Status. *American Economic Review 102*(6), 2437–2471.

De Ridder, M., B. Grassi, and G. Morzenti (2021). The Hitchhiker's Guide to Markup Estimation. *Working paper*.

Deb, S., J. Eeckhout, A. Patel, and L. Warren (2022). Market Power and Wage Inequality. *Working paper*.

Di Addario, S., P. Kline, R. Saggio, and M. Solvsten (2020). It Ain't Where You're From, It's Where You're At: Hiring Origins, Firm Heterogeneity, and Wages. *Working paper*.

Dobbelaere, S. and J. Mairesse (2013). Panel Data Estimates of the Production Function and Product and Labor Market Imperfections. *Journal of Applied Econometrics 28*(1), 1–46.

Dube, A., J. Jacobs, S. Naidu, and S. Suri (2018). Monopsony in Online Labor Markets. NBER Working papers 24416, National Bureau of Economic Research.

Edmond, C., V. Midrigan, and D. Xu (2015). Competition, Markups, and the Gains from International Trade. *American Economic Review 105*(10), 3183–3221.

Edmond, C., V. Midrigan, and D. Xu (2018). How Costly are Markups? *Working paper No. 24800, National Bureau of Economic Research*.

Eeckhout, J. and P. Kircher (2011). Identifying Sorting – In Theory. *Review of Economic Studies 78*(3), 872–906.

Elsby, M. and A. Gottfries (2021). Firm Dynamics, On-the-Job Search and Labor Market Fluctuations. *Review of Economic Studies*.

Engbom, N., C. Moser, and J. Sauermann (2022). Firm Pay Dynamics. *Journal of Econometrics*.

Eslava, M., J. Haltiwanger, and N. Urdaneta (2023). The Size and Life-cycle Growth of Plants: The Role of Productivity, Demand and Wedges. *Review of Economic Studies*.

Faggio, G., K. Salvanes, and J. Van Reenen (2007). The Evolution of Inequality in Productivity and Wages: Panel Data Evidence. *Working paper 13351, National Bureau of Economic Research*.

Fougere, D., E. Gautier, and S. Roux (2016). Understanding Wage Floor Setting in Industry-Level Agreements: Evidence from France. *IZA discussion paper no. 10290*.

Garicano, L., J. Van Reenen, and C. Lelarge (2016). Firm Size Distortions and the Productivity Distribution: Evidence from France. *American Economic Review 106*(11).

Garin, A. and F. Silverio (2019). How Responsive are Wages to Demand within the Firm? Evidence from Idiosyncratic Export Demand Shocks. *Working paper*.

Gouin-Bonenfant, E. (2020). Productivity Dispersion, Between-Firm Competition, and the Labor Share. *Working paper*.

Gourio, F. and L. Rudanko (2014). Customer Capital. *Review of Economic Studies 81*(3), 1102–1136.

Haanwinckel, D. (2020). Supply, Demand, Institutions, and Firms: A Theory of Labor Market Sorting and the Wage Distribution. *Working paper*.

Jarosch, G., J. Nimczik, and I. Sorkin (2021). Granular Search, Market Structure, and Wages. *Working paper*.

Jäger, S., B. Schoefer, S. Young, and J. Zweimüller (2020). Wages and the Value of Nonemployment. *Quarterly Journal of Economics 135*(4), 1905–1963.

Kline, P., N. Petkova, H. Williams, and O. Zidar (2019). Who Profits from Patents? Evidence from Innovative Firms. *Quarterly Journal of Economics 134*(3), 1343–1404.

Kline, P., R. Saggio, and M. Solvsten (2020). Leave-Out Estimation of Variance Components. *Econometrica 88*(5), 1859–1898.

Kroft, K., Y. Luo, M. Mogstad, and B. Setzler (2021). Imperfect Competition and Rents in Labor and Product Markets: The Case of the Construction Industry. *Working paper*.

Krueger, A. and L. Summers (1988). Efficiency Wages and the Inter-Industry Wage Structure. *Econometrica 56*(2), 259–293.

Lamadon, T., M. Mogstad, and B. Setzler (2019). Imperfect Competition, Compensating Differentials, and Rent Sharing in the U.S. Labor Market. *Working paper*.

Le Barbanchon, T., R. Rathelot, and A. Roulet (2019). Unemployment Insurance and Reservation Wages: Evidence from Administrative Data. *Journal of Public Economics 171*, 1–17.

Levinsohn, J. and A. Petrin (2003). Estimating Production Functions Using Inputs to Control for Unobservables. *Review of Economic Studies 70*(2), 317–341.

MacKenzie, G. (2019). Trade and Market Power in Product and Labor Markets. *Working paper*.

Manning, A. (2011). Monopsony in Motion: Imperfect Competition in Labor Markets. *Princeton University Press*.

Melitz, M. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica 71*, 1695–1725.

Mertens, M. (2020). Micro-Mechanisms Behind Declining Labor Shares: Market Power, Production Processes, and Global Competition. *Working paper*.

Naouas, A. and F. Romans (2014). La négociation salariale d'entreprise de 2004 à 2010. *DARES report*.

Olley, S. and A. Pakes (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica 64*(6), 1263–1297.

Postel-Vinay, F. and J. Robin (2002). Equilibrium Wage Dispersion with Worker and Employer Heterogeneity. *Econometrica 70*(6), 2295–2350.

Rubens, M. (2021). Market Structure, Oligopsony Power, and Productivity. *Working paper*.

Schmieder, J., T. Von Wachter, and J. Heining (2018). The Costs of Job Displacement over the Business Cycle and Its Sources: Evidence from Germany. *Working paper*.

Schubert, G., A. Stansbury, and B. Taska (2019). Getting Labor Markets Right: Outside Options and Occupational Mobility. *Working paper*.

Slichter, S. (1950). Notes on the Structure of Wages. *Review of Economics and Statistics 32*(1), 80–91.

Song, J., D. Price, F. Guvenen, N. Bloom, and T. Von Wachter (2019). Firming Up Inequality. *Quarterly Journal of Economics 134*(1), 1–50.

Sorkin, I. (2018). Ranking Firms Using Revealed Preference. *Quarterly Journal of Economics 133*(3), 1331–1393.

Stole, L. and J. Zwiebel (1996). Intra-Firm Bargaining under Non-Binding Contracts. *Review of Economic Studies 63*(3), 375–410.

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

Van Reenen, J. (1996). The Creation and Capture of Rents: Wages and Innovation in a Panel of U.K. Companies. *Quarterly Journal of Economics 111*(1), 195–226.

Webber, D. (2015). Firm Market Power and the U.S. Earnings Distribution. *Labor Economics 35*, 123–134.

Wooldridge, J. (2009). On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables. *Economics Letters 104*(3), 112–114.

Online Appendix

Understanding High-Wage Firms

Horng Chern Wong
Department of Economics, Stockholm University
Email: horngchernwong@gmail.com

A Appendix: Data, Institutions, and Measurement

A.1 Wage determination in France

Wages in France are mainly determined at three levels of aggregation – the national level, the industry level, and the firm level. At the national level, the French government sets the national minimum wage. At the industry level, labor unions and employers' organizations negotiate industry wage floors. At the firm level, wage bargaining occurs between an individual firm and labor union representatives, representing the collective group of employees at the firm. This allows firms to depart upwards of the national minimum wage or industry wage floor.

The national minimum wage as of 2016 is 9.67 Euros per hour. In the same year, approximately 15% of workers in the French economy are minimum wage workers, defined as workers earning at, or at most 5% above, the minimum wage. In the manufacturing sector, on which the analysis in the paper is based, approximately 10% of workers are minimum wage workers.

Collective wage bargaining between individual firms and their employees is prevalent. The 1982 Auroux Laws require firms in which a labor union representative is present to bargain over wages with the union annually. Among firms with 50 employees or more, the presence of at least one union representative is a binding legal requirement.[34] According to the French Ministry of Labor, among firms with 20 to 49 employees, 34% had at least one labor union representative in 2010 (Naouas and Romans, 2014). Among firms with 11 to 19 employees, the corresponding number is 22%.

The vast majority of union-employer bargaining occurred at the firm level, rather than at the establishment level. Only 9% of multi-establishment firms negotiated wages with their employees at the establishment level. Among workers employed by firms with at least 20 employees, 70% of them are covered by firm level collective bargaining agreements. These collective bargaining agreements extend to all workers within the firm, regardless of whether the worker holds a union membership (Fougere, Gautier, and Roux, 2016).

[34] See Garicano, Van Reenen, and Lelarge (2016) for further details about the specific restrictions faced by firms with at least 50 employees.

A.2 Data and 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.

A.3 Summary statistics

	Employees	
Sample size		
People-years	9,233,319	
Firm-years	126,836	
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 9: Summary statistics: manufacturing sector employers and employees (2009-2016).

Table 10: Summary statistics for two-digit French manufacturing sectors.

Sector	# Observations	Sales share	Employment share	Average ϕ	Price-cost markups	Labor wedges
Textile	4,850	1.9%	2.3%	2.79	1.59	0.66
Apparel	3,157	1.6%	2.1%	2.76	1.73	0.64
Leather	1,433	0.5%	0.8%	2.74	1.68	0.92
Wood products (except furniture)	6,859	2.2%	2.8%	2.75	1.38	0.52
Paper	5,257	5.6%	4.8%	2.82	1.37	0.50
Recorded media	7,817	1.8%	2.6%	2.79	1.78	0.62
Chemicals	6,277	11.4%	7.8%	2.84	1.41	0.45
Pharmaceutical	380	2.5%	1.5%	2.94	1.46	0.29
Rubber & plastics	13,333	12.1%	13.3%	2.81	1.41	0.54
Non-metallic minerals	9,295	7.8%	7.7%	2.79	1.46	0.51
Basic metals	3,343	8.5%	6.0%	2.81	1.38	0.50
Fabricated metals (except machinery)	22,845	9.4%	11.9%	2.80	1.51	0.54
Computers, electronic, & optical	4,460	6.7%	7.1%	2.85	1.55	0.61
Electrical equipment	5,416	3.4%	3.8%	2.83	1.37	0.78
Machinery & equipment	12,785	7.5%	8.3%	2.83	1.30	0.42
Motor vehicles	4,189	7.5%	6.4%	2.83	1.28	0.53
Other transport equipment	948	2.9%	2.4%	2.85	1.47	1.43
Furniture	7,037	2.1%	3.1%	2.78	1.62	0.70
Other manufacturing	4,032	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	126,836	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 labor wedges in each sector.

B Appendix: Estimation

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 Robustness of 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 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 5, 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 5 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:

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

where $w_{it}^r = w_{it} - x_{it}'\hat{\beta}$ 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 6 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 6 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 7 and 8 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.

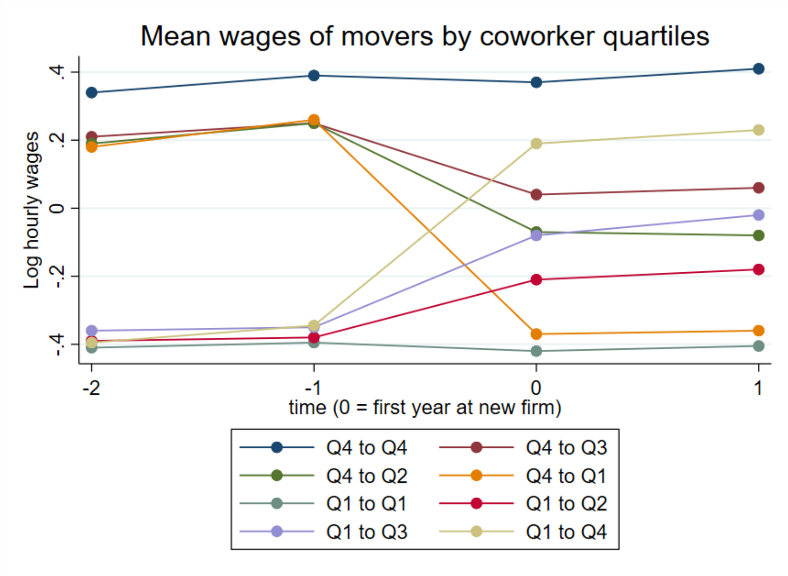

Figure 5: Worker mobility and wage changes by quartiles of coworker effects (2009-2016).

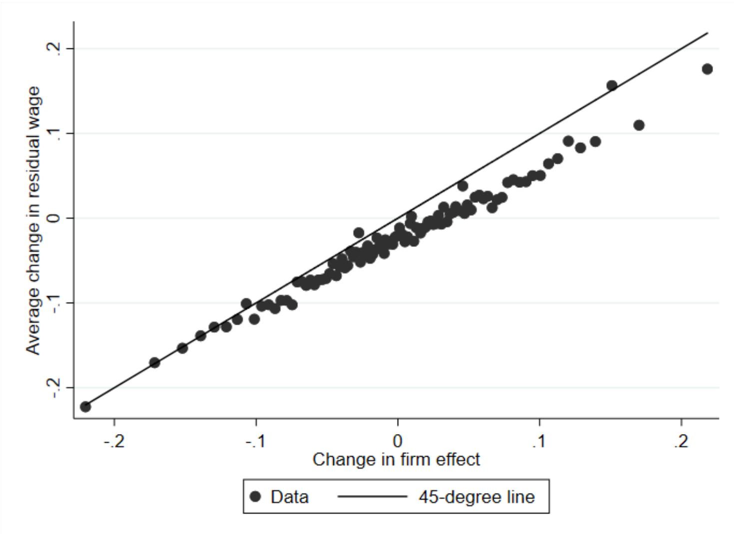

Figure 6: Average wage changes from worker mobility by declines of changes in firm premia (2009-2016).

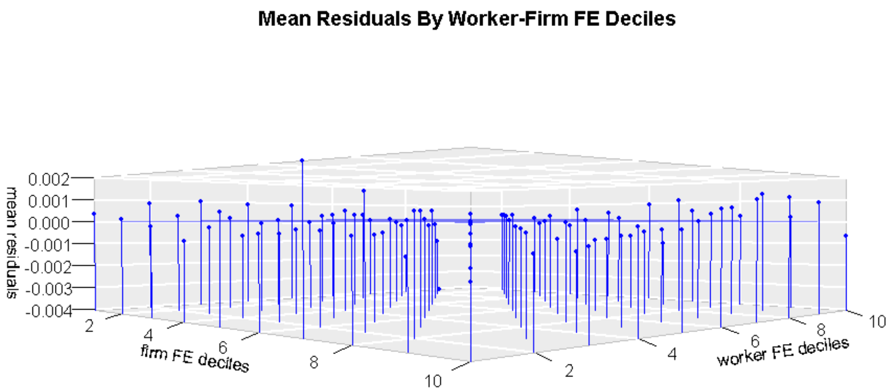

Figure 7: Mean estimated residuals by worker-firm deciles (2014)

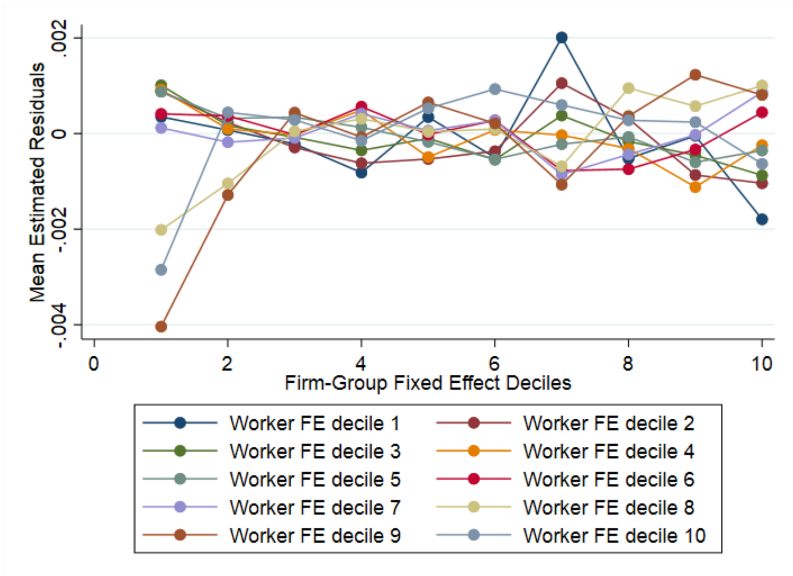

Figure 8: Mean estimated residuals by worker-firm deciles (2016)

B.3 Production function estimation: implementation

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

$$y_{jt} = \Psi_s(\tilde{k}_{jt}, h_{jt}, \tilde{m}_{jt}, \mu_{jt}, p_{jt}, \mathbf{Z}_{jt}; \beta, \zeta) + \epsilon_{jt} \tag{9}$$

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.[35]

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 $\{\beta, \zeta\}$:

$$\omega_{jt}(\beta, \zeta) = \hat{\Psi}_{jt} - f_s(\tilde{k}_{jt}, h_{jt}, \tilde{m}_{jt}; \beta) - B_s(\mathbf{p_x}(p_{jt}, \mathbf{Z}_{jt}), \tilde{\mathbf{x}}_{jt}, h_{jt}; \beta, \zeta) \tag{10}$$

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

$$\omega_{jt} = g_s(\omega_{jt-1}) + \varpi_{jt} \tag{11}$$

where $g_s(.)$ is a flexible function and ϖ_{jt} is a productivity shock.[36] Combining equation (6) and the law of motion for productivity (7), I obtain productivity shocks ϖ_{jt} as a function of the parameters of interest:

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

I then form the following moment conditions:

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

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,

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

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

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 production functions. I explain these choices below.

Which production function to estimate? The simplest production function to estimate is a sector-specific Cobb-Douglas function: $y = \beta_{k,s}k + \beta_{h,s}h + \beta_{m,s}m + \omega$. However, this restricts the output elasticities to a constant.[37] This imposes the constraint that within sectors labor elasticities of output are constant across firms. In addition, as equation (4) shows, in this case all variation in α_h are attributed to labor wedges, while variation in α_m 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, $B_s(\mathbf{p_x}(p_{jt}, \mathbf{Z}_{jt}); \beta)$, so output prices p_{jt} do not interact with input expenditures $\tilde{\mathbf{x}}_{jt}$. Under translog, $B_s(\mathbf{p_x}(p_{jt}, \mathbf{Z}_{jt}), \tilde{\mathbf{x}}_{jt}, h_{jt}; \beta, \zeta)$, 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.[38]

Which variables are inputs into production? The standard approach is to estimate a three-input production function with capital, labor, and intermediate inputs. The French firm balance sheet data reports two types of intermediate inputs – materials and services. I assume that materials are flexible intermediate inputs; services are typically part of firms' fixed overhead costs.

[37] 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.

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

B.4 Markups and labor wedges: assessment of input and output price biases

This section compares the estimated markups and labor wedges under various specifications that address one or each of the following: (i) demand shifters that may affect unobserved markups in the control function, (ii) output price bias, (iii) input price bias. In all specifications, the estimated production functions are translog. Table 11 reports the Pearson correlations between the estimated markups and labor wedges across specifications. Almost all pairwise correlations are above 0.90.

Table 11: Labor wedge correlations across specifications.

Labor wedges	(1)	(2)	(3)	(4)	(5)	Markups	(1)	(2)	(3)	(4)	(5)
(1)	1					(1)	1				
(2)	0.921	1				(2)	0.979	1			
(3)	0.898	0.975	1			(3)	0.968	0.989	1		
(4)	0.879	0.956	0.934	1		(4)	0.965	0.989	0.977	1	
(5)	0.919	0.998	0.974	0.959	1	(5)	0.980	0.993	0.988	0.990	1

This table correlates the estimated markups and labor wedges across different specifications: those that control for markup variation in the control function, address output price biases, and address input price biases. The correlations are Pearson correlations. Markups and labor wedges are trimmed by 1% on each side of the respective distributions. The specifications are:
(1): No markup controls, does not address output and input price biases.
(2): Only controls for markups.
(3): Only addresses output price bias.
(4): Controls for markups and addresses output price bias.
(5): Controls for markups and addresses output and input price biases.

B.5 Estimating labor wedges using hiring wages only

A caveat for the results presented in Section 5 is that firm wage premia and labor wedges are estimated for all workers; both new hires and incumbent workers. As discussed in Section 3, it may be important to allow the wages of incumbent workers to be determined separately from those of new hires. In this section, I estimate labor wedges using hiring wages only, following Di Addario et al. (2020). I do not take a stance on the wage-setting protocol for incumbent workers.

To repeat the main estimation exercise 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 across firms, I then compute the average worker ability at each firm 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, labor wedges are measured as follows:

$$\Lambda^n_{jt} = \frac{W^n_{jt}L_{jt}}{P_{jt}Y_{jt}} \cdot \mu_{jt} \cdot \alpha^{-1}_{h,jt}$$

Λ^n represents the labor wedges for new hires.

Table 12 below shows that the estimated price-cost markups are similar to those estimated using all workers in Table 2 in Section 5. However, the estimated labor wedges are lower in thise case: new hires are paid a lower share of their marginal revenue product than incumbent workers. This is consistent with the findings of Kline et al. (2019), who show that patent-induced labor productivity shocks pass through to incumbent workers' wages, but not the wages of new hires.

Table 12: Summary statistics for estimated firm wage premia and labor wedges 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
Λ	0.45	0.40	0.30	0.53	0.20	0.05	0.06
μ	1.49	1.38	1.18	1.68	0.07	0.04	0.02
# firms				12,826			

This table reports the summary statistics for estimated firm wage premia and labor wedges using hiring wages only (Di Addario et al., 2020). Variances are reported for the logarithms of those variables. 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. Markups and labor wedges are winsorized by 2%.

C Appendix: Theory

C.1 Firm wage premia with outside wages

As before, workers bargain collectively with their employer j and bargaining is efficient: workers and firms jointly choose wages, prices, materials, and capital to maximize total rents, taking into account the product demand curve and labor supply curve. Firms have an outside option of zero profits. The firm-specific labor supply curve is now $H_j = \mathcal{H}(\Phi_j - \Phi^o, A_j)$; workers do not supply labor unless firms pay at least the exogenous outside wage Φ^o. Workers and firms maximize the following Nash product:

$$\max_{\Phi_j, P_j, M_j, K_j} \Big((\Phi_j - \Phi^o)H_j\Big)^{\kappa} \Big(\Pi_j\Big)^{1-\kappa}$$

subject to $H_j = \mathcal{H}(\Phi_j - \Phi^o, A_j)$, $Y_j = \mathcal{G}(P_j, D_j)$, and $Y_j = \Omega_j F(K_j, M_j, H_j)$. The firm's profit is $\Pi_j = P_j Y_j - \Phi_j H_j - P_m M_j - P_k K_j$. The firm-specific wage premium is:

$$\Phi_j = \Phi^o + \kappa \underbrace{\left(\frac{P_j Y_j - P_m M_j - P_k K_j}{H_j} - \Phi^o\right)}_{\text{total rents per effective labor}} + (1-\kappa) \underbrace{\Big[\lambda_j (MRPH_j - \Phi^o)\Big]}_{\text{Monopsony rents accrued to workers}} \tag{12}$$

Equation (12) shows that the firm wage premium is again a weighted average of a pure bargaining outcome and a pure monopsony outcome. When $\kappa = 0$, workers receive a mark down of monopsony rents in addition to the outside wage. The markdown λ_j is determined by the firm-specific labor supply elasticity. In this case, workers do not receive rents from the firm's product market power. When $\kappa = 1$, workers receive the total amount of rents generated by firms' labor and product market power.

Firm wage premia can be written in exactly the same form as in equation (2). The labor wedge Λ_j in this case is:

$$\Lambda_j = \frac{1}{1 - (1-\kappa)(1-\lambda_j)\frac{\Phi^o}{\Phi_j}} \left[\kappa \left(1 - \frac{\alpha_{m,j} + \alpha_{k,j}}{\mu_j}\right) \frac{\mu_j}{\alpha_{h,j}} + (1-\kappa)\lambda_j\right] \tag{13}$$

Labor wages are therefore higher when workers have outside wages, all else equal.

Estimating workers' bargaining power. In Section 3, I proposed a control function approach to address unobserved variation in amenities when estimating bargaining power. The estimating equation assumed that outside wages are zero. I now adjust the estimating equation to account for positive outside wages. The adjusted estimating equation is:

$$\tilde{\Lambda}_{jst} = \kappa \mathcal{M}_{jst} + (1-\kappa)\lambda(\Phi_{jst}, \mathcal{A}(\Phi_{jst}, \Phi_{jst} H_{jst})) + \tilde{\epsilon}_{jst}$$

where $\tilde{\Lambda}_{jst} \equiv \frac{\Phi_{jst}-\Phi^o_{jst}}{MRPH_{jst}-\Phi^o_{jst}}$, $\mathcal{M}_{jst} \equiv \frac{\left(1-\frac{\alpha_{m,j}+\alpha_{k,j}}{\mu_j}\right)\frac{\mu_j}{\alpha_{h,j}}MRPH_{jst}-\Phi^o_{jst}}{MRPH_{jst}-\Phi^o_{jst}}$, and $\tilde{\epsilon}$ is a residual capturing measurement error. As in Section 3, I approximate the wage markdown function $\lambda(.)$ with a 4^{th}-order polynomial in wage premia and wage bills. The wage markdowns are then computed using the estimated bargaining parameter: $\lambda_{jst} = \frac{1}{1-\hat{\kappa}}\left(\tilde{\Lambda}_{jst}-\hat{\kappa}\mathcal{M}_{jst}-\hat{\tilde{\epsilon}}_{jst}\right)$.

Implementing the estimation procedure requires measuring the outside wage. One option is to set Φ^o equal to the level of unemployment benefits. However, Jäger et al. (2020) show that even large reforms to unemployment benefit levels in Austria did not materially affect wages. Similarly, Le Barbanchon et al. (2019) show that extending the potential unemployment benefit duration in France did not affect reservation wages reported by jobseekers. Given that the model implies that firms paying a wage below the outside wage will not be able to hire any workers, I set outside wages to the minimum observed wage within each 5-digit sector.

The estimated workers' bargaining power using this measure of outside wages is reported in Table 13. These estimates are similar to the ones that assume zero outside wages in Table 3. I then compute the implied monopsonistic wage markdown, taking the estimated bargaining power in column (4) of Table 13. The wage markdowns at the average firm is 0.55 under $\Phi^o = 0$ in Table 4. The markdowns at the average firm computed with the current measure of Φ^o is 0.44, around 10p.p. lower. That is, the implied labor supply elasticity to the average firm in the former is 1.22, while in the latter it is 0.79.

Table 13: Estimated workers' bargaining power (when workers have outside wages).

$\tilde{\Lambda}_{jst}$	(1)	(2)	(3)	(4)
$\mathcal{M}_{jst}$	0.065	0.065	0.083	0.083
	(0.011)	(0.011)	(0.012)	(0.012)
Year fixed effects	Yes	Yes	Yes	Yes
Sector fixed effects	No	Yes	No	Yes
Variation	firms	firms	firm-groups	firm-groups
Number of firms		126,836		

This table reports the estimated workers' bargaining power parameter. In column (2), sector fixed effects are at the 5-digit level. In column (4), sector fixed effects are at the 2-digit level, since firm-groups are constructed within 2-digit sectors. Robust standard errors are reported in parentheses.

Table 14: Comparing wage markdowns across high-wage and low-wage firms (when workers have outside wages).

Summary statistics	Mean	Median	25^{th} Pct	75^{th} Pct	Var	Var (i)	Var (ii)
Markdowns (λ)	0.44	0.39	0.30	0.49	0.07	0.05	0.03

This table reports the summary statistics in 2016 for the estimated monopsonistic/oligopsonistic wage markdowns. Wage markdowns are computed using the estimated bargaining parameter κ from specification (4) in Table 13. The variance is for $\log \lambda$. 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. Each variable is winsorized by 2%.

C.2 Firm wage premia with Stole & Zwiebel (1996) bargaining

Consider a setting in which firms bargain individually with their employees. Workers supply one unit of labor inelastically. Firms produce goods with only labor inputs. The labor market is characterized by search frictions. Firms post vacancies V_j subject to a convex vacancy posting cost $c(V_j)$. The product market is imperfectly competitive; firms face the following product demand curve $Y_j = P_j^{-\sigma}$. The production function is $Y_j = \Omega_j H_j^{\alpha_h}$. There are no idiosyncratic shocks to firms. Firms steady state size is $H_j = \frac{q}{\delta} V_j$, where q is the job-filling rate and δ is the separation rate. Firms post vacancies to maximize profits:

$$\max_{V_j} \; P_j Y_j - \Phi_j H_j - c(V_j)$$

subject to the product demand curve and the firm size constraint. The solution to the Stole and Zwiebel (1996) bargaining problem is then:

$$(1-\kappa)(\Phi_j - \Phi_j^o) = \kappa (MRPH_j - \frac{\partial \Phi_j}{\partial H_j} H_j - \Phi_j)$$

Solving this differential equation yields the following firm wage premium equation:

$$\Phi_j = \left(\frac{\kappa \mu \alpha_h^{-1}}{(1-\kappa)\mu\alpha_h^{-1} + \kappa} \right) MRPH_j + (1-\kappa)\Phi^o \tag{14}$$

where markups are constant $\mu = \frac{\sigma}{\sigma - 1}$ and the marginal revenue product of labor is $MRPH_j = \mu^{-1} \alpha_h \frac{P_j Y_j}{H_j}$.

Comparison with collective (efficient) bargaining. When $\alpha_k = \alpha_m = 0$ and labor supply is completely inelastic (as is the case when deriving equation (14) under Stole-Zwiebel bargaining), the firm wage premium equation (12) becomes:

$$\Phi_j = \kappa \mu \alpha_h^{-1} MRPH_j + (1-\kappa)\Phi^o \tag{15}$$

Comparing equation (15) with equation (14) shows that, under collective (efficient) bargaining, workers are able to extract a higher share of $MRPH$ as wages than under individual bargaining, since $\frac{1}{(1-\kappa)\mu\alpha_h^{-1}+\kappa} < 1$.

C.3 Social planner's allocation

I now define a social planner's equilibrium to assess the implications of collective bargaining for the efficiency of the decentralized market equilibrium. The social planner chooses capital, materials, and labor at each firm to maximize household utility, subject to the same preferences, production technologies, and aggregate resource constraint as the decentralized market economy. The planner's problem:

$$\max_{H_j, K_j M_j} \; C - \frac{H^{1+\varphi}}{1+\varphi}$$

subject to:

$$C + K + M = Y, \qquad Y = \left[\int_0^1 \tilde{D}_s^{\frac{1}{\theta}} Y_s^{\frac{\theta-1}{\theta}} \, ds\right]^{\frac{\theta}{\theta-1}}, \qquad Y_s = \left(\sum_{j\in s} \tilde{D}_{js}^{\frac{1}{\sigma}} Y_{js}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

$$K = \int_s \sum_{j\in s} K_{js} \, ds, \qquad M = \int_s \sum_{j\in s} M_{js} \, ds, \qquad Y_{js} = \Omega_{js} K_{js}^{\alpha_k} M_{js}^{\alpha_m} H_{js}^{\alpha_h}$$

$$H = \left[\int_0^1 \tilde{A}_s^{-\frac{1}{\nu}} H_s^{\frac{\nu+1}{\nu}} \, ds\right]^{\frac{\nu}{1+\nu}}, \qquad H_s = \left(\sum_j \tilde{A}_{js}^{-\frac{1}{\eta}} H_{js}^{\frac{\eta+1}{\eta}}\right)^{\frac{\eta}{\eta+1}}$$

The planner's aggregate and firm-level labor allocations are characterized by:

$$H^{\varphi} = \underbrace{\alpha_h \frac{Y}{H}}_{MPL} \qquad \text{and} \qquad H^{\varphi}\left(\frac{H_{js}}{H_s}\right)^{\frac{1}{\eta}}\left(\frac{H_s}{H}\right)^{\frac{1}{\nu}} = \underbrace{\alpha_h \frac{Y_{js}}{H_{js}}}_{MPL_{js}} \tilde{D}_s^{\frac{1}{\theta}} \tilde{D}_{js}^{\frac{1}{\sigma}} \left(\frac{Y_{js}}{Y_s}\right)^{-\frac{1}{\sigma}} \left(\frac{Y_s}{Y}\right)^{-\frac{1}{\theta}}$$

Table 15: Labor allocation in the decentralized and social planner's equilibrium.

	Decentralized equilibrium	Planner's equilibrium
Aggregate labor demand	$\Phi = H^{\varphi} = \frac{\Lambda}{\mu}\mathbf{\Theta}\alpha_h \frac{Y}{H}$	$H^{\varphi} = \alpha_h \frac{Y}{H}$
Firm-level labor demand	$\Phi_{js} = \Phi \tilde{A}_{js}^{-\frac{1}{\eta}} \tilde{A}_s^{-\frac{1}{\nu}} \left(\frac{H_{js}}{H_s}\right)^{\frac{1}{\eta}} \left(\frac{H_s}{H}\right)^{\frac{1}{\nu}}$ $= \frac{\Lambda_{js}}{\mu_{js}} \alpha_h \frac{P_{js}Y_{js}}{H_{js}}$	$H^{\varphi} \tilde{A}_{js}^{-\frac{1}{\eta}} \tilde{A}_s^{-\frac{1}{\nu}} \left(\frac{H_{js}}{H_s}\right)^{\frac{1}{\eta}} \left(\frac{H_s}{H}\right)^{\frac{1}{\nu}}$ $= \alpha_h \frac{Y_{js}}{H_{js}} \tilde{D}_s^{\frac{1}{\theta}} \tilde{D}_{js}^{\frac{1}{\sigma}} \left(\frac{Y_{js}}{Y_s}\right)^{-\frac{1}{\sigma}} \left(\frac{Y_s}{Y}\right)^{-\frac{1}{\theta}}$
Firm-level capital demand	$P_{k,js} = e^{\tau_{js}} = \mu_{js}^{-1} \alpha_k \frac{P_{js}Y_{js}}{K_{js}}$	$1 = \alpha_k \frac{Y_{js}}{K_{js}} \tilde{D}_s^{\frac{1}{\theta}} \tilde{D}_{js}^{\frac{1}{\sigma}} \left(\frac{Y_{js}}{Y_s}\right)^{-\frac{1}{\sigma}} \left(\frac{Y_s}{Y}\right)^{-\frac{1}{\theta}}$
Firm-level material demand	$P_m = 1 = \mu_{js}^{-1} \alpha_m \frac{P_{js}Y_{js}}{M_{js}}$	$1 = \alpha_m \frac{Y_{js}}{M_{js}} \tilde{D}_s^{\frac{1}{\theta}} \tilde{D}_{js}^{\frac{1}{\sigma}} \left(\frac{Y_{js}}{Y_s}\right)^{-\frac{1}{\sigma}} \left(\frac{Y_s}{Y}\right)^{-\frac{1}{\theta}}$

The decentralized market allocation coincides with the social planner's input allocation when firms take output prices and wages as given. To see this, Table 15 compares the first-order conditions associated with each factor input. Let $\mathbf{\Theta}$ denote a misallocation wedge on aggregate labor demand:

$$\mathbf{\Theta} = \int_s \left[\sum_{j \in s} \left(\frac{\Lambda_{js}/\Lambda}{\mu_{js}/\mu} \right) \frac{P_{js}Y_{js}}{P_sY_s} \right] \frac{P_sY_s}{PY} \, ds$$

where $\mathbf{\Theta} = 1$ if there is no dispersion in the labor wedge ($\Lambda_{js} = \Lambda$) and price-cost markups ($\mu_{js} = \mu$), and $\mathbf{\Theta} < 1$ if larger firms have lower labor wedges and charge higher markups. The wedge $\Lambda \equiv \kappa\big(1 - \frac{\alpha_k + \alpha_m}{\mu}\big)\frac{\mu}{\alpha_h} + (1-\kappa)\lambda$ is defined as the common labor wedge when price-cost markups and wage markdowns are constant across firms: $\mu \equiv \frac{\sigma}{\sigma - 1}$ and $\lambda = \frac{\eta}{1+\eta}$. That is, when firms behave monopolistically in the goods market and monopolistically in the labor market.

Comparing the aggregate labor demand and firm-level input demand conditions in Table 15 shows that both the dispersion and the level of markups and labor wedges distort aggregate employment and firm-level input allocations in the decentralized equilibrium away from the planner's choice. The social planner chooses the allocation of labor across firms such that the marginal product of labor intersects the firm-specific labor supply curve. Similarly, the planner chooses capital and materials such that their marginal revenue products are equalized across firms. When there is no dispersion in markups and markdowns, there is no labor misallocation ($\mathbf{\Theta} = 1$); the common labor wedge (Λ) and common markup (μ) act as a uniform tax on aggregate labor demand.

How does worker bargaining power affect the efficiency of labor allocation in the decentralized equilibrium? To simplify, suppose that $\tau_{js} = 1$. Suppose workers have full bargaining power ($\kappa = 1$). The firm-specific labor wedge becomes $\Lambda_{js} = \big(1 - \frac{\alpha_k + \alpha_m}{\mu_{js}}\big)\frac{\mu_{js}}{\alpha_h}$ and aggregate labor demand in the decentralized equilibrium is characterized by:

$$\begin{aligned} \Phi &= \frac{Y}{H} \left\{ \int_s \left[\sum_{j \in s} \left(1 - \frac{\alpha_k + \alpha_m}{\mu_{js}} \right) \frac{P_{js}Y_{js}}{P_sY_s} \right] \frac{P_sY_s}{PY} \, ds \right\} \\ &= \alpha_h \frac{Y}{H} \left\{ \int_s \left[\sum_{j \in s} \left(\frac{1 - \frac{\alpha_k + \alpha_m}{\mu_{js}}}{1 - \alpha_k - \alpha_m} \right) \frac{P_{js}Y_{js}}{P_sY_s} \right] \frac{P_sY_s}{PY} \, ds \right\} \end{aligned}$$

Note that full worker bargaining power implies that firms make zero profits. However, this does not deliver the social planner's labor demand condition. Under full worker bargaining power, the wedge between the aggregate wage Φ and the aggregate marginal product of labor $\alpha_h \frac{Y}{H}$ represents a subsidy instead of a tax, since $\big(\frac{1 - \frac{\alpha_k + \alpha_m}{\mu_{js}}}{1 - \alpha_k - \alpha_m}\big) \geq 1$. That is, because bargaining allows workers to capture rents from product market power, it partially offsets firms' incentives to restrict production and thereby, employment of labor. Nevertheless, because markups distort also distort firms' demand for capital and materials, full bargaining power does not restore the social planner's capital and material input choice.

However, when firms possess labor market power, but not product market power, full worker bargaining power restores the social planner's equilibrium. To see this, suppose that firms take output prices as given ($\mu_{js} = 1$), but they still have labor market power ($\lambda_{js} < 1$). Then, the aggregate labor demand condition in the decentralized equilibrium coincides with the planner's condition. Since wage markdowns now represent the only distortion to labor demand, and capital and material demands are no longer distorted, full worker bargaining power restores the social planner's equilibrium.

D Appendix: Additional Tables and Figures

Table 16: Competition and the direct component of shock passthrough.

Shocks	$\sigma = 1.1$	$\sigma = 5$	$\sigma = 10$	$\eta = 1$	$\eta = 5$	$\eta = 10$
Δ TFPQ	0.05	1.05	1.52	1.27	0.65	0.41
Δ product appeal	0.46	0.26	0.17	0.23	0.12	0.08
Δ amenity	-0.46	-0.26	-0.17	-0.23	-0.12	-0.08

This table reports the size of the *direct* component of shock passthrough under different degrees substitutability of product varieties and jobs. The passthrough measures are with respect to a positive 1% shock. When varying σ in the first three columns, η is kept at the baseline calibrated value of 1.14. When varying η in the last three columns, σ is kept at the baseline calibrated value of 6.54.

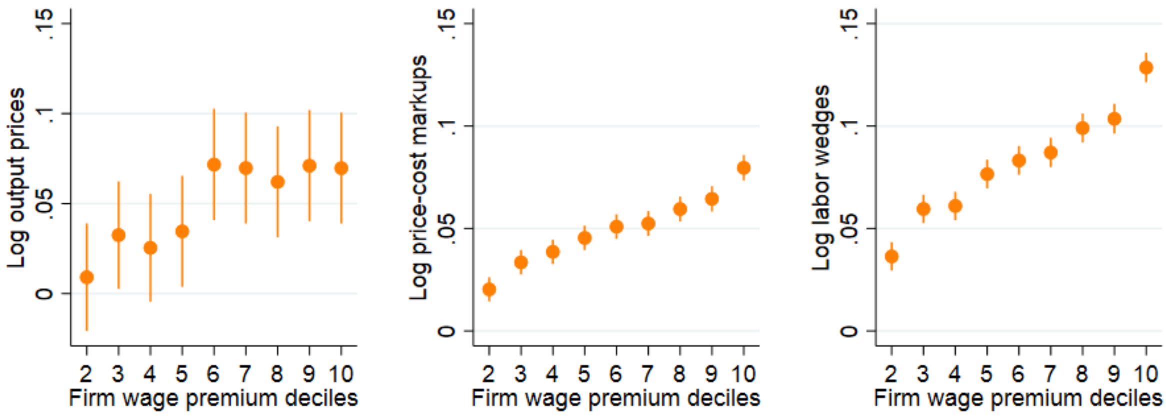

Figure 9: Output prices, markups, and labor wedges by high-wage status.

Notes: This figure shows how quantity TFP, output prices, price-cost markups, and labor wedges vary by deciles of firm wage premia relative to firms in the first decile (low-wage firms). These are unconditional correlations. Decile 10 represents high-wage firms. Confidence intervals at the 95% level are plotted.

Table 17: Correlations between firm wage premia and the sources of firm heterogeneity.

	Wage premium	TFPQ	Appeal	Amenity
Wage premium (ϕ_{js})	1.00	0.11	0.13	0.28
TFPQ (ω_{js})	0.11	1.00	-0.36	0.09
Product appeal (d_{js})	0.13	-0.36	1.00	0.28
Non-wage amenity (a_{js})	0.28	0.09	0.28	1.00

This table reports the Pearson correlation coefficients between estimated firm wage premia, estimated TFPQ, measured product appeal, and measured non-wage amenities in 2016. Variables are in logs.

E Appendix: Extension with Two Skill Groups

As discussed in Section 2.3, one limitation of the current analysis is that the model does not explain the sorting of workers of different skills to firms of different productivity. To relax this assumption, I extend the analysis in Section 5 to a setting with a high-skilled and a low-skilled occupation with different degrees of complementarity with firm productivity. 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).

Estimating firm wage premia. Let the subscript $s = \{h, l\}$ denote high and low-skilled labor. The estimation procedure is as described in Section 3.2. However, firm-group effects are now occupation-specific:

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

where i denotes the individual, j denotes the firm, $g(j)$ denotes the group of firm j at time t, $s(i,t)$ denotes worker i's occupational group at time t, ι_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:

$$y_j = f(\tilde{n}_j, k_j, m_j) + \omega_j$$

I approximate $f(.)$ with a translog functional form, where k denotes capital, m denotes materials, and $\tilde{n}$ denotes the total amount of effective labor at firm j. Following Lamadon et al. (2019), I assume that the efficiency of each skill group $e_{h,j}$ and $e_{l,j}$ are firm-specific. If e_h and ω are positively correlated, then more productive firms hire more high-skilled workers – positive sorting. With a slight abuse of notation, let $h_j = e_{h,j} + n_{h,j}$ and $l_j = e_{l,j} + n_{l,j}$ now denote high-skilled and low-skilled labor in efficiency units, where n_h and n_l denote total hours in each skill group.

Skill-group-specific worker efficiency can be measured as the difference between the skill-group-specific average wage at a firm j and the corresponding firm wage premium, $\bar{w}_{s,j} = e_{s,j} + \phi_{s,g(j)}$ where $s = \{h, l\}$. All lowercase letters are in logs. The firm-specific high-skilled and low-skilled labor wedges can be measured as:

$$\Lambda_{h,j} = \left(\frac{W_{h,j}N_{h,j}}{P_m M_j}\right)\left(\frac{\alpha_{m,j}}{\alpha_{n,j}}\right)\left(\frac{H_j + L_j}{H_j}\right)$$

$$\Lambda_{l,j} = \left(\frac{W_{l,j}N_{l,j}}{P_m M_j}\right)\left(\frac{\alpha_{m,j}}{\alpha_{n,j}}\right)\left(\frac{H_j + L_j}{L_j}\right)$$

I then estimate the skill-group-specific wage bargaining power (κ_h, κ_l) following the same approach as in Section 3.

Main results. Table 18 reports the estimated firm wage premia, labor wedges, and wage markdowns by skill group. Comparing the first and second rows shows that high-skilled workers receive higher wages, but have similar wage dispersion. Comparing the third and fourth rows shows that high-skilled workers obtain a substantially larger share of their marginal revenue productivity than do low-skilled workers.

Table 18: Summary statistics for estimated firm wage premia, labor wedges, and monopsony markdowns by skill group in 2016.

Panel A	Mean	Median	25^{th} Pct	75^{th} Pct	Var
ϕ_h	2.87	2.88	2.81	2.92	0.01
ϕ_l	2.26	2.26	2.21	2.32	0.01
Λ_h	0.83	0.74	0.57	0.98	0.17
Λ_l	0.49	0.43	0.28	0.62	0.37
λ_h	0.50	0.49	0.40	0.58	0.07
λ_l	0.47	0.48	0.38	0.56	0.15

This table reports the summary statistics for estimated firm wage premia, labor wedges, and wage markdowns by skill group. Variances are for the log of the corresponding variable. Wage markdowns are computed using the estimated bargaining power parameters in specifications (2) and (4) in Table 19 as the baseline.

Before measuring the monopsony markdowns, I first estimate the bargaining power for each skill group. Table 19 report the estimates. Comparing columns (2) and (4), I find that high-skilled workers obtain about 18% of the economic rents, while low-skilled workers obtain only 1%. The fifth and sixth rows of Table 18 reports the distribution of monopsony markdowns received by each skill group. The markdowns are similar between the two skill groups. Therefore, the implied labor supply elasticities are also similar.

Finally, I compare how labor wedges vary across deciles of firm wage premia. Firm wage premia are within firm weighted averages of the skill-specific firm wage premium at a given firm, with weights being the employment share of a given skill-group in the firm. Figure 10 presents the findings. Consistent with the finding that high-skilled workers have a higher bargaining power, labor wedges of high-skilled workers are increasing in wage premia, while labor wedges of low-skilled workers are decreasing in wage premia.

At the same time, the skill wage premium, defined as the ratio of average high-skill wages to average average low-skill wages, is larger among high-wage firms.

Table 19: Estimated workers' bargaining power.

Labor wedge	High-skilled		Low-skilled	
	(1)	(2)	(3)	(4)
$\tilde{\mu}_j$	0.247	0.180	0.149	0.010
	(0.002)	(0.004)	(0.007)	(0.003)
Year fixed effects	Yes	Yes	Yes	Yes
Sector fixed effects	No	Yes	No	Yes
Number of firms	114,950			

This table reports the estimated workers' bargaining power by skill group. Sector fixed effects are at the 2-digit level since firm-groups are constructed within 2-digit sectors. Robust standard errors are reported in parentheses.

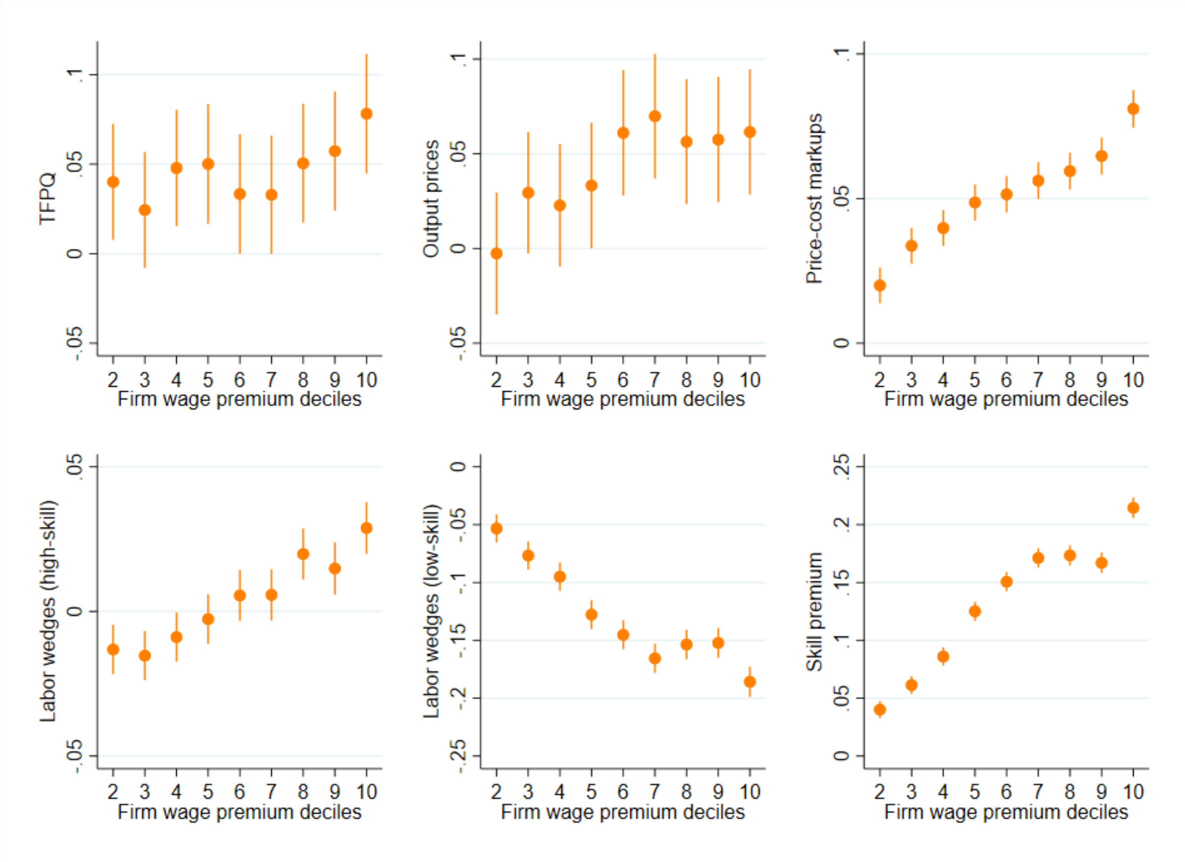

Figure 10: Output prices, markups, and labor wedges by skill and high-wage status, conditional on quantity TFP.

Notes: This figure shows how quantity TFP, output prices, price-cost markups, labor wedges, wage markdowns, and skill wage premium vary by deciles of firm wage premia relative to firms in the first decile, controlling for TFPQ, year fixed effects and 5-digit sector fixed effects. All variables are in logs. Firm wage premia are constructed at the firm level by computing weighted average of skill-specific wage premia within firms, with the weights being the employment share of each skill-group within the firm. Decile 10 represents high-wage firms. Confidence intervals at the 95% level are plotted.