Trends in Worker Bargaining Power

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Abstract

This paper examines trends in worker bargaining power in the United States and France. I find that bargaining power has shifted in favor of firms over the last decades, with a consistent trend observed in both countries. These patterns help explain recent dynamics of unemployment and labor share uncovering that firms leveraged their negotiation position to hire an inefficiently high number of employees. Policy interventions, such as marginal taxes on wage and profit, can restore labor market efficiency. Perhaps surprisingly, factors such as technology, competition, trade, and outsourcing appear to have a limited contribution on the decline in bargaining power. However, gender and occupation disparities are pivotal, with male and non-routine workers experiencing the most pronounced reduction in bargaining power.

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1 Introduction

The labor share in developed economies has declined over the last four decades: wages stagnated even though productivity has been increasing (Karabarbounis and Neiman, 2014, Greenspon et al., 2021). At the same time, firm profitability increased. These trends draw attention to how employers and workers share economic surplus and whether it has changed over time. While this is a central question in macroeconomics, its answer requires overcoming significant empirical challenges.

With this aim, I study workers' ability to capture the surplus they generate in their compensation, namely *worker bargaining power*. I use a heterogeneous firm model with wage negotiation to derive a structural equation that links wages to firm productivity. Through this equation, I then estimate worker bargaining power leveraging granular firm and employer-employee data. I find an average worker bargaining power of 17% in the United States and 25% in France. My estimates reveal a considerable imbalance among parties in the wage negotiation process in favor of employers, holding a bargaining power of 83% and 75% in the U.S. and France, respectively. When estimating it over time, I find that bargaining power is not constant; on the contrary, it has been declining in the U.S. and France since the 90s. In the U.S., worker bargaining power followed a hump-shaped trend: it was 16% in the 60s, then grew until peaking at more than 30% in the 80s, and after that, it declined almost linearly to its lowest level, 15%, in the 2010s. In France, on the other hand, it was around 40% in the mid-90s and decreased to 20% in 2019.

These estimates can help account for key recent macroeconomic trends. In a calibration exercise, I show that a decrease in bargaining power leads to a new equilibrium with lower unemployment and labor share. Specifically, I quantify that the observed decline in worker bargaining power alone can account for around 85% of the recent changes in unemployment and labor share in the U.S. economy. Using the theoretical framework, I further show that firms hire an inefficiently high number of workers leveraging their bargaining power. Therefore, I propose wage and profit taxes as policy interventions aimed at reducing the negative externalities generated by firms' behavior and restoring efficiency in the labor market. Finally, I exploit the granularity of the data to shed light on the sources of the decline in bargaining power. Suggestive evidence points to gender and occupation as the most critical margins behind the aggregate decline suggesting that technology, competition, trade, and outsourcing had only a small contribution. In what follows, I discuss these contributions in detail.

To guide my empirical analysis, I introduce firm heterogeneity into a workhorse model with random search frictions in the labor markets à la Diamond (1982), Mortensen (1982), and Pissarides (1985). In this framework, firms need to employ workers to produce but cannot hire them directly: they have to post vacancies in the labor market. Workers are searching for jobs and finding vacancies with an endogenous probability. When a match between a firm and an unemployed worker occurs, wage negotiation takes place. Such a negotiation defines the split of the surplus that both parties gain from the match, and the way it is shared depends on the bargaining power that workers and employers have. In equilibrium, wages are therefore determined by the sum of three components: the marginal productivity of labor, worker outside option, and labor market conditions. Conditioning on the latter, worker bargaining power determines the productivity level reflected in labor compensation.

I bring this structural relationship to the data and obtain estimates of time-varying worker bargaining power with minimal changes from the standard version of models with random search frictions. Estimating the wage equation presents several challenges: first, it includes unobservable terms such as indicators of marginal productivity, worker outside options, and labor market conditions; and second, wages are an equilibrium outcome that leads to an inherited simultaneity problem. I solve these problems with a combination of control function approach, instrumental variables, and fixed effects. More specifically, I estimate firms' production function using the method initially proposed by Olley and Pakes (1996) and recently used in the analysis of markups (De Loecker et al., 2020). This structural method relies on the idea that although productivity is unobservable in the data, it is possible to control for it after imposing that firms behave optimally. In this sense, the observed input choices are assumed to be the outcome of an optimization process and thus can be used to infer firm productivity indirectly. I provide several robustness checks to functional form misspecification, the presence of market power in the product market, and omitted output and input price biases (De Loecker et al., 2016, Bond et al., 2021, De Ridder et al., 2022). I use the estimates of the production function to construct a model-consistent indicator of worker productivity, and I instrument it with its lagged realizations to address the endogeneity issue. In doing so, I exploit the stochastic process of productivity and the flexibility of wage negotiation. Indeed, both in the model and the control function approach, productivity is assumed to have a Markov structure, and wages are renegotiated period by period between workers and employers. Hence, under these assumptions, lagged productivity is a valid instrument and allows me to estimate the pass-through to wages.[1] Finally, I use a rich set of fixed effects to control for labor market conditions.[2]

I apply these methods to data on U.S. firms from Compustat and rich administrative matched employer-employee data from France. The former offers financial information on all publicly listed firms in the U.S. for which wage information has been available over the last 60 years. With the aim of analyzing the most extended possible period, it thus offers a unique time coverage for firm-level data allowing to analyze the U.S. labor market for over half a century. Administrative French data, on the other hand, include matched employer-employee information on the universe of private firms and workforce in the French economy since the mid-90s. Hence, they allow to include a richer worker dimension in the analysis to investigate heterogeneous bargaining power and shed light on the sources of its decline. These two datasets are complementary as they allow me to uncover an aggregate phenomenon in two of the largest economies in the world.

[1] Results are robust to using additional lags in productivity, current shocks, or focusing only on new hires.

[2] Although restrictive on the cross-sectional variation, I show that relaxing this assumption does not change the findings of the paper.

Armed with these time-varying estimates of bargaining power, I feed them back into the theoretical framework to study how changes in bargaining power affect the labor market. In the model, a decline in worker bargaining power has first a direct effect on wages pushing them downward, closer to their outside option. As a result, firms now face lower labor costs and want to hire more workers; thus, they respond by posting more vacancies. This increase in vacancies makes the market tighter, indirectly pushing wages upwards.[3] To analyze the quantitative implications for the economy, I calibrate the model to the period with the highest bargaining power in the U.S. and France and then simulate a change in its value to its current level. The response of the economies leads to a new steady state with lower unemployment and labor share, implying that the direct effect of wages is stronger than the indirect one through vacancy posting. This result is crucial for understanding recent developments in the U.S. and France in the labor markets.

I use the model to analyze the labor market's efficiency by comparing the decentralized equilibrium with a constrained efficient one. A well-known result in this class of models is that (constrained) efficiency is reached when firm bargaining power equals the elasticity of matches to vacancies (Hosios, 1990).[4,5] However, being this a knife-edge condition, there is no a priori reason why it should hold in the data, and, indeed, it does not, thus implying that firms do not internalize the frictions in the labor market in their behavior. Building on this, I propose policy instruments such as marginal taxes on wages and profits to restore efficiency. Intervening with marginal taxes makes firms internalize the effect of posting new vacancies on the labor market and leads the economy towards an efficient level of unemployment. Given the extreme asymmetry in importance between employers and employees in wage negotiations, such interventions have to be very large.

Finally, after having unraveled how worker bargaining power evolved in the U.S. and France and shed light on its implications on the economy, I provide suggestive evidence about the sources of the recent decline in worker bargaining power. In doing so, I exploit the information in the matched employer-employee data in France to understand which firm or worker characteristics could drive this aggregate phenomenon. Surprisingly, factors such as technology (Schivardi and Schmitz, 2020, Kirov and Traina, 2021, Leduc and Liu, 2022), competition (Autor et al., 2020), trade (Autor et al., 2013), and outsourcing (Bilal and Lhuillier, 2021) seem to have little role in the erosion of worker bargaining power. However, the evolution of bargaining power presents significant differences when looking at the gender and occupation composition of the workforce as well as at managers' education. In line with recent evidence (Card et al., 2016, Biasi and Sarsons, 2022, Roussille, 2021), I find that the bargaining power of male employees is more than double that of female workers. Interestingly, this *gender bargaining power gap* has been shrinking in recent years, with female

[3]This *congestion externality* arises as a new vacancy decreases the probability of finding a worker for other firms, thus resulting in the upward-sloping relation between wages and the vacancy-to-unemployment ratio, the so-called *wage curve*.

[4]Or, equivalently, worker bargaining power must be equal to the elasticity of matches to unemployment.

[5]This result relies on having a Cobb-Douglas matching function, the most common specification in the literature. Abstracting from functional forms, the negative of the worker bargaining power must be equal to the elasticity of the job filling rate to the tightness ratio in order to have an efficient equilibrium.

workers having a stable value, whereas male employees experienced a deterioration of their negotiation power. The shrinking of the *gender bargaining power gap* and the erosion of male employees' bargaining power are in line and could help explain the reduction in the gender wage gap that occurred in France (Palladino et al., 2021, Crivellaro, 2014). A simple counterfactual exercise shows that 11% of the total decline can be attributed to the increase of women in the labor force, while the remaining 89% is attributable to within-gender dynamics, mostly attributable to male workers.

Additionally, following recent evidence of job polarization (Jaimovich and Siu, 2020, Patel, 2021), I estimate worker bargaining power for workers performing routine an non-routine occupations, further differentieting the latter into abstract and manual. Evidence show that occupations requiring higher skills and education, i.e. non-routine occupations, have the highest bargaining power. Surprisingly, however, most of the decline in bargaining power is concentrated among non-routine workers and, more specifically, in non-routine abstract occupations.[6] Overall, these findings are consistent and can rationalize the declining college wage premium in France (Crivellaro, 2014).

Related Literature. This paper contributes to several strands of the literature. The first is the empirical literature on rent-sharing in the labor market (Card et al., 2018, Guiso and Pistaferri, 2020). Most studies in this literature assume a structural relation between wages and rents (or quasi-rents) and leverage productivity variation to estimate pass-through elasticities.[7] This methodology relies on proxying rents with measures such as log revenues, log value added, or log profits per worker. Early work in this area analyzed between-firm variation, while the focus of recent papers has shifted to within-firm with the availability of employee data. These recent papers find lower rent-sharing elasticities with due to the combination of unobserved worker quality in the cross-sectional analysis, measurement error, and insurance within the firm (Card et al., 2018).[8,9] The contribution of this paper to this literature is twofold. First, I compute an indicator of worker productivity using methods from the industrial organization literature that is model-consistent and can be used to map model primitives to the empirical analysis directly. Second, and most importantly, I analyze how the extent to which employers share rents with workers has changed over time in a way that allows me to take into account other phenomena that took place simultaneously, such as technological change, industry concentration, and changes in workforce composition.[10] This

[6]de Almeida Vilaresa and Reisc (2021) finds similar results in Portugal.

[7]As noted by Card et al. (2018), this is the analog of the literature in international economics or industrial organization studying the pass-through of cost shocks to prices (Berman et al., 2012, Goldberg and Hellerstein, 2013, Weyl and Fabinger, 2013, Gorodnichenko and Talavera, 2017, Alvarez et al., 2025)

[8]Blanchflower et al. (1996), Estevao and Tevlin (2003), Barth et al. (2016), Kline et al. (2019) all analyze the United States, finding values ranging between 0.06, and 0.47. The seminal Guiso et al. (2005) finds an elasticity of 0.07 in Italy; Card et al. (2016), and Bagger et al. (2014) analyze firms and workers in the Portuguese and Danish labor markets, finding values of 0.05 and 0.09, respectively. Margolis et al. (2001) and Fakhfakh and FitzRoy (2004) analyze French manufacturing finding values of 0.06 and 0.12.

[9]Lately, Jäger et al. (2020) and Schubert et al. (2021) have used a different approach and studied changes in outside options in wage negotiation settings to estimate implied rent-sharing elasticities.

[10]Bell et al. (2023) studies rent-sharing evolution on a selected sample of British firms and industry data in the U.S. and European countries.

methodology allows me to look at the main drivers for such decline, and I find that changes in labor force composition are the main candidates.[11]

Second, this paper contributes to the literature analyzing imperfections in the labor market with macroeconomic and industrial organization approaches. Within the macroeconomic literature, I contribute to the strand that envisages wages as the outcome of a negotiation. This process requires specifying the bargaining power of the parties involved, which is quantitatively important for model predictions, and it is generally assumed to be a symmetric bargaining with a 50/50 split between employees and employers (Jaimovich et al., 2021, Dix-Carneiro et al., 2021, Cacciatore and Ghironi, 2021, among others). I provide a theory-consistent value for bargaining power, and I show that this value changes over time leading to significant implications for the economy. Moreover, a new interest in monopsony and wage-setting power has risen within this literature (Manning, 2021), with papers providing new empirical insights (Azar et al., 2022, Goolsbee and Syverson, 2019, Dube et al., 2020)[12], theoretical frameworks (Berger et al., 2022, Jarosch et al., 2019) and quantification of efficiency losses (Azkarate-Askasua and Zerecero, 2024, Trottner, 2022). A recent number of papers have focused on studying the consequences of a decline in worker bargaining power following the influential Krueger (2018)'s call in his 2018 *Jackson Hole* address. Stansbury and Summers (2020) highlights the (potentially) leading role of this decline in the recent increases in firm profitability and profit share, while Lombardi et al. (2023) and Ratner and Sim (2022) make the case that it plays a crucial role in explaining inflation dynamics. Drautzburg et al. (2021) shows the importance of bargaining power in determining aggregate fluctuations with significant welfare costs. Finally, de Almeida Vilaresa and Reisc (2021) builds a dynamic search-and-matching model and estimates it on Portuguese data. My results provide novel time series evidence for worker bargaining power in two of the largest economies in the world, finding a significant decline in both the U.S. and France. Finally, a parallel strand of this literature that builds on insight from the industrial organization has focused on estimating firm-level markdowns, i.e., the distance between marginal productivity and wages. Prime examples are Yeh et al. (2022) and Kirov and Traina (2021) in the U.S., Mertens (2022) in Germany, and Wong (2023) in France. I incorporate these methods in a structural analysis that allows me to identify worker bargaining power and its evolution over time that can be used in future research.

Road-Map. The rest of the paper is structured as follows. Section 2 introduces the theoretical framework that microfounds the empirical analysis. Section 3 describes the data and Section 4 the estimation strategy. Section 5 presents the main results of the paper, i.e. the estimates of bargaining power, and Section 6 provides several extensions. Section 7 discusses and quantifies the implications for the total economy. Section 8 provides suggestive evidence

[11] Several recent papers have proposed a novel method to measure rent-elasticity taking into account worker heterogeneity (Lochner and Schulz, 2022, Chan et al., 2021, Wong, 2023). This approach combines standard production function techniques with worker abilities computed from a two-way fixed effect as in Abowd et al. (1999). Although restrictive on the substitutability between workers, it is a promising avenue for this literature. I build on these insights in Section 6.

[12] See Sokolova and Sorensen (2021) for a recent review of this literature.

on what the causes for the decline in bargaining power could be. Finally, Section 9 concludes.

2 A DMP Model with Nash Bargaining

I use a heterogeneous firm model with random search frictions in the labor market à la Diamond-Mortensen-Pissarides (Diamond, 1982, Mortensen, 1982 and Pissarides, 1985) to microfound the empirical analysis. Firms are heterogeneous in their total factor productivity (TFP) and need labor inputs to produce. Due to the frictions in the labor market, they cannot directly hire an employee and need to post job vacancies to find workers. On the other hand, individuals are either employed and working or unemployed and searching for vacancies. Meetings between job vacancies and the unemployed are governed by a matching function followed by a wage negotiation. Workers and firms separate at an exogenous probability.

2.1 Firms

Firms maximize profits and the firm problem can be formulated as:

$$\begin{aligned} \max_{v_{it}} \quad & \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \left(F(A_{it}, N_{it}) - N_{it} w_{it} - \kappa v_{it} \right) \right] \qquad (1) \\ \text{s.t. } & N_{it+1} = (1-s)N_{it} + v_{it} q(\theta_t) \\ & A_{it+1} = g(A_{it}) + \nu_{it+1} \end{aligned}$$

where $F(\cdot)$ is the production function of the firm that takes as inputs the idiosyncratic productivity, A_{it} and the number of employees, N_{it}. v_{it}, the choice variable, is the number of job vacancies to open in period t. Finally, w_{it} represents worker wage and κ the cost of opening a vacancy. The two constraints describe how labor and productivity evolve at the firm level. The law of motion of labor implies that each job has an exogenous possibility of being destroyed, s, and that each vacancy has an endogenous possibility of being filled, $q(\theta_t)$ with θ being the tightness ratio, i.e. the ratio of vacancies over unemployment. Firm productivity, on the other hand, follows a Markov process with $g(\cdot)$ governing the evolution over time and ν being an idiosyncratic shock every period.

2.2 Workers

Workers have linear utility, are risk neutral and can be either employed (E) or unemployed (U). The respective Bellman values are:

$$E_t = w_t + \beta \mathbb{E}[(1-s)E_{t+1} + sU_{t+1}] \qquad (2)$$

$$U_t = b + \beta \mathbb{E}[p(\theta_t)E_{t+1} + (1-p(\theta_t))U_{t+1}] \qquad (3)$$

with b and $p(\theta)$ being unemployment benefits and the endogenous probability of finding a job, respectively. Workers are all identical, so no worker subscript is needed. The utility of an employed worker is given by the wage they earn plus the continuation value of being employed. Similarly, the utility of an unemployed worker is given by the unemployment benefits they receive plus the continuation value consisting in the sum of the expectation of becoming employed and staying unemployed.

2.3 Labor Market

The labor market presents random search frictions. Namely, firms cannot directly hire workers and have to post vacancies at an (exogenous) cost κ and wait for workers to find them. In addition, unemployed workers constantly search for jobs and have to find a vacancy to become employed.

Matching Function

The dynamics of the labor market, i.e. the number of matches happening, are governed by a matching function, $M(v, u)$, that determines the number of new matches given the current numbers of vacancies and unemployed workers. This function is increasing in both arguments and exhibits constant returns to scale. A key variable that describes the labor market conditions is the tightness ratio, i.e. the ratio of vacancies over unemployment, $\theta = \frac{v}{u}$. That helps us defining the probabilities at which vacancies meet workers, the job filling probability, $q(\theta) = \frac{M(v,u)}{v} = M\left(1, \frac{1}{\theta}\right)$, and workers find vacancies, the job finding probability, $p(\theta) = M\left(\frac{v}{u}, 1\right) = M(\theta, 1) = \theta q(\theta)$. The job-finding and job-filling probabilities as well as the tightness ratio are taken as given by agents.

Vacancies

The value of a filled vacancy and an unfilled one can be expressed as

$$J_{it} = \text{MPN}_{it} - w_{it} + \beta \mathbb{E}[sV_{it+1} + (1-s)J_{it+1}] \tag{4}$$

$$V_{it} = \max\{0, \beta \mathbb{E}[q(\theta_t)J_{it+1} + (1 - q(\theta_t))V_{it+1}] - \kappa\} \tag{5}$$

where MPN is the marginal productivity of labor. The value of a filled vacancy is given by the marginal productivity of the workers that fill it net of their wage plus the continuation value of such vacancy. The value of an unfilled vacancy instead is the difference between the expected future benefits and the cost of opening it, κ_t. In equilibrium, it must hold that the marginal cost of opening a vacancy is equal to its expected value. The resulting zero-profit condition can be expressed as:

$$\kappa_t = \beta \mathbb{E}[q(\theta_t)J_{it+1}] \tag{6}$$

Wages

Once a match occurs, the wage is negotiated between the firm and the newly hired worker according to the Nash bargaining protocol. Specifically, the surplus generated by a match is divided among the parties according to their relative bargaining power:

$$w = \arg\max_{w} \underbrace{(W-U)^{\tau}}_{\text{Worker Surplus}} \times \underbrace{J^{1-\tau}}_{\text{Firm Surplus}} \tag{7}$$

with the two terms representing worker' and firm's surplus from the match. τ is worker bargaining power, and (1-τ) is firm bargaining power. Substituting the Bellman values and using the free entry condition, we can find an equilibrium equation for wages:

$$w = \tau \text{MPN} + (1-\tau)b + \tau\theta\kappa \tag{8}$$

This typical result in DMP models with Nash bargaining states that three components determine wages: 1) productivity, 2) worker outside option, and 3) market conditions weighted by the bargaining power of workers and firms.[13]

3 Data

This paper uses data from two distinct countries, the United States and France, to estimate bargaining power dynamics. The U.S. analysis is based on Compustat data, while the analysis for France integrates several administrative datasets.

3.1 The United States

To describe the U.S. labor market over an extended period, I use firm-level data from S&P's Compustat. This database provides financial information on publicly listed U.S. firms from 1960 to 2019, including revenues, physical capital, intermediate inputs, number of employees, and labor costs. A detailed list of variables and descriptive statistics are presented in Appendix C. One limitation of this database is that firms are not required to report wages, so only a subset does. Therefore, the analysis focuses on the manufacturing industry, where wage information is available for approximately 37% of the workforce, with around 14,000 firm-year observations.

3.2 France

In France, the analysis draws on various administrative data sources to construct detailed worker- and firm-level information. The primary firm-level data comes from the FICUS/FARE database, which provides financial information on all French firms from 1994 to 2019. It includes revenues, value added, fixed assets, and industry classification derived from annual tax filings. Employee information comes from DADS *Postes*, which provides matched employer-employee data based on compulsory earnings data, covering all jobs in France from 1993 to 2019. This database includes information on wages, hours worked, contract

[13]In this setting, firms negotiate wages with each worker individually. In Section 6 I extend this framework allowing firms to also internalize the effect of a new hire on the rest of the workforce (Cahuc et al., 2008).

type, occupation, and geographical location, along with unique firm identifiers.[14] Detailed sample construction, variable selection, and data preparation are described in Appendix C. The resulting sample includes around 9 million firm-year and 227 million employee/job-year observations.

This study also incorporates additional data sources for robustness and extensions. Demographic information from the DADS data allows for the construction of a worker panel covering 4% of the workforce until 2001 and 8% thereafter, capturing workers born in October of even years until 2001 and every year starting in 2002. This panel is used in robustness exercises that incorporate worker experience and ability. Product-level revenue and quantity data are obtained from the *Enquête Annuelle de Production* (EAP), which covers a representative sample of manufacturing firms with at least 20 employees or €5 million in revenues. This data is used to compute firm-level prices, following De Ridder et al. (2022), to show that using expenditure data does not bias results. Additionally, survey data from the *Enquête annuelle d'entreprise dans l'industrie* (EAE) provides insights into outsourcing practices by reporting expenditures on external workers—employees of another firm working under a contracting agreement and partially under the surveyed firm's authority.[15] Finally, information and communication technology (ICT) data come from the *Enquête sur les technologies de l'information et de la communication dans les entreprises* (TIC Entreprises), which surveys a representative sample of firms with at least 10 employees.

In the remainder of the paper, I focus mainly on the entire economy to identify aggregate trends and on the manufacturing industry to provide a consistent comparison with the U.S. results. Moreover, analyses of worker-level information will solely focus on manufacturing for computational reasons.

4 An Empirical Framework to Estimate Bargaining Power

This section introduces the methodology used to estimate worker bargaining power, aiming to provide an econometric procedure to recover τ from Equation (8). However, several challenges arise in estimating this equation. First, the productivity of a worker is not directly observable, so MPN must be estimated. Second, Equation (8) is an equilibrium equation, which inherently presents an endogeneity bias. Finally, information on unemployment benefits, vacancy costs, and market conditions is partially unobservable. In the following paragraphs, I will discuss how these challenges are addressed.

4.1 Measuring Productivity

To measure worker productivity consistent with the framework described in Section 2, I need an indicator of the value added by an additional worker in each firm—the marginal

[14] Employee data from the DADS database is anonymized, making it impossible to follow workers over time. However, each year's data includes current and lagged values for each variable, allowing for the tracking of each job across two consecutive years.

[15] See Bilal and Lhuillier (2021) for more details.

productivity of labor: $\text{MPN}_{it} = \frac{\partial F(\cdot)}{\partial N_{it}} = \varepsilon_{Y,N}\frac{Y_{it}}{N_{it}}$.

Although Y_{it} and N_{it} can be found in the data, the output elasticity of labor, $\varepsilon_{Y,N}$, a parameter of the production function, is unobservable. Estimating the production function raises several issues. Most importantly, TFP productivity, another unobservable component, affects both input choices and output leading to the simultaneity bias (Ackerberg et al., 2015). I adopt the control function or proxy approach proposed by Olley and Pakes (1996) to estimate the production function.[16] This method assumes that TFP productivity is unobservable to the econometrician but observable to the firm, allowing the use of other observable data with assumptions on firm behavior to control for unobservable TFP. Details of this estimation procedure are provided in Appendix D.

The empirical framework to estimate the production function is more general than the theoretical framework described above, where labor is the only factor of production. Here, I introduce a Cobb-Douglas production function with labor and capital. In Section 6, I further relax the functional form by implementing a Translog specification and introducing intermediate inputs.

It is well-known that the control function approach functions might suffer from omitted output and input price bias when revenues and expenditures rather than physical quantities are observed (De Loecker et al., 2016, Bond et al., 2021). This is always the case with only information from balance sheets and income statements. I tackle this issue in two ways. First, I add additional controls to proxy for this omitted information (De Loecker et al., 2020, De Ridder et al., 2022). Second, I use price information from the EAP survey to estimate the production function on quantities, finding a high correlation between revenue and quantity estimates (Mairesse and Jaumandreu, 2005). I discuss both demand shifters and quantity estimates in more detail in Appendix D.

Finally, I assume that firms do not have market power in product markets. If they do, the productivity term in Equation (8) will become a measure of revenue productivity rather than output productivity. In this case, I need to estimate the revenue elasticity of labor instead of the output elasticity. I discuss this further and show how to incorporate markups in the estimation of bargaining power in Section 6.

4.2 Estimating Bargaining Power

Even with data on the marginal productivity of labor, estimating Equation (8) presents two additional issues. First, there is an endogeneity bias stemming from the wage equation being an equilibrium condition. Second, there are unobservable terms such as the worker's outside option, the tightness ratio, and vacancy costs.

To address the endogeneity bias, I use an instrumental variable strategy. Specifically, I instrument current MPN with its lagged value. The relevance of lagged values as instruments for current levels comes from the serial correlation of productivity, which is already used in estimating the production function. Additionally, Equation (1) shows the link betwee

[16] A number of papers have built on this, see for example Levinsohn and Petrin (2003), Ackerberg et al. (2015) and Gandhi et al. (2020). Ackerberg et al. (2015) offers a review of the literature.

the current realization of productivity and its lagged value. The exclusion restriction, which ensures that lagged productivity affects wages only through current productivity, is guaranteed by two features of the framework described in Section 2. These features are the timing of the hiring process and the static nature of the Nash bargaining protocol. Firms hire workers in the current period who start producing only in the next period and take market conditions ($\kappa\theta$) as given. Moreover, wages are renegotiated every period, so they reflect only today's productivity.

To account for worker outside options and labor market conditions, I include a set of sector interacted with period fixed effects. This means that workers have the same outside option in a given industry in a given year, and firms face the same labor market conditions in a given industry and year. Although these can vary over time, they do not differ across workers/firms within the same period.[17] While this approach does not allow the identification of specific outside options and labor market conditions, combining the IV strategy with fixed effects enables the estimation of the coefficient on the marginal productivity of labor, which is worker bargaining power.

The target equation for my empirical analysis is:

$$\omega_{ist} = \tau_{ST}\text{MPN}_{ist} + \Upsilon_{ist} + \varepsilon_{ist} \tag{9}$$

where ω_{ist} represents wages and MPN_{ist} is marginal productivity of labor of firm i in sector s in year t. Υ_{ist} is a set of fixed effects and ε is an idiosyncratic error. Finally, τ_{ST} represents worker bargaining power in industry S and time T. I use capital letters as both S and T might be different from s and t in the empirical specification.

Instrument Validity Timing and information assumptions guarantee the validity of the instruments in this setting. As discussed above, firms hire workers in the current period who start producing in the next period, and firms take θ as given. This ensures that the exclusion restriction holds, meaning that lagged productivity affects wages only through current productivity. If this were not the case and lagged productivity affected current wages through another channel, the exclusion restriction would be violated.

There is no formal test to identify other channels that might affect lagged productivity realization. Therefore, I perform a robustness exercise using another instrument that implicitly allows lagged productivity to affect current wages. I use current productivity shocks as instruments for current productivity, following the approach of Chan et al. (2021). This follows directly from the stochastic process of TFP, which includes a persistent element and a temporary shock. Appendix E shows the results of this exercise, which confirm similar results for bargaining power, thereby validating the instrument.

To further test the information assumption, I estimate bargaining power for very small firms, i.e., those with fewer than ten employees. The rationale is that strategic interactions in the labor market might make my estimate only a reduced-form result (Berger et al., 2022).

[17] I relax this assumption and provide several extensions in Section Section 6 and Section 8.

Table 1: Bargaining Power

	USA	France	
	Manu	All	Manu
τ	0.17	0.21	0.25
	(0.01)	(0.001)	(0.002)
Controls	Yes	Yes	Yes

Notes: This table presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (9). The sample covers the manufacturing industry in the US from 1960 to 2019 (column 1), the entire economy in France from 1994 to 2019 (column 2), and the manufacturing industry in France from 1994 to 2019 (column 3). Standard errors are clustered at the firm level. All regressions include fixed effects for 4-digit industries interacted with year indicators. T is defined as the entire period of analysis, so that τ is assumed to be constant over time.

By focusing on very small firms, I aim to study a sample where hiring choices are unlikely to affect other participants in the labor market. Table B.4 shows that the main result of the paper—the trend discussed in the next section—is robust even when allowing for strategic interactions.

5 Worker Bargaining Power in the U.S. and France

This section presents the main results of this paper. First, I estimate worker bargaining power by keeping it constant throughout the entire period to provide a benchmark with existing literature. This exercise validates the methodology and provides an average value that reflects the relative power of workers and firms, useful for calibration exercises. Then, I focus on the main contribution of this paper: estimating the trend in bargaining power in the U.S. and France over time.

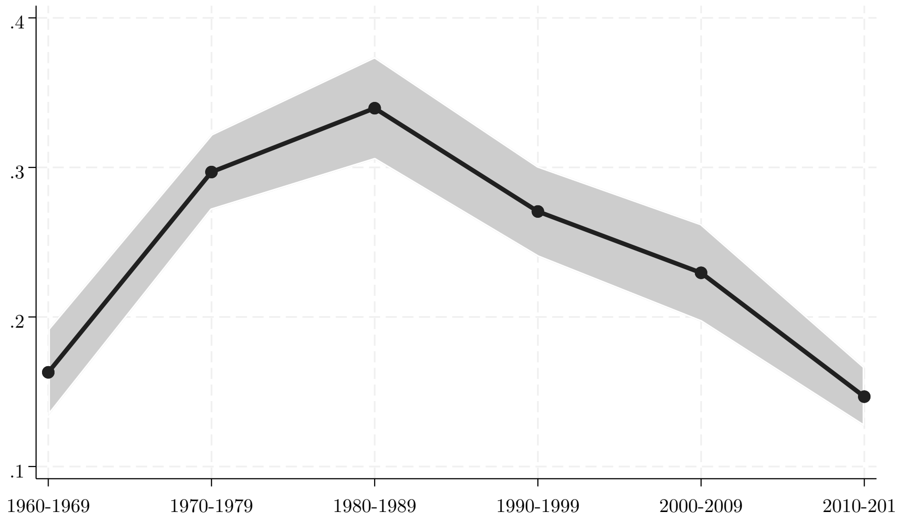
5.1 Constant Bargaining Power

Table 1 presents the result of estimating bargaining power from Equation (9) keeping it constant throughout the whole period.[18] The first column refers to the manufacturing industry in the U.S., while the second and third columns to the whole economy and the manufacturing industry in France, respectively. Each specification includes sector-by-year fixed effects, which, as mentioned in Section 4, capture time-varying worker outside options and labor market conditions for workers and firms. This means that firms face the same labor market conditions only within a narrowly defined industry in a given year, and the same applies to workers.

The results reveal a significant imbalance in the relative importance that workers and firms have in the wage negotiation process, with firms holding much greater power than workers. In the U.S., workers have a bargaining power of only 17%. While this figure aligns with existing literature, it is striking in its implications. It indicates that only a small portion of labor productivity is reflected in workers' compensation, meaning that employers have almost five times more bargaining power over wages compared to employees. Analyzing this

[18]Table B.1 in the Appendix shows the first stage for each columns in Table 1.

Figure 1: Trends in Bargaining Power in U.S. Manufacturing



Notes: This figure presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (9). The sample covers the manufacturing industry in the U.S. from 1960 to 2019. Standard errors are clustered at the firm level. All regressions include fixed effects for 4-digit industries interacted with year indicators. T is defined as a decade, so that τ is allowed to vary every ten years.

through the lens of Equation (8), it becomes clear that wages are much closer to the outside option than to the marginal productivity of labor under current market conditions.

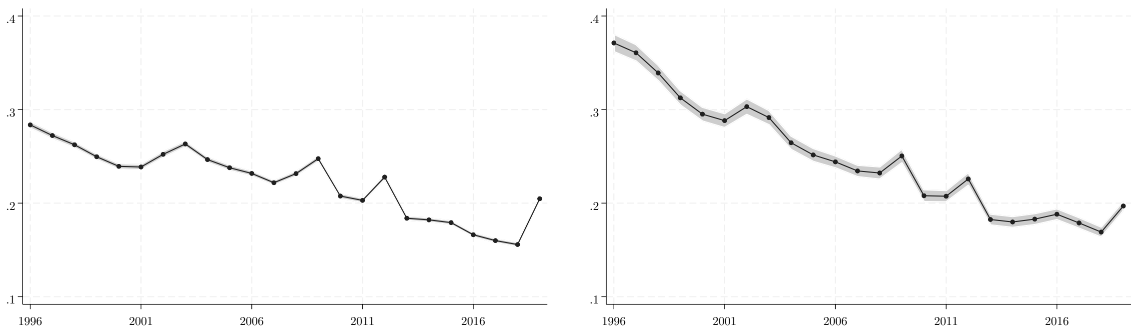
In contrast, Columns 2 and 3 show that bargaining power in France is higher than in the U.S., both for the entire economy and the manufacturing sector. French firms exhibit approximately four times more bargaining power over wages compared to employees. Interestingly, the data also reveal that bargaining power in manufacturing is higher than in the general economy. In the manufacturing sector, firm bargaining power is only three times higher than that of workers, indicating a more equitable distribution of the joint surplus. However, this relationship remains skewed in favor of firms.

To further validate this structural measure of worker bargaining power, I compare it with a nonparametric measure of labor market concentration, the Herfindahl-Hirschman Index (HHI), at the regional level. For this purpose, I leverage worker information in France and restrict the analysis to firms whose entire workforce is located within a single region and estimate worker bargaining power at the regional level. Figure A.1 compares the structural estimates of worker bargaining power with the employment HHI (computed using employment shares) across regions, showing a strong correlation (86%) between these measures, thus reinforcing the robustness of the approach.

5.2 Trends in Bargaining Power

Figure 1 and Figure 2 present the main results of this paper: the evolution of bargaining power over time. In France, bargaining power can vary on an annual basis, while in the U.S. I pool across decades due to the smaller sample. The figures plot the coefficients with the corresponding 95% confidence intervals, revealing striking patterns.

Figure 2: Trends in Bargaining Power in France



(a) Overall Economy (b) Manufacturing

Notes: This figure presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (9). The sample covers the entire economy in France from 1994 to 2019 (panel a) and the manufacturing industry in France from 1994 to 2019 (panel b). Standard errors are clustered at the firm level. All regressions include fixed effects for 4-digit industries interacted with year indicators. T is defined as a year, so that τ is allowed to vary annually.

Figure 1 shows that bargaining power in the U.S. follows a hump-shaped trend, starting at a very low level of around 16% in the 1960s. It increases sharply over the following years, reaching its peak at approximately 34% in the 1980s. Thereafter, it decreases steadily and almost linearly, decade after decade, until it reaches its minimum, below 15%, during the period 2010-2019. This figure is remarkable as it demonstrates the substantial changes in the importance of employers and employees in the wage-setting process over time. The power that workers had in the 1980s when negotiating their salaries more than halved over the subsequent years. This means that, assuming productivity and labor market conditions were constant, wages would be much lower now than they were 40 years ago. This decline reflects a significant shift in the balance of power towards employers, impacting wage dynamics and potentially contributing to broader economic inequality.

Figure 2, on the other hand, shows the evolution of bargaining power in France, highlighting a stark decline from 1995 to 2019. This pattern is consistent across the entire economy and the manufacturing industry.[19] Looking at Figure 2a, we can see that the bargaining power of French workers was around 30% in the mid-1990s and decreased to its lowest level of approximately 15% in 2018. Hence, similarly to the U.S., it halved over two decades. This decline also experienced fluctuations, with a rebound in the early 2000s and around 2008. Both the trends and levels align with the results found for the U.S. in Figure 1.

Finally, Figure 2b shows the trend in bargaining power in the French manufacturing industry. Although the decline is very similar to that in the whole economy, the levels are shifted upwards in this case. Bargaining power in French manufacturing declined from 40% to around 20% over the 1995-2019 period.This indicates a notable disparity between the manufacturing sector and the broader economy, suggesting that specific industry dynamics and structural factors play a role in shaping bargaining power trends.

[19] Table B.3 shows estimates of worker bargaining power for 2-digit sectors within manufacturing. Despite the heterogeneity in levels, it shows that the bargaining power decline occurred in the entire industry.

6 Extensions

In this section, I extend the framework to account for (i) imperfect competition in the output market and (ii) worker heterogeneity. Additional robustness checks—including alternative functional forms, different wage negotiation protocols, and first-differences—are presented in Appendix F.

6.1 The Role of Markups

The framework in Section 2 considers firms as price-takers in the output market. However, recent papers document that product market concentration has been increasing, firms are exerting substantial market power, and have heterogeneous markups (De Loecker et al., 2020, Autor et al., 2020). Therefore, I incorporate a notion of imperfect competition in the output market without specifying its source. Introducing heterogeneous markups in the framework outlines in Section 2, the firm's profit maximization becomes:

$$\begin{aligned}\Pi_{it} &= \max_{v_{it}} \ \pi_{it} + \beta \mathbb{E}[\Pi_{it+1}] \\ &= \max_{v_{it}} P_{it} F(A_{it}, N_{it}) - N_{it} w_{it} - \kappa_t v_{it} + \beta \mathbb{E}[\Pi_{it+1}]\end{aligned} \tag{10}$$

The value of a filled vacancy now incorporates the effect of prices due to a new worker:

$$J_{it} = \text{MRPN}_{it} - w_{it} + \beta \mathbb{E}[s V_{it+1} + (1-s) J_{it+1}] \tag{11}$$

with MRPN being the marginal revenue productivity of the worker at firm i. Consequently, wages are determined as:

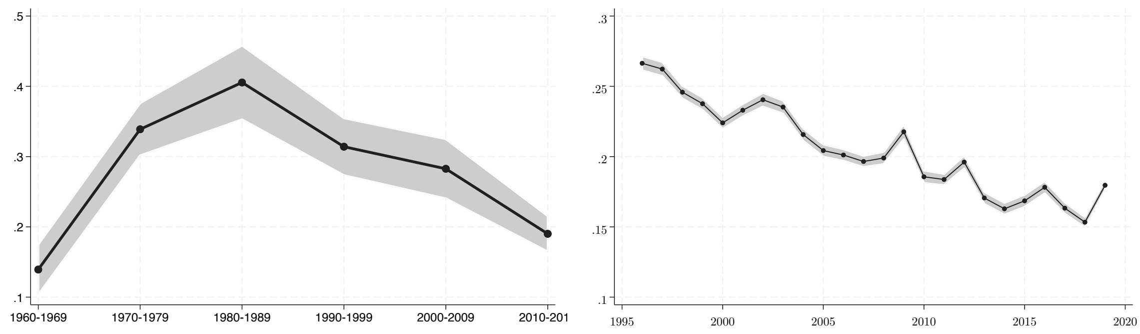
$$w = \tau \text{MRPN} + (1-\tau) b + \tau \kappa \theta \tag{12}$$

The difference from Equation (8) is that firms now face less than perfectly elastic residual demand and internalize this margin in their output choices. Therefore, to estimate how the surplus is shared between employers and workers, we now need an indicator of the marginal revenue productivity rather than physical productivity.

6.1.1 Measuring Marginal Revenue Productivity

The framework described in the previous paragraph and summarized in Equation (12) poses the additional challenge of measuring the marginal revenue productivity of a worker. To do so, I need to estimate output elasticity of the revenue function rather than of the production function. I consider two cases. First, I assume that markups are constant and vary at the same level of variation as the production function. An example would be markups stemming from monopolistic competition and CES demand—in this case the output of the production function estimation is the revenue elasticity (Bond et al., 2021). Therefore, Figure 1 and Figure 2 would show worker bargaining power in a setting with imperfect competition in the

Figure 3: Bargaining Power with Product Market Imperfections



(a) U.S. (b) France

Notes: This figure presents estimates of worker bargaining power (τ), defined as the coefficient on revenue productivity in Equation (12). The sample covers the manufacturing industry in the U.S. from 1960 to 2019 and the manufacturing industry in France from 1994 to 2019. Standard errors are clustered at the firm level. All regressions include fixed effects for 4-digit industries interacted with year indicators.

output market.

Second, I consider variable markups following recent evidence on heterogeneity in product market power across firms. In this case, the marginal revenue productivity is a combination of physical efficiency and elasticity of the residual demand curve, which can be expressed as:

$$\text{MRPN}_{it} = \frac{\varepsilon_{Y,N}}{\mu_{it}} \frac{R_{it}}{N_{it}} \tag{13}$$

with μ_{it} being markup of firm i at time t. At this point, I use the approach proposed by Hall (1988) to derive a markup formula. This approach derives the following markup formula from the static cost minimization problem with respect to a flexible inputs:

$$\mu_{it} = \varepsilon_{Y,V} \frac{R_{it}}{P^V V_{it}} \tag{14}$$

with V being the flexible input. To bring Equation (13) to the data, I augment the production function adding intermediate inputs as the flexible input and estimate it using the methodology described in Section 4.[20] Recovered elasticities and markups, I use them to construct the marginal revenue productivity following Equation (13) and estimate worker bargaining power from Equation (12). I leave the details of markups estimation in Appendix D.

The two panels in Figure 3 show that incorporating imperfect competition in output market does not alter the overall dynamics: the hump-shaped evolution in the U.S. and the steady decline in France remain intact, which confirms the robustness of the baseline results. There is evidence of a modest level shift in the estimated values that works in opposite directions in the two countries. In the U.S., the estimated bargaining power is slightly higher

[20]The literature finds that estimating gross output function on revenue data can lead to biased elasticities (De Loecker et al., 2016, Bond et al., 2021). In Appendix D I use output price information to show the high correlation ($> 90\%$) in estimates relying on revenue or quantity data as well as for the resulting bargaining power estimates.

when markups are accounted for—consistent with the generally high level of U.S. markups amplifying the revenue side of the marginal productivity measure—whereas in France, it is a bit lower, reflecting the comparatively lower markup levels in the French economy.[21] This asymmetric adjustment reinforces our interpretation that product market imperfections affect the absolute level of the estimated worker bargaining power but leave the underlying trend unchanged.

6.2 The Role of Worker Heterogeneity

Thus far, worker heterogeneity was modeled only through sector-by-period variation, placing most variation on the firm side. In this section, I incorporate additional worker dimensions by (i) allowing occupation-specific differences in productivity and (ii) directly modeling individual differences in outside options and local labor market conditions.

6.2.1 Occupation Composition

Recent studies document significant shifts in occupational composition over time (Jaimovich and Siu, 2020, Patel, 2021), suggesting that the mix and roles of occupations within firms have evolved. To account for these changes in my estimation of worker bargaining power, I introduce occupation-specific heterogeneity into the wage equation. In doing so, I extract an occupation-specific component that captures differences in abilities, wage premia, and unobserved skills, and then use this information to adjust the measure of labor input in both the production function and the subsequent bargaining power estimation.[22]

In practice, I estimate a pseudo-Mincer regression of the form:

$$\ln w^o_{jit} = \alpha^o_t + \psi_{i(j,i)t} + X_{jt}\Gamma_t + \varepsilon_{jit} \tag{15}$$

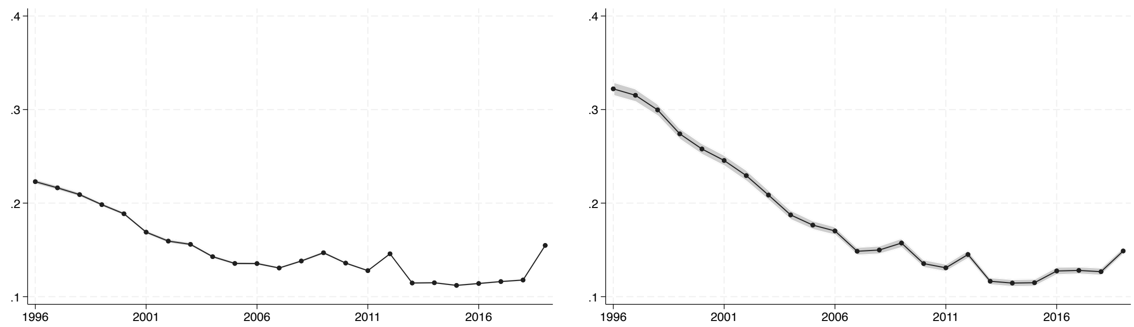
where w^o_{jit} denotes the wage of worker j in occupation o at firm i in period t, α^o_t represents time-varying occupation fixed effects for occupation o, $\psi_{i(j,i)t}$ captures time-varying firm fixed effects for firm i when worker j works at firm i, X_{jt} includes individual controls such as a polynomial in age, location, gender, and contract type.ε_{jit} is an idiosyncratic shock uncorrelated with the other variables. For computational ease, the pseudo-Mincer regression is estimated on a random 20% subsample of workers.

Although these occupation fixed effects do not lend themselves to a direct structural interpretation—as is typical in two-way fixed effect wage regression models (AKM, hereafter - Abowd et al., 1999, Bonhomme et al., 2023)—they effectively capture all persistent differences between occupations, such as abilities, wage premia, average unobserved worker

[21] For instance, De Loecker et al. (2020) report an average markup of 1.53 in the U.S. over the period 2006-2016, whereas De Ridder et al. (2022) report an average markup of 1.38 in France over the period 2009-2019.

[22] A few recent papers have combined the proxy method for estimating production function with the two-way fixed effects of workers and firms proposed by Abowd et al. (1999) to allow for worker-specific productivity (Lochner and Schulz, 2022, Chan et al., 2021, Wong, 2023). While I cannot implement such a procedure because my sample of analysis does not include worker identifiers, it also does not capture variation in productivity over time, thus not allowing us to make an analysis of changes over time, which is the main contribution of this paper.

Figure 4: Bargaining Power Accounting for Occupational Composition



(a) Total Economy (b) Manufacturing

Notes: This figure presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (9). The sample covers the entire economy in France from 1994 to 2019 (panel a) and the manufacturing industry in France from 1994 to 2019 (panel b). Standard errors are clustered at the firm level. All regressions include fixed effects for 4-digit industries interacted with year indicators. In this figure, productivity and wages are expressed in efficiency units, incorporating occupation fixed effects estimated from Equation (15), and T is defined as a year, so that τ is allowed to vary annually.

skills.

A detailed plot of the estimated occupation fixed effects (by 2-digit occupation) is provided in Figure A.2, where, for instance, the fixed effects for business heads consistently exceed those for low-skill craftsman. This evidence supports the use of these estimates to capture occupational heterogeneity in the analysis of worker bargaining power.[23]

Armed with the estimated occupation fixed effects, α_t^o, I construct an efficiency-adjusted measure of a firm's workforce by weighting each worker's hours by the exponential of the corresponding occupation effect:

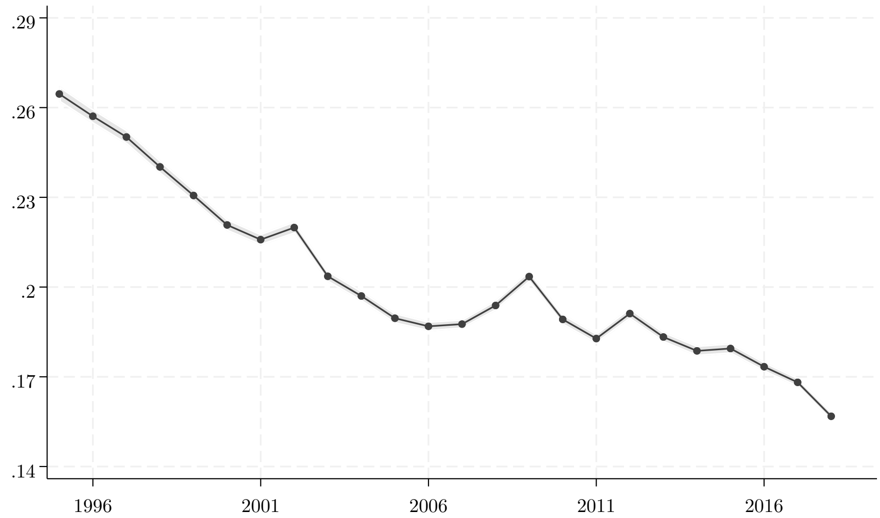
$$\tilde{H}_{it} = \sum_j \exp(\alpha_t^o) h_{ijt}^o,$$

where h_{jit}^o denotes the hours worked by worker j in occupation o at firm i. This transformed measure is then used in the estimation of the firm production function and, subsequently, to derive the marginal productivity of (efficiency) labor. Moreover, also wages are corrected for occupational differences by dividing total wages by the efficiency-adjusted hours, yielding an hourly wage in efficiency units.

Figure 4 presents the estimates of worker bargaining power when occupational composition is incorporated. The figure shows that the overall downward trend in bargaining power—previously observed in Figure 2—remains robust even after adjusting for changes in the occupational mix. Notably, the decline in bargaining power is more pronounced during the first half of the sample period when worker heterogeneity is taken into account, while in the later years the decline appears to plateau, with hints of an initial recovery. Furthermore, the rebound in bargaining power around 2003, evident when all workers are treated as homogeneous, vanishes once occupational composition is explicitly modeled. This suggests

[23]Figure A.3 compares the estimated α_t^o with average worker fixed effects by occupation resulting from a AKM model estimated on the panel version of the French employee data and averaging the resulting worker abilities by occupation. The correlation is $> 96\%$.

Figure 5: Bargaining Power with Worker Heterogeneity in Manufacturing



Notes: This figure presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (16). The sample covers the manufacturing industry in France from 1994 to 2019. Standard errors are clustered at the firm level. All regressions include time-varying 4-digit industry fixed effects, a polynomial in age, and dummies for location, gender, occupation, and type of contract, with all worker information interacted with period dummies. Here, T is defined as a year, so that τ is allowed to vary annually.

that the apparent rebound may be driven, at least in part, by compositional shifts related to the evolving role of different occupations in the production process—a topic that is further discussed in Section 8.

6.2.2 Worker-level Analysis

While the previous section addressed occupational composition by extracting occupation-specific fixed effects, further heterogeneity may stem from differences in workers' outside options and local labor market conditions. In the baseline specification (Equation (9)), all workers within a narrowly defined sector share the same outside option. To enrich this framework, I leverage detailed employer-employee matched data and extend the wage equation to include individual-level characteristics in the following specification:

$$w_{jist} = \tau_{ST} MPN_{ist} + X_{jst}\Gamma_t + \Upsilon_{ist} + \varepsilon_{jist},$$

where w_{jist} is the wage of worker j at firm i in sector s at time t, and X_{jst} is a vector of worker-specific controls. In this specification, X_{jst} includes a third-order polynomial in age, as well as dummies for location, gender, occupation (at the 2-digit level), and type of contract (distinguishing fixed from permanent contracts).[24] These controls capture the non-linear effects of age on outside options and account for variations in local labor market conditions, gender-specific factors, and other relevant dimensions of worker heterogeneity. All these covariates are interacted with time dummies, allowing their effect to potentially change over

[24]Worker's age is standardized at 40, and the linear term is omitted to avoid collinearity with time fixed effects (Card et al., 2018).

time.

Figure 5 presents the resulting estimates for the manufacturing sector. The figure clearly shows that—even after incorporating this richer set of worker-level information—the downward trend in worker bargaining power remains striking. Workers negotiating their wages in the 2010s exhibit much lower bargaining power compared to those in the mid-1990s, a finding that reinforces the notion of an increasingly asymmetric wage-setting process. Notably, similar to the estimates accounting for occupational composition, most of the decline occurs in the first half of the period, with a more moderate decrease in later years and no indication of recovery. This persistent trend suggests that the observed changes in bargaining power are robust to the inclusion of detailed worker heterogeneity.

7 Implications for the Economy

I quantitatively assess the changes in the economy due to bargaining power changes using the model described in Section 2 and abstracting from firm size and idiosyncratic productivity for the sake of exposition. Specifically, I calibrate the model to a steady state corresponding to the period with the highest bargaining power and then analyze the new steady state equilibrium after changing the bargaining power to the period with the lowest value. Equilibrium definition and model calibration are described in Appendix G.

Table 2 shows the results of this experiment. In both panels, column 2 reports the values of labor share (normalized to 1) and unemployment in the initial period, and column 3 the equilibrium values keeping the same calibration and changing only worker bargaining power to its lowest level. Columns 4 and 5 show the empirical counterparts.[25]

The model predicts that both labor share and unemployment decrease significantly following the decline in worker bargaining power. The mechanism is straightforward: as worker bargaining power decreases wages get closer to the outside option and hiring new workers becomes less costly. Thus, firms want to hire more and post new job vacancies. As a result, unemployment decreases.[26]

In the U.S. calibration, a decline in worker bargaining power from 0.34 in the 1980s to 0.15 in the 2010s reduces the normalized labor share from 1 to 0.92 and lowers the unemployment rate from 7.5% to 6.3%. In France, where bargaining power falls from 0.28 to 0.16, the model predicts a smaller decline in the labor share—from 1 to 0.96—and a drop in unemployment from 11.3% to 9.0%. These findings suggest that, in the U.S., the reduction in worker bargaining power can largely explain the observed decrease in the labor share over time, while in France, institutional features such as collective bargaining likely mitigate the impact of individual wage negotiations.

[25] The source of this data is FRED, Federal Reserve Bank of St. Louis, with the series UNRATE, PRS85006173 for the US, and LRHUTTTTFRA156S, and LABSHPFRA156NRUG for France. I apply an HP filter to each series to recover the trend.

[26] The increase of vacancies competing for the same amount of unemployed workers also generates a counterveiling force, the so-called congestion externality, i.e., a decrease in the probabiliry that a vacancy matches with an unemployed worker. Table 2 shows that the direct positive effect of declining worker bargaining power on labot share and unemployment strictly dominates.

Table 2: Changes in Unemployment and Wages

Variable	Model		Data	
	80s	10s	80s	10s
Unemp.	7.5	6.4	7.5	6.2
Labor Share	1	0.92	1	0.91
Barg. Power	0.34	0.15	0.34	0.15

(a) U.S.

Variable	Model		Data	
	95	18	95	18
Unemp.	11.3	9.0	11.3	8.7
Labor Share	1	0.96	1	0.99
Barg. Power	0.28	0.16	0.28	0.16

(b) France

Notes: This table presents the changes in unemployment and labor share, as predicted by the model and observed in the data, following a decline in worker bargaining power from the period with the highest value to the period with the lowest value. In Table 2a, column 2 reports model values for the 1980s and column 3 for the 2010s; columns 4 and 5 show the corresponding empirical values. In Table 2b, column 2 reports model values for 1995 and column 3 for 2018; columns 4 and 5 show the corresponding empirical values.

7.1 Efficiency and Policy Interventions

I now examine the efficiency of the decentralized labor market implied by the model. In a standard DMP framework, the decentralized equilibrium is efficient if the elasticity of the job filling rate with respect to market tightness equals the negative of the worker's bargaining power (Hosios, 1990):

$$\frac{q'\left(\theta^{ss}\right)\theta^{ss}}{q\left(\theta^{ss}\right)} = -\tau. \tag{16}$$

For a Cobb-Douglas matching function $M(v,u) = A^z v^\alpha u^{1-\alpha}$, this condition requires $1-\alpha = \tau$, where α is the elasticity of matches to vacancies. Empirical estimates of α typically range from 0.3 to 0.5 (Petrongolo and Pissarides, 2001, Brügemann, 2008), while recent nonparametric estimates yield values from 0.15 to 0.3 (Lange and Papageorgiou, 2020).[27] Taken together with my new estimates of worker bargaining power, these findings indicate that the decentralized equilibrium is not efficient—firms do not fully internalize the congestion externality associated with vacancy posting—which would, in turn, support a higher steady state unemployment rate (10.4%).

To restore efficiency, I consider two policy interventions—marginal wage and profit taxes—that force agents to internalize the vacancy-posting externality. While both taxes reduce firms' surplus, they operate differently. A wage tax reduces workers' net earnings, prompting firms to raise gross wages to attract labor and thereby discouraging excessive vacancy posting. In contrast, a profit tax directly reduces firm profits, yielding a similar effect on vacancy posting but also lowering wages. Table 3 reports the tax rates required to achieve the efficient equilibrium. For example, in the U.S. calibration for the 1980s, a wage tax rate of 0.55 raises unemployment from 7.5% to 10.4%, while a profit tax rate of 0.80 is needed for the same outcome; in the 2010s, the corresponding rates are 0.58 and 0.91, respectively. Figure A.5 illustrates all possible combinations of these taxes, showing that a more pronounced decline in bargaining power necessitates stronger interventions to restore (constrained) efficiency.

[27] I focus on the U.S. for this part as it is where the most evidence on the elasticity of the filling rate is available.

Table 3: Interventions To Restore Efficiency

Variable	80s		10s	
Unemp.	7.5	10.4	6.4	10.4
Wages	0.92	0.98	0.84	0.98
Tax Rate	0	0.55	0	0.58

(a) Wage Tax

Variable	80s		10s	
Unemp.	7.5	10.4	6.4	10.4
Wages	0.92	0.89	0.84	0.77
Tax Rate	0	0.80	0	0.91

(b) Profit Tax

Notes: This table presents estimates of the interventions needed to restore labor market efficiency, as predicted by the model for the U.S. In Table 3a (Wage Tax), columns report model values for the 80s and 10s along with the corresponding empirical values; Table 3b (Profit Tax) displays analogous estimates.

8 What is Behind the Decline in Worker Bargaining Power?

In Section 5, I document an aggregate decline in worker bargaining power over the past decades common to both the U.S. and France, and in Section 7, I show that this decline helps explain the simultaneous fall in unemployment and labor share. In this section, I investigate potential drivers of this decline by examining heterogeneity in bargaining power across different groups.[28] Although worker bargaining power is treated as an exogenous parameter in the analysis, differentiating firms and workers by specific characteristics provides suggestive evidence on which factors may be contributing to the overall decline.

Traditional culprits of market power, especially between employers and employees, relate to specific firm-level characteristics, such as technology, product market competition, trade, outsourcing, and management composition. I investigate how each of these factor relates to worker bargaining power using the following specification:

$$\omega_{ist} = \tau_{BT}\text{MPN}_{ist} + \tau_{CT}\text{MPN}_{ist} \times \mathbb{1}_{\text{CT}} + \Upsilon_{ist} + \varepsilon_{ist}, \tag{17}$$

where $\mathbb{1}_{\text{CT}}$ is an indicator for a given firm characteristic. τ_{BT} captures worker bargaining power for the baseline group, i.e. the groups without the specific firm characteristic, and τ_{CT} the bargaining power difference between groups. This specification allows me to estimate group-specific bargaining power. At the same time, I interact control variables with the group indicator to ensure that each group faces its own labor market conditions. All results are reported in Appendix B.[29] My analysis of these dimensions reveals that while they are associated with systematic differences in worker bargaining power at the firm level, for example employees at more technologically advanced firms exhibit lower worker bargaining power, their evolution over time remains relatively stable. Overall, these results suggest that, although firm-level characteristics do influence the level of worker bargaining power, these factors cannot account for the aggregate decline observed in the economy.

In contrast, worker-level characteristics appear to be more relevant for the aggregate

[28] I complement the primary datasets used already in Section 5 with additional data sources for the specific characteristics of analysis. See Section 3 and Appendix C for a detailed exposition.

[29] Table B.5 presents the estimates of worker bargaining power for firms with and without ICT adoption as a proxy for technological advancement; Table B.6 for firms in corporate groups versus those at independent firms as a proxy for market dominance; Table B.7 for exporting and non-exporting firms; Table B.8 for outsourcing and non-outsourcing firms; Table B.9 for firms with and without a university-educated manager.

dynamics. In the remainder of this section, I focus on two primary worker-level dimensions—gender and occupation—that seem to play a central role in both the level and the evolution of bargaining power.

8.1 Gender

Gender plays a crucial role in wage negotiations (Biasi and Sarsons, 2022), influencing both the propensity to negotiate (Babcock and Laschever, 2003) and the salary demands made by workers (Roussille, 2021, Biasi and Sarsons, 2022). To investigate whether worker bargaining power differs by gender, I define a binary indicator $\mathbb{1}_{\mathrm{G}}$ that equals 1 for male workers and 0 for female workers, and interact this indicator with individual productivity measures and labor market controls. This yields the following specification:

$$w_{jist} = \tau_{FT}\,\mathrm{MPN}_{ist} + \tau_{MT}\,\mathrm{MPN}_{ist} \times \mathbb{1}_{\mathrm{G}} + X_{jst}\Gamma_t + \Upsilon_{ist} + \varepsilon_{jist}, \tag{18}$$

where the coefficient τ_{FT} captures female workers' bargaining power and the coefficient of the interaction term, τ_{MT}, captures the difference in male workers' bargaining power. Importantly, I include gender-specific controls—such as a polynomial in age, and dummies for industry, location, occupation, and contract type, all interacted with period indicators—to ensure that differences in the productivity-wage gradient truly reflect differences in bargaining power rather than differences in outside options or local labor market conditions.

Table 4 presents the estimates of worker bargaining power for male and female employees. Over the full sample, male employees exhibit an average bargaining power of 0.24, compared to 0.10 for female employees—a gender bargaining power gap of 14 percentage points. When the sample is divided into three subperiods, the gender gap narrows from 18 percentage points in 1996–2003, to 14 points in 2004–2010, and finally to 10 points in 2011–2018. This evolution aligns with the 27% reduction in the unconditional gender pay gap from 2002 to 2019 documented by Palladino et al. (2024).

In addition to these between-group differences, the gender-specific dynamics reveal that female employees, who begin at a significantly lower bargaining power level, experience an initial decline to 0.09 in the early 2000s, followed by an increase to 0.11 in the most recent period. By contrast, male employees exhibit a steady decline—from 0.28 in the early subperiod to 0.21 in the latest period. Thus, the narrowing of the gender gap is driven primarily by a decline in male bargaining power rather than by substantial improvements among female workers.

Finally, the table reports an increasing share of female workers in the labor force—from 46% to 48% over the sample period. To assess the impact of this compositional change on aggregate worker bargaining power, I construct a counterfactual in which group-specific bargaining power remains at the initial levels while the workforce composition is updated to its current values. This counterfactual analysis indicates that only about 11% of the overall decline in aggregate worker bargaining power can be attributed to the increased share of female workers. The remaining 89% of the decline is driven by changes within the groups,

Table 4: Worker Bargaining Power by Gender

	All Period	1996–03	2004–10	2011–18
Male Employees	0.24	0.28	0.23	0.21
	(0.002)	(0.003)	(0.003)	(0.003)
Female Employees	0.10	0.10	0.09	0.11
	(0.002)	(0.004)	(0.004)	(0.004)
Δ Between Groups (Male − Female)	0.14	0.18	0.14	0.10
	(0.001)	(0.001)	(0.001)	(0.001)
Δ Over Time: Male Employees	–	–	-0.05	-0.02
	–	–	(0.001)	(0.001)
Δ Over Time: Female Employees	–	–	-0.01	0.02
	–	–	(0.005)	(0.001)
Share of Female Labor Force	0.47	0.46	0.47	0.48

Notes: This table presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (18). The sample covers France from 1995 to 2018, using gender as the grouping variable, and standard errors are clustered at the firm level. All regressions include 4-digit industry fixed effects interacted with year and gender indicators, along with a polynomial in age and dummies for location, occupation, and contract type (all interacted with period and gender indicators). Columns report estimates for the full sample ("All Period") and for three subperiods (1996–03, 2004–10, and 2011–18). The first two rows present the estimated bargaining power for male and female employees, respectively; the third row shows the between-group difference (Male − Female); and the fourth and fifth rows report changes in bargaining power within each group over time.

particularly the significant reduction in male workers' bargaining power.

8.2 Occupation

The U.S. and France have both experienced job polarization—the disappearance of easily automatable, routine jobs in favor of non-routine occupations that are less susceptible to automation (Jaimovich and Siu, 2020, Patel, 2021).[30] Acemoglu and Restrepo (2022) shows that such polarization is a key driver of rising wage inequality.

While previous estimates of bargaining power assumed uniform productivity and bargaining power across workers within a firm, I now incorporate occupational heterogeneity to explore job-specific patterns in bargaining power. To do this, I first classify workers following the literature on job polarization into two broad categories: routine and non-routine occupations (Autor et al., 2003).[31] Then, within the non-routine group, I further distinguish between abstract and manual occupations (omitting the "non-routine" label for simplicity). This hierarchical classification enables me to capture potential differences in market power across worker types.

[30] Figure A.4 displays the evolution of employment shares by worker type in my sample. The share of routine jobs has declined steadily since the mid-90s, whereas the employment share of abstract and manual occupations has grown, mirroring trends observed in the U.S.

[31] See Albertini et al. (2017) and Patel (2021) for details on the classification at the 2-digit and 4-digit levels in the French labor market.

To estimate occupation-specific bargaining power, I allow for differential marginal productivity across occupations. With this aim, I specify a firm production function that incorporates distinct labor inputs. For example, the production function may be written as

$$F(A, R, NR, K)$$

or, more flexibly, as

$$F(A, R, AB, M, K),$$

where R denotes routine labor, NR non-routine labor, and AB and M denote abstract and manual labor, respectively. I then estimate the production function using the methodology described in Section 4 to recover output elasticities for each worker type. From these elasticities, I construct type-specific indicators of marginal productivity as

$$\text{MPO} = \varepsilon_{Y,O}\frac{Y}{O},$$

with O representing the labor input for each group. Finally, I define an indicator variable specifying the occupation type, $\mathbb{1}_{\text{O}}$ and interact it with individual productivity measures and labor market controls. This yields the following specification for the routing non-routine case:

$$w_{jist} = \tau_{RT}\,\text{MPR}_{ist} + \tau_{NRT}\,\text{MPNR}_{ist} \times \mathbb{1}_{\text{NR}} + X_{jst}\Gamma_t + \Upsilon_{ist} + \varepsilon_{jist}, \tag{19}$$

where the coefficient τ_{RT} captures the bargaining power of routine workers, and τ_{NRT} the difference for non-routine workers. Also in this case, I include occupation-specific controls—such as a polynomial in age, and dummies for industry, location, occupation, and contract type, all interacted with period indicators—to ensure that differences in the productivity-wage gradient truly reflect differences in bargaining power rather than differences in outside options or local labor market conditions. The case with three occupation, routine, abstract, and manual, presents an additional productivity term interacted with an indicator for the third type of occupation.

Table 5 shows the resulting estimates of bargaining power for each worker type. In the first panel, workers are classified into routine and non-routine groups: non-routine workers consistently exhibit higher bargaining power (0.21) than routine workers (0.10). However, over time, non-routine workers experienced a larger decline in bargaining power compared to routine workers. Until the early 2010s, only non-routine abstract workers saw a decrease, while routine workers' bargaining power remained stable; thereafter, routine workers began to experience a modest decline as well. In the second panel, which further distinguishes non-routine workers into abstract and manual groups, the evidence reveals substantial heterogeneity: abstract workers have the highest bargaining power (0.23), while manual workers have the lowest (0.07). Moreover, the decline in bargaining power among non-routine workers is driven entirely by abstract occupations, which experienced a significant deterioration in their bargaining position, whereas manual workers' bargaining power remained relatively unchanged throughout the period.

Table 5 shows the resulting estimates of bargaining power for each worker type. In Panel A, workers are classified into routine and non-routine groups. The results indicate that non-routine workers consistently exhibit higher bargaining power (0.21) compared to routine workers (0.10). Over time, the non-routine group shows a larger decline in bargaining power relative to the routine group. In the early subperiod (1996–2003), the difference is particularly pronounced, while routine workers' bargaining power remains stable; later, routine workers begin to experience a modest decline as well.

Panel B provides a further breakdown of the non-routine group into abstract and manual occupations. Here, abstract workers exhibit the highest bargaining power (0.23), while manual workers have the lowest (0.07). Importantly, when analyzing the evolution over time, the decline in bargaining power among non-routine workers is entirely driven by abstract occupations, which experience a marked deterioration in their bargaining position—from higher values in the initial subperiod to substantially lower values in the most recent period. In contrast, manual workers' bargaining power remains relatively unchanged over time.

Overall, these detailed results suggest that the observed aggregate decline in worker bargaining power is not uniform across occupations. Rather, the decline appears to be driven primarily by within-group dynamics, especially a significant reduction in the bargaining power of abstract occupations. This finding suggests that shifts in the labor market—such as those due to technological change or changes in the demand for high-skill labor—may disproportionately affect workers in abstract occupations, contributing substantially to the overall trend.

9 Conclusions

This paper proposes a novel measure of worker bargaining power by combining insights from macroeconomic theory with modern empirical techniques. I document a common phenomenon in the U.S. and France—a substantial aggregate decline in worker bargaining power over the last 30 years. Using state-of-the-art methods to estimate firm production functions, I demonstrate that this decline is robust to the incorporation of technical change, imperfect competition in output markets, and more sophisticated wage negotiation models. Furthermore, by leveraging rich employer-employee matched data, I show that the downward trend persists even when accounting for occupational composition and worker heterogeneity.

Building on these findings, I explore the macroeconomic implications of declining worker bargaining power. The analysis suggests that a reduction in bargaining power leads to a new steady state characterized by lower unemployment and lower labor share. In quantitative terms, the estimated changes in bargaining power can account for important shifts in recent U.S. and French macroeconomic outcomes.

These results are significant not only for enhancing our understanding of wage negotiation dynamics, but also for informing policy. The inefficiently low worker bargaining power appears to exacerbate congestion externalities in the labor market. Firms, benefiting

Table 5: Worker Bargaining Power by Occupation Type

Panel A: Routine and Non-Routine				
Bargaining Power	All Period	1996–03	2004–10	2011–18
Non-Routine (NR)	0.21	0.29	0.18	0.15
	(0.002)	(0.003)	(0.003)	(0.003)
Routine (R)	0.10	0.12	0.11	0.09
	(0.002)	(0.002)	(0.002)	(0.002)
Δ Between Groups (NR − R)	0.11	0.17	0.07	0.07
	(0.001)	(0.001)	(0.001)	(0.001)
Δ Over Time (NR)	–	–	-0.12	-0.02
	–	–	(0.003)	(0.001)
Δ Over Time (R)	–	–	-0.01	-0.02
	–	–	(0.007)	(0.007)

Panel B: Abstract, Routine, and Manual				
Bargaining Power	All Period	1996–03	2004–10	2011–18
Abstract (A)	0.23	0.32	0.24	0.18
	(0.002)	(0.004)	(0.004)	(0.004)
Routine (R)	0.10	0.12	0.11	0.09
	(0.002)	(0.004)	(0.004)	(0.003)
Manual (M)	0.07	0.07	0.07	0.06
	(0.002)	(0.004)	(0.004)	(0.004)
Δ Between Groups (A − R)	0.13	0.20	0.13	0.09
	(0.001)	(0.001)	(0.001)	(0.001)
Δ Between Groups (R − M)	0.04	0.06	0.04	0.02
	(0.001)	(0.001)	(0.001)	(0.001)
Δ Over Time: Abstract	–	–	-0.08	-0.06
	–	–	(0.001)	(0.001)
Δ Over Time: Routine	–	–	-0.01	-0.02
	–	–	(0.007)	(0.007)
Δ Over Time: Manual	–	–	-0.00	-0.00
	–	–	(0.001)	(0.001)

Notes: This table presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (19). The sample covers France from 1996 to 2018, using occupation type as the grouping variable, and standard errors are clustered at the firm level. All regressions include 4-digit industry fixed effects interacted with year and occupation indicators, along with a polynomial in age and dummies for location, occupation, and contract type (all interacted with period and occupation indicators). Columns report estimates for the full sample ("All Period") and for three subperiods (1996–03, 2004–10, and 2011–18). Panel A presents estimates for workers classified into routine (R) and non-routine (NR) jobs, while Panel B further disaggregates non-routine workers into abstract (A) and manual (M) categories (with routine repeated for reference). In each panel, the rows report the estimated bargaining power for each group, the between-group differences, and the change within each group over time. Shares by occupation type are shown in Figure A.4.

from their stronger negotiating position, post an excessive number of job vacancies. This overposting reduces the probability that any one vacancy results in a successful match, thereby imposing negative externalities on the labor market as a whole. Therefore, I propose two complementary policy interventions to restore the labor markets' efficiency, i.e., wage and profit marginal taxes.

I also examine potential drivers of the aggregate decline in worker bargaining power. While traditional factors such as technology, competition, trade, and outsourcing are associations with differences in levels of worker bargaining power at the firm level, their contribution to the overall decline appears limited. In contrast, worker characteristics play a notable role. In particular, I find a significant *gender bargaining power gap*, with male workers systematically having higher bargaining power than female workers. Notably, the gap has narrowed over time, primarily due to a decline in male bargaining power rather than improvements in female outcomes. Moreover, an analysis across occupations—categorized by the degree of automability—reveals that the decline is most pronounced among non-routine abstract occupations, which are typically associated with high-skill labor and the college wage premium.

Although suggestive, this evidence signal a clear path for future research, and proper identification of the causes of the aggregate decline in worker bargaining power is needed. I hope this paper provides convincing evidence of an aggregate phenomenon that took place both in the U.S. and France, bringing the importance of workers in the wage negotiation process to the core of future research. Taking into account its current dynamics and unraveling the causes of such a decline are first-order questions to improve our understanding of the labor markets.

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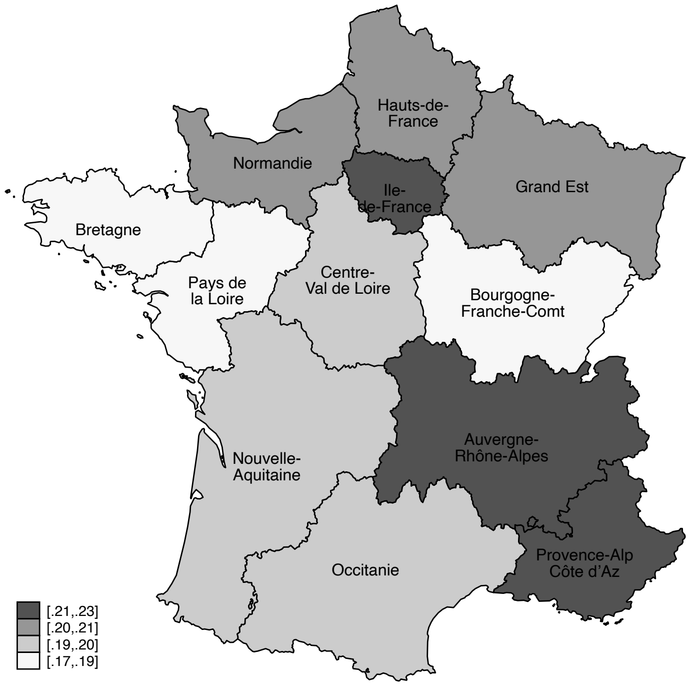
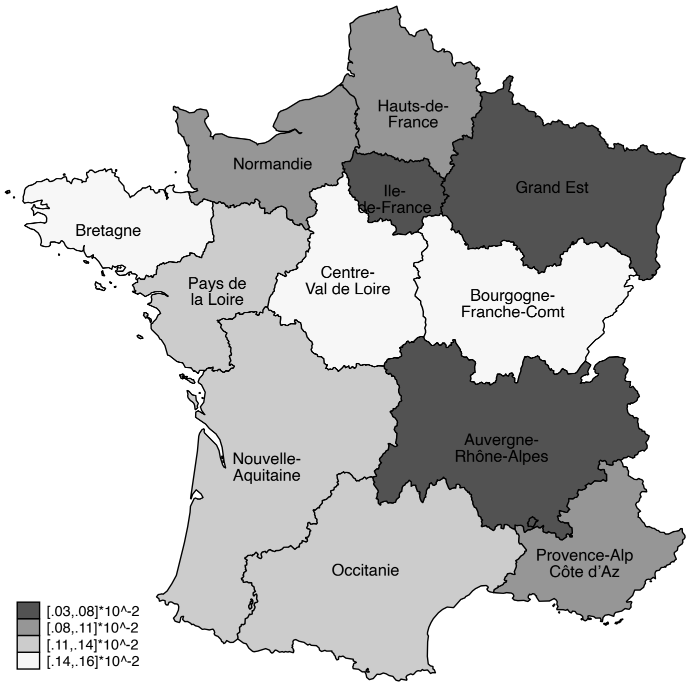
A Additional Figures

Figure A.1: Comparison of Worker Bargaining Power and Employment Concentration



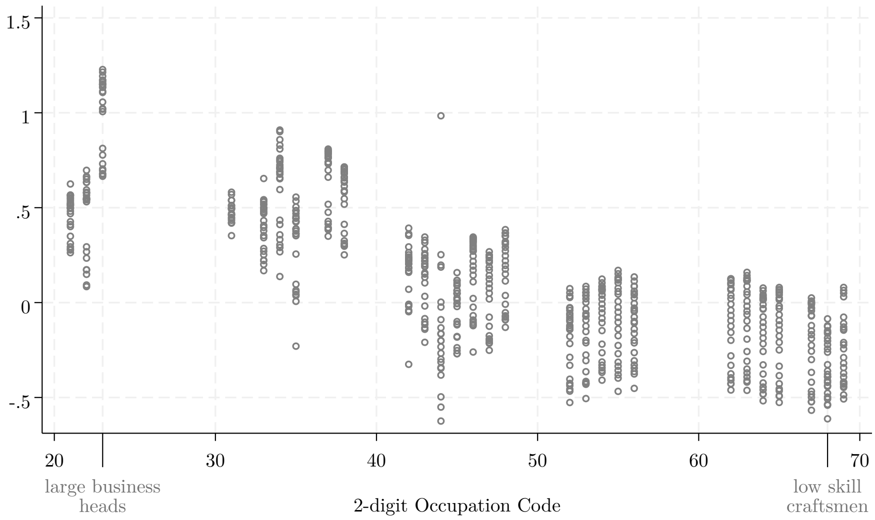
(a) Worker Bargaining Power



(b) Employment Concentration (HHI)

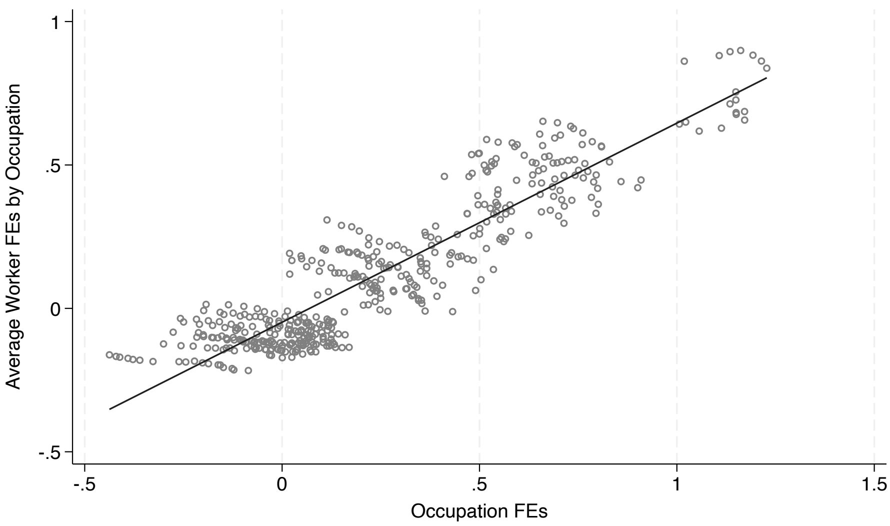
Notes: This figure compares estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (9), in Panel (a) to the employment HHI, computed using employment shares, in Panel (b). The sample covers French manufacturing firms whose entire workforce is located in the same region from 1994 to 2019, and standard errors are clustered at the firm level. All regressions include fixed effects for 4-digit industries interacted with year indicators. Estimates are computed separately by region while pooling observations across years. Darker gray indicates higher worker bargaining power or lower labor market concentration.

Figure A.2: Occupation Fixed Effects



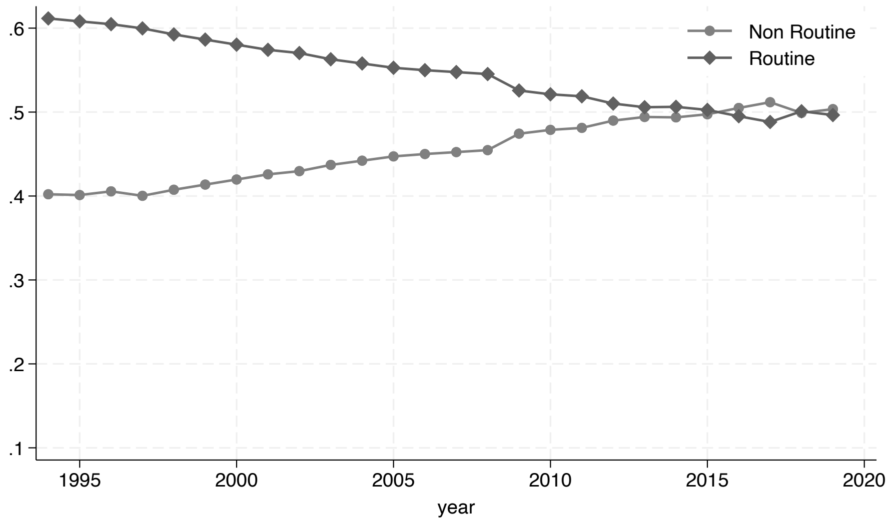
Notes: This figure presents the occupation fixed effects estimated from Equation (15). The sample covers a 20% random subsample of the total workforce in France from 1994 to 2019, and each occupation is defined at the 2-digit level. Within-occupation variation reflects changes over time. The figure shows two examples: large business heads (code 23) and low-skill laborers, craftsmen (code 68).

Figure A.3: Correlation Between Occupation FEs and AKM FEs

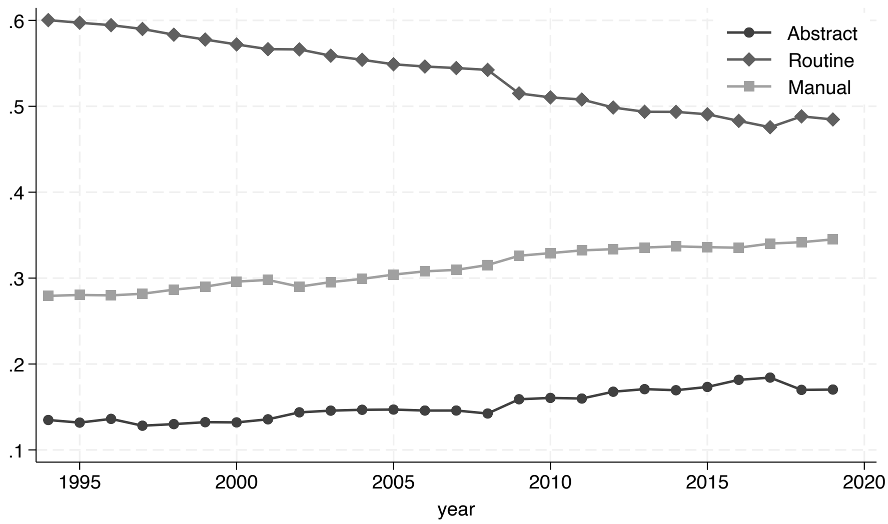


Notes: This figure presents the correlation between worker fixed effects averaged across occupations (y-axis) and occupation fixed effects (x-axis). Worker fixed effects are obtained from a two-way fixed effects regression of log wages on worker and firm fixed effects, controlling for observable characteristics. The sample covers Panel DADS data for employees born in October from 2002, with occupations defined at the 2-digit level. Occupation fixed effects are estimated from Equation (15) using a 20% random subsample of the total workforce in France from 1960 to 2019.

Figure A.4: Job Polarization in France



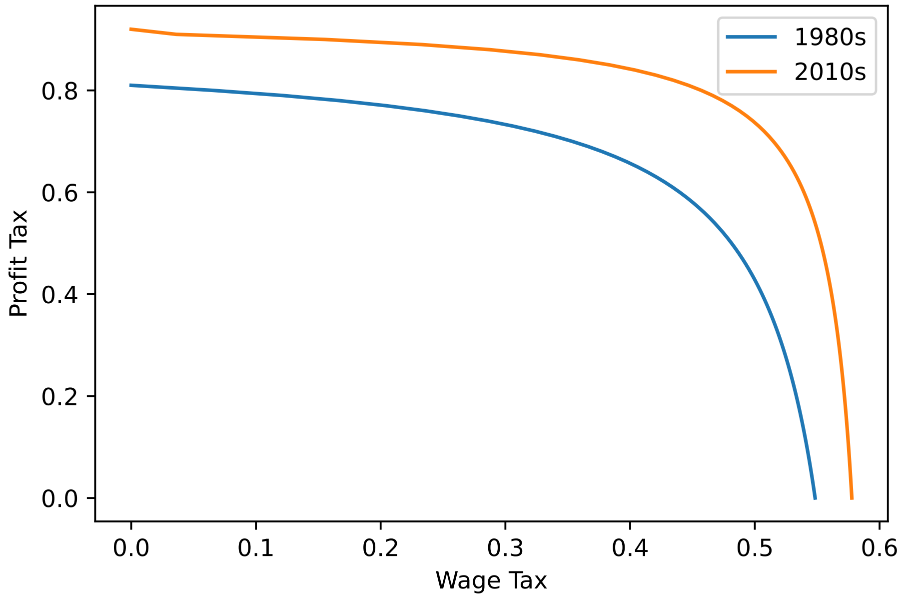
(a) Routine and Non-Routine



(b) Abstract, Manual, and Routine

Notes: This figure presents the evolution of different types of occupations over time according to their automability degree, following the classification in Albertini et al. (2017). The sample covers the entire economy in France from 1994 to 2019. Panel (a) shows non-routine and routine jobs, while panel (b) further distinguishes between non-routine abstract and non-routine manual jobs.

Figure A.5: Combinations of Wage and Profit Taxes



Notes: This figure presents the set of wage and profit tax combinations that restore labor market efficiency in the model. Each point on the curve represents a pair of tax rates that, when applied together, lets firms internalize the vacancy-posting externality and achieve the constrained efficient equilibrium.

B Additional Tables

Table B.1: Bargaining Power: First Stage

	USA	France	
	Manu	All	Manu
MPN_{-1}	0.93	0.77	0.79
	(0.02)	(0.0005)	(0.001)
Controls	Yes	Yes	Yes
F Stat	2750	$>$1m	$>$300k

Notes: This table presents the first-stage regression results for the IV strategy, where lagged marginal productivity (MPN_{-1}) is used as an instrument for current productivity in Equation (9). The sample covers US manufacturing and the French sample (both overall and manufacturing), and standard errors are clustered at the firm level. All regressions include fixed effects for 4-digit industries interacted with year indicators.

Table B.2: Bargaining Power Across Industries

industry	Bargaining Power				Representativeness	
	all	1997	2008	2019	VA (%)	EMP (%)
B. Mining	0.11	0.12	0.11	0.11	$<$1%	$<$1%
C. Manufacturing	0.25	0.37	0.24	0.21	26%	26%
E. Water/Waste	0.18	0.21	0.17	0.18	1%	1%
F. Construction	0.23	0.25	0.26	0.26	15%	13%
G. Wholesale/Retail	0.20	0.24	0.23	0.20	28%	25%
H. Transportation	0.20	0.26	0.21	0.20	5%	6%
I. Accommodation	0.11	0.10	0.13	0.14	5%	6%
J. Information/Communication	0.27	0.36	0.30	0.24	4%	3%
K. Finance/Insurance	0.28	0.28	0.17	0.26	$<$1%	$<$1%
L. Real Estate	0.25	0.28	0.26	0.24	$<$1%	$<$1%
M. Professional Activities	0.26	0.40	0.28	0.23	4%	4%
N. Administrative	0.24	0.32	0.24	0.24	4%	6%
P. Education	0.26	0.32	0.30	0.27	$<$1%	$<$1%
Q. Health/Social	0.06	0.18	0.09	0.03	4%	4%
R. Arts	0.18	0.21	0.24	0.20	$<$1%	$<$1%
S. Others	0.22	0.20	0.22	0.26	1%	1%

Notes: This table presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (9). The sample covers France for different industries, with columns reporting estimates for the full sample ("All Period") and for three points in time (1997, 2008, and 2019). Standard errors are clustered at the firm level. All regressions include fixed effects for 4-digit industries interacted with year indicators. Estimates are computed separately by industry while pooling observations across years. The "Representativeness" columns report the share of value added (VA) and employment (EMP) for each industry in the sample.

Table B.3: Bargaining Power Across Manufacturing Sectors

sector	Bargaining Power				Representativeness	
	all	1997	2008	2019	VA (%)	EMP (%)
10	0.19	0.21	0.21	0.20	12%	13%
11	0.15	0.21	0.15	0.15	1%	1%
13	0.30	0.39	0.28	0.17	3%	3%
14	0.37	0.54	0.33	0.26	3%	4%
15	0.27	0.43	0.30	0.18	1%	1%
16	0.23	0.36	0.26	0.17	3%	3%
17	0.25	0.38	0.26	0.18	3%	3%
18	0.33	0.66	0.35	0.20	4%	4%
20	0.24	0.30	0.23	0.24	5%	4%
21	0.24	0.29	0.22	0.23	2%	1%
22	0.25	0.42	0.25	0.19	7%	7%
23	0.20	0.28	0.19	0.17	4%	4%
24	0.24	0.37	0.24	0.23	2%	2%
25	0.26	0.42	0.29	0.22	16%	17%
26	0.29		0.26	0.22	5%	4%
27	0.25	0.44	0.24	0.21	4%	4%
28	0.26	0.43	0.25	0.21	8%	8%
29	0.23	0.35	0.22	0.20	3%	3%
30	0.24	0.28	0.19	0.20	1%	1%
31	0.24	0.35	0.19	0.19	2%	3%
32	0.21	0.30	0.20	0.21	4%	4%
33	0.24	0.41	0.20	0.25	7%	7%

Notes: This table presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (9), in France for all 2-digit sectors within the Manufacturing industry. The sample covers France for these sectors, and standard errors are clustered at the firm level. All regressions include fixed effects for 4-digit industries interacted with year indicators. Columns report estimates for the full sample (All Period") and for three points in time (1997, 2008, and 2019). Estimates are computed separately by industry while pooling observations across years. The Representativeness" columns report the share of value added (VA) and employment (EMP) for each industry in the sample.

Table B.5: Worker Bargaining Power by ICT Adoption

	All Period	2008–12	2013–19
ICT Firms	0.27	0.31	0.25
	(0.006)	(0.011)	(0.006)
Non-ICT Firms	0.29	0.34	0.27
	(0.007)	(0.011)	(0.008)
Δ Between Groups	-0.02	-0.04	-0.01
(ICT − Non-ICT)	(0.009)	(0.016)	(0.010)
Δ Within Group: ICT	–	–	-0.05
	–	–	(0.013)
Δ Within Group: Non-ICT	–	–	-0.08
	–	–	(0.014)
Share ICT Firms	0.46	0.43	0.49

Notes: This table presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (17). The sample covers France from 2008 to 2019, using ICT adoption (proxied by ERP software usage) as the grouping variable. Standard errors are clustered at the firm level. All regressions include 4-digit industry fixed effects interacted with year and ICT indicators. Columns report estimates for the full sample ("All Period") and for two subperiods (2008–12 and 2013–19). The first two rows present the estimated bargaining power for workers at firms with and without ICT, respectively; the third row shows the between-group difference (ICT Firms − Non-ICT Firms); and the fourth and fifth rows report the changes in bargaining power over time for each group between the subperiods.

Table B.4: Bargaining Power by Firm Size

Bargaining Power	All Period	1997–03	2004–10	2011–18
$<$10 employees	0.21	0.30	0.21	0.16
	(.003)	(.005)	(.004)	(.003)
10-24 employees	0.30	0.41	0.31	0.24
	(.003)	(.006)	(.005)	(.004)
25-49 employees	0.28	0.38	0.30	0.23
	(.004)	(.004)	(.004)	(.004)
50+ employees	0.26	0.31	0.26	0.22
	(.004)	(.006)	(.005)	(.005)
Controls	Yes	Yes	Yes	Yes

Notes: This table presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (9). The sample covers France from 1997 to 2018, and standard errors are clustered at the firm level. All regressions include 4-digit industry fixed effects interacted with year indicators, along with fixed effects for firm size interacted with year indicators. Columns report estimates for the full sample ("All Period") and for three subperiods (1997–03, 2004–10, and 2011–18).

Table B.6: Worker Bargaining Power by Corporate Group

	All Period	1999–03	2004–08	2015–19
Firms in Group	0.23	0.28	0.24	0.18
	(0.003)	(0.002)	(0.002)	(0.001)
Firms not in Group	0.28	0.32	0.26	0.20
	(0.003)	(0.002)	(0.001)	(0.001)
Δ Between Groups	-0.05	-0.05	-0.02	-0.02
(In Group − Not in Group)	(0.003)	(0.003)	(0.002)	(0.002)
Δ Over Time: In Group	–	–	-0.03	-0.06
	–	–	(0.003)	(0.002)
Δ Over Time: Not in Group	–	–	-0.07	-0.06
	–	–	(0.002)	(0.002)
Share of Firms in Group	0.27	0.19	0.23	0.37

Notes: This table presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (17). The sample covers France from 1999 to 2019, using being in a corporate group as the grouping variable. Standard errors are clustered at the firm level. All regressions include 4-digit industry fixed effects interacted with year and corporate group indicators. Columns report estimates for the full sample ("All Period") and for three subperiods (1999–03, 2004–08, and 2015–19). The first two rows present the estimated bargaining power for employees at firms in corporate groups and for those at independent firms, respectively; the third row shows the between-group difference (Firms in Group − Firms not in Group); and the fourth and fifth rows report the changes in bargaining power for each group over time.

Table B.7: Worker Bargaining Power by Export Status

	All Period	1995–99	2000–03	2004–07
Exporting Firms	0.28	0.33	0.28	0.23
	(0.003)	(0.005)	(0.005)	(0.004)
Non-Exporting Firms	0.31	0.37	0.31	0.26
	(0.003)	(0.005)	(0.004)	(0.004)
Δ Between Groups	-0.03	-0.04	-0.03	-0.03
(Exporting − Non-Exporting)	(0.004)	(0.007)	(0.006)	(0.006)
Δ Over Time: Exporting Firms	–	–	-0.05	-0.05
	–	–	(0.005)	(0.005)
Δ Over Time: Non-Exporting Firms	–	–	-0.06	-0.05
	–	–	(0.005)	(0.004)
Share of Exporting Firms	0.45	0.45	0.45	0.46

Notes: This table presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (17). The sample covers France from 1995 to 2007, using export status as the grouping variable. Standard errors are clustered at the firm level. All regressions include 4-digit industry fixed effects interacted with year and export indicators. Columns report estimates for the full sample ("All Period") and for three subperiods (1995–99, 2000–03, and 2004–07). The first two rows present the estimated bargaining power for workers at exporting and non-exporting firms, respectively; the third row shows the between-group difference (Exporting Firms − Non-Exporting Firms); and the fourth and fifth rows report changes in bargaining power for each group.

Table B.8: Worker Bargaining Power by Outsourcing Status

	All Period	1995–99	2000–03	2004–07
Outsourcing Firms	0.30	0.35	0.30	0.26
	(0.005)	(0.007)	(0.006)	(0.006)
Non-Outsourcing Firms	0.37	0.45	0.38	0.32
	(0.008)	(0.012)	(0.011)	(0.009)
Δ Between Groups	-0.07	-0.10	-0.08	-0.05
(Outsourcing − Non-Outsourcing)	(0.008)	(0.013)	(0.012)	(0.011)
Δ Over Time: Outsourcing	–	–	-0.05	-0.03
	–	–	(0.007)	(0.006)
Δ Over Time: Non-Outsourcing	–	–	-0.08	-0.06
	–	–	(0.005)	(0.004)
Share of Outsourcing Firms	0.72	0.69	0.70	0.74

Notes: This table presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (17). The sample covers France from 1995 to 2007, using outsourcing status (firms hiring external workers) as the grouping variable. Standard errors are clustered at the firm level. All regressions include 4-digit industry fixed effects interacted with year and outsourcing indicators. Columns report estimates for the full sample ("All Period") and for three subperiods (1995–99, 2000–03, and 2004–07). The first two rows present the estimated bargaining power for workers at outsourcing and non-outsourcing firms, respectively; the third row shows the between-group difference (Outsourcing Firms − Non-Outsourcing Firms); and the fourth and fifth rows report changes in bargaining power for each group.

Table B.9: Worker Bargaining Power by Manager Education

	All Period	2002–10	2011–19
Firms with Univ. Manager	0.26	0.29	0.23
	(0.008)	(0.014)	(0.013)
Firms without Univ. Manager	0.28	0.29	0.28
	(0.008)	(0.013)	(0.013)
Δ Between Groups (With - Without)	-0.02	-0.00	-0.04
	(0.008)	(0.012)	(0.010)
Δ Over Time: With Univ. Manager	–	–	-0.06
	–	–	(0.002)
Δ Over Time: Without Univ. Manager	–	–	-0.01
	–	–	(0.016)
Share of Firms with Univ. Manager	0.36	0.33	0.39

Notes: This table presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (17). The sample covers France from 2002 to 2019, using the presence of a manager with a university degree as the grouping variable, and standard errors are clustered at the firm level. All regressions include 4-digit industry fixed effects interacted with year and manager indicators. Columns report estimates for the full sample ("All Period") and for two subperiods (2002–10 and 2011–19). The first two rows present the estimated bargaining power for workers at firms with and without a university-educated manager, respectively; the third row shows the between-group difference (Firms with Univ. Manager − Firms without Univ. Manager); and the fourth and fifth rows report changes in bargaining power within each group over time.

C Data

C.1 The United States

Compustat data is obtained from Standard and Poor's Compustat North America database and covers the period from 1960 to 2019. It has been extensively studied in the economic literature and I follow the data cleaning and preparation procedure of Keller and Yeaple (2009) and Demirer (2022). My analysis focuses only on U.S. firms with positive sales and input expenditure and with more than 10 employees. I drop the first and last percentile of each variable and deflate all indicators using GDP deflators from the Bureau of Economic Analysis with 2012 as benchmark year. Table C.1 shows the list of variables used and Table C.2 presents summary statistics. On average, listed firms are large (both in terms of revenues and of number of employees) and capital intensive. Among these, the ones that do report wages are even larger and more capital intensive.

Table C.1: List of Variables Compustat

Variable	Compustat
Revenues	SALES
Value added	Sales - Materials
Capital	PPEGT
Materials	COGS + XSGA - DP - XLR
Labor	EMP
Wages	XLR/EMP

Notes: This table presents the list of variables used in Compustat, with each variable name paired with its corresponding Compustat code.

Table C.2: Summary Statistics: Manufacturing, 1960 - 2019

	All	Reporting	Non-Reporting	Δ
Revenues	1,185	3,849	924	2,925***
Capital	345	1,259	256	1,003***
Employees	6	21	5	16***
Wages	35	35	.	.
Observations	148,757	13,794	134,963	146,583

Notes: This table presents summary statistics for firms in Compustat. All variables are expressed in real terms; revenues and capital are reported in USD millions, while the number of employees and wages are reported in thousands.

C.2 France

Panel Construction

The FICUS-FARE dataset is produced annually and is subject to different methodologies almost every year, thus creating a panel is not straightforward. I follow the guidelines of the data provider (INSEE) and keep only firms subject to the BRN tax filling scheme, thus dropping all the ones subject to the simplified scheme RSI. This selection guarantees

Table C.3: List of Variables FARE/FICUS

Variable	FICUS	FARE
Firm id	SIREN	SIREN
Industry	APE	APE_DIFF
Revenues	CATOTAL	REDI_R310
Value added	VAHT	REDI_R003
Total fixed assets	IMMOCOR + AMIMCOR	IMMO_CORP + K_DEP
Materials	ACHAMPR + ACHAMAR	REDI_R212 + REDI_R210
Export turnover	CAEXPOR	

Notes: This table presents the list of variables used in the FARE/FICUS database, with each variable paired with its corresponding code in FICUS and FARE.

comparability of data over time (Dalvit, 2021). I further drop all firms for which matching to the DADS data is not possible. DADS data are anonymized thus it is not possible to construct a panel for workers. However, the unique firm identifier for each worker-job observation allows to have a repeated cross-section of the workforce at each firm over time.

Variable Choice

FICUS and FARE provide the same information over different periods of time. FICUS was indeed discontinued in 2007 and replaced by FARE in 2008. I use these two data sources to take information on firms for my analysis. More specifically, revenue is total firm's sales, value added is pre-tax, capital is measured as total tangible assets, and intermediate inputs are defined as the sum of expenditures and stock of materials and merchandises (Burstein et al., 2020, De Ridder et al., 2022). Finally export turnover is the total amount of sales generated from exporting abroad. Table C.3 shows the variables I used in my analysis and the correspondence between FICUS and FARE. From DADS, on the other hand, I take information on workers' gross wages, number of hours worked, occupation at the 2-digit level (finer level is available only for a subset of years), gender, age, and administrative region of the workplace (finer level is available only for a subset of years).

Data Preparation

With the matched employer-employee dataset ready, I perform some standard data cleaning. More specifically, I drop firms with nonsensical id (INSEE signals observation with problematic identifiers) and with nonpositive items from balance sheet or income statement. I then keep firms with at least the equivalent of two full-time workers and trim every variable at the 0.5% to account for potential measurement errors and extreme values. Finally, I use deflators from EU KLEMS to transform nominal values in real,specifically gross output deflators for revenues, value added deflators for value added and wages, capital deflators for capital and intermediate input deflators for materials.[32] Table C.4 shows summary statistics for my sample of analysis.

[32]At the time of writing the paper, EU KLEMS deflators are available only until 2017 so I extrapolate from the existing data information for 2018 and 2019.

Table C.4: Summary statistics

(a) Firms

	p1	p25	p50	p75	p99	Mean	N
Sales	113	510	1,041	2,406	41,756	3,231	8,987,284
Value Added	35	186	353	754	9,818	877	8,856,811
Materials	1	107	334	998	24,605	1,566	8,987,284
Capital	5	106	270	733	19,528	1,223	8,987,284

(b) Workers

	p1	p25	p50	p75	p99	Mean	N
Wages	6.0	10.3	12.7	16.9	45.0	15.5	227,043,310

Notes: This table presents summary statistics for firms and employees in matched employer-employee dataset in France. All variables are expressed in real terms; firm variables are reported in thousands of Euros, while worker variables in Euros.

Additional Sources: Panel of Employees

Employees information are offered also in a panel version in which employees are followed over time (Panel tous salariés). Such information are available only for a random subsample of employees born in October of every other year until 2001 and in every year from 2002 onward. That means that such information covers only 4% and 8% of the entire workforce, respectively. Despite this difference in information, all the steps for preparing the sample are the same as for the other DADS data. In addition to the general information available in the general DADS database, the panel version includes as well demography characteristics such as education.

Additional Sources: Product-level Information

EAP survey offers information on revenues and quantity of products sold at the 10-digit level. I use this survey to extract information on the number of products produced by each firm and to construct a measure of firm-level prices, following De Ridder et al. (2022). More specifically, I define a product as the combination of 10-digit code and a unit of account. For each product then I compute the price as the ratio of revenues over quantity. Then I standardize the resulting prices by the revenue-weighted average price of the product in every year. Finally, firm-level price is defined as the revenue-weighted-average average of the standardized prices of each product produced by each firm.

Additional Sources: ICT Information

The TIC Entreprises is an annual survey commissioned by Eurostat on information and communication technologies and e-commerce. It covers a representative sample of firms with 10 or more employees and makes it possible to assess the progress of ICT use in European businesses. I follow Schivardi and Schmitz (2020) and classify firms as adopting ICT if they have access to an ERP software. Or, alternatively, if they employee ICT personnel.

Additional Sources: EAE Survey

The Annual Business Survey in the Industry provides statistics on the main economic indicators in the industry. The main information are collected through a questionnaire and concern which activities are carried out, economic results, investments, subcontracting, etc. It covers the period from 1995 to 2007. In particular, I use information on outsourcing activities.

D Production Function Estimation

I start by writing the production function in logs assuming that it takes a Cobb-Douglas form with labor and capital:

$$y_{it} = a_{it} + \varepsilon_{Y,N} n_{it} + \varepsilon_{Y,K} k_{it} \tag{D.1}$$

where each lowercase letter represents the logarithm of the corresponding uppercase variable. a is firm-specific TFP, whereas n and k are firm i's labor and capital, respectively. The productivity term can be decomposed into three components: a constant (β_0), an idiosyncratic productivity (ω_{it}) and an exogenous shock (ν_{it}), so that we can rewrite the production function as:

$$y_{it} = \beta_0 + \omega_{it} + \varepsilon_{Y,N} n_{it} + \varepsilon_{Y,K} k_{it} + \nu_{it} \tag{D.2}$$

Estimating this equation is challenging as (unobserved) productivity correlates with input choices and output produced. Hence, I use the input demand function for material to control for ω. The intuition is that firms are aware of their productivity level and choose their intermediate inputs accordingly. Therefore, the input demand function will take productivity as an argument (among other): $m = m(\omega, \Lambda)$, with Λ representing the remaining state variables that firms use to take decision on inputs. As long as this function is increasing in ω—meaning that more productive firms demand more intermediate inputs—and that firm productivity is the only unobservable firm characteristic, it can be inverted and used as a control function for productivity, i.e. $\omega = m^{-1}(m, \Lambda)$.[33] Hence, Equation (D.2) can be rewritten as:

$$y_{it} = \beta_0 + m_t^{-1}(m_{it}, \Lambda_{it}) + \varepsilon_{Y,N} n_{it} + \varepsilon_{Y,K} k_{it} + \nu_{it} \tag{D.3}$$

The first step of the estimation procedure consists therefore in estimating this equation. However, given that the inverted input demand is unobservable, it has to be flexibly approximated using a polynomial approximation. Doing that does not allow to identify separately the output elasticities but to jointly estimate the right-hand side purged by the error term.

[33] In the original paper, the authors leave this function indexed by t to embed the underlying market structure. In my framework this includes also the bargaining power common across firms.

Therefore, it estimates the following equation:

$$y_{it} = \underbrace{\Phi_{it}}_{\beta_0+m_t^{-1}(m_{it},\Lambda_{it})+\varepsilon_{Y,N}n_{it}+\varepsilon_{Y,K}k_{it}} + \nu_{it} \tag{D.4}$$

The second step exploits the stochastic process of productivity and the result from the first step to estimate the output elasticities. More specifically, productivity is assumed to follow a first-order Markov process:

$$\omega_{it} = g(\omega_{it-1}) + \xi_{it} \tag{D.5}$$

Combining Equation (D.4) and Equation (D.5) gives a non-linear equation that can be estimated

$$\hat{\Phi}_{it} - \varepsilon_{Y,N}n_{it} - \varepsilon_{Y,K}k_{it} = g(\hat{\Phi}_{it-1} - \varepsilon_{Y,N}n_{it-1} - \varepsilon_{Y,K}k_{it-1}) + \xi_{it} \tag{D.6}$$

where also in this case the function $g(\cdot)$ can be flexibly approximated. Assuming that TFP follows an AR(1) process with the parameter ρ governing the persistence, it is possible to construct the following set of moment conditions to estimate the output elasticities:

$$\mathbb{E}\left[\xi\left(\beta_0, \varepsilon_{Y,N}, \varepsilon_{Y,K}, \rho\right) \times \mathbf{z}\right] = \mathbf{0} \tag{D.7}$$

where $\mathbf{z}$ is the set of admissible instruments consistent with the structural model and includes current and lagged values of labor and capital.

Common Bargaining Power In the framework that I study, bargaining power is common to all firms within an industry. This is ideal to estimate the production function as I can control for it with industry fixed effects. As discussed above, a crucial assumption in the control function approach is that firm productivity is the only unobservable firm-level characteristic and this allows to proxy the mapping from observed input choices to TFP. If that was not the case, and bargaining power was firm-specific, this mapping would break and I would not be able to distinguish between productivity and bargaining power as determinants for input demand. A potential solution to this issue would be to use prices (in this case wages) to control for firm-specific bargaining power thus to overcome such a limitation and to be able to construct a distribution of bargaining power. This is, however, beyond the scope of this paper and I leave it for future research.

D.1 Revenues vs Quantities

The method described so far requires the econometrician to observe and use physical quantities in the estimation. The reason is twofold. On one hand, we are estimating the production function and the aim is to recover output elasticities and firm productivity. On the other, prices play an important role in firms' decision and their effect can confound the results.

In order to recover physical quantities, I use deflators to purge prices from revenues and input expenditures. This is an effective strategy if prices are common across firms and in such case using fixed effects controls for them as well in the estimation strategy. If prices are, however, firm-specific and each firm has some degree of market power, using deflators does not allow to recover quantities.[34] In this case, the error term would include both the measurement error term as well as the omitted output (and input) price. I follow De Loecker et al. (2020) and include demand shifters to control for firm prices. This is an exact control when output prices, controlling for productivity, reflect input price variation and the demand is of the nested logit form.

D.1.1 Firm-specific Prices

I use price information for a subsample of French firms to compare estimates using revenues and expenditure data and estimates using quantities.

More specifically, I use output quantities and a rich set of firm information to control for omitted input price.[35] I follow Mertens (2022) and De Loecker et al. (2016) and estimate the following production function:

$$q_{it} = \beta_0 + m_t^{-1}(m_{it}, \Lambda_{it}) + \varepsilon_{Y,N} n_{it} + \varepsilon_{Y,K} k_{it} + B(\cdot)_{it} + \nu_{it} \tag{D.8}$$

The difference with Equation (D.3) is threefold. First output is now denoted as q rather than y to highlight that this is physical quantity. Second, input demand m takes as argument as well the number of products produced by the firm. Finally, the presence of function $B(\cdot)$. This is the control function for input prices and it takes as argument a vector of information including firm-specific output price (π), weighted average of firms' product market shares in terms of revenues (ms), location dummy (ld), and 4-digit sector dummy (sd).[36]

In line with previous studies (Mairesse and Jaumandreu, 2005, De Ridder et al., 2022), I find that the distribution of labor elasticities based on revenue or quantity data are remarkably similar, with a cross-industry correlation of 93% for the Cobb-Douglas specification and a within-industry correlation of 93% for the translog specification.

Table D.1 reports worker bargaining power estimates using productivity measures derived from both revenue and physical quantity data, focusing on firms in the French manufacturing sector for which output prices are available. These results demonstrate that the output price bias often encountered in markup estimations (see, e.g., Bond et al. (2021) and De Loecker et al. (2016), with a solution proposed by Kirov et al. (2022)) does not affect this setting.

[34] De Loecker et al. (2016) describes how output prices and input prices affect the estimates of the production function.

[35] I describe in Appendix C how I construct firm output prices

[36] When estimating a translog specification, all the arguments in the price control function enter the production function linearly and interacted with each input term (Mertens, 2022).

Table D.1: Bargaining Power: Revenues vs Quantities

Bargaining Power	All Period	2009–14	2015–19	Δ
Revenue, CD	0.18	0.19	0.16	-0.03
	(.004)	(.005)	(.005)	(.005)
Quantity, CD	0.17	0.19	0.16	-0.03
	(.004)	(.005)	(.005)	(.005)
Revenue, T	0.21	0.23	0.20	-0.02
	(.006)	(.007)	(.007)	(.007)
Quantity, T	0.23	0.24	0.22	-0.02
	(.005)	(.006)	(.006)	(.006)
Controls	Yes	Yes	Yes	Yes

Notes: This table presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (9). The sample covers all manufacturing firms in France for which price information are available, thus comparing results using revenues versus quantity in the estimation of the production function. Standard errors are clustered at the firm level. All regressions include fixed effects for 4-digit industries interacted with year indicators. Columns report estimates for the full sample ("All Period") and for two subperiods (2009–14 and 2015–19). The first two rows present estimates using a Cobb–Douglas specification with revenue and quantity data, respectively; the next two rows present estimates using a Translog specification with revenue and quantity data, respectively.

E Alternative Instruments

In this Section, I explore alternative instruments for estimating bargaining power to address concerns related to the validity of the instrument used in the benchmark estimation. More specifically, I study various alternatives exploiting the stochastic process of productivity and exploring the possibility of having sticky wages. More specifically, I start by instrumenting marginal productivity with TFP innovation shocks rather than lagged values following from the framework introduced in Section 2. The idea here is that such shocks might be more unexpected than a persistent shock in the previous period and should therefore solve any potential endogeneity concern linked to the strategy outlined in Section 4. After that, I fully exploit the assumed Markov process of productivity and instrument the current marginal productivity of labor with a polynomial expansion of its lagged value to approximate a Markov process. That follows from the second step of the proxy method used to estimate firms' production function and allows for a more flexible stochastic approach. In addition, I relate to the recent literature showing wage stickiness and instrument current productivity progressively with second, third, and forth lags. Finally, I leverage employees' information to estimate bargaining power only for new hires. Table E.1 shows the results of these robustness checks in the US. The estimate of bargaining power is extremely stable across the different specifications and robust to alternative instruments. Table E.2 shows the outcome of these estimation in France. The estimates of bargaining power are very robust also in this case.

Table E.1: Alternative Instruments in the US

	(1)	(2)	(3)	(4)	(5)	(6)
τ	0.17	0.16	0.17	0.17	0.17	0.16
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Industry x Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (9). The sample covers the manufacturing industry in the US from 1960 to 2019. Standard errors are clustered at the firm level. All regressions include fixed effects for 4-digit industries interacted with year indicators. Column 1 reports the benchmark estimation from Table 1; Column 2 reports estimation using productivity shocks as instruments; Column 3 reports estimation using a third-order polynomial approximation of a Markov process; and Columns 4–6 report estimation using second, third, and fourth lags as instruments, respectively.

Table E.2: Alternative Instruments in France

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
τ	0.25	0.23	0.25	0.26	0.27	0.28	0.19	0.18
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (9). The sample covers French manufacturing firms from 1994 to 2019, and standard errors are clustered at the firm level. All regressions include fixed effects for 4-digit industries interacted with year indicators. Column 1 reports the benchmark estimation from Table 1; Column 2 uses productivity shocks as instruments; Column 3 employs a third-order polynomial approximation of a Markov process; Columns 4–6 use second, third, and fourth lags as instruments, respectively; Column 7 reports the estimate of bargaining power in the benchmark case using employee data (which includes additional nonlinear controls for age, gender, location, occupation, and contract type); and Column 8 reports estimates of bargaining power only for new hires.

F Additional Robustness Exercises

Here I describe how alternative production technologies, wage negotiations and production function estimations enter my framework.

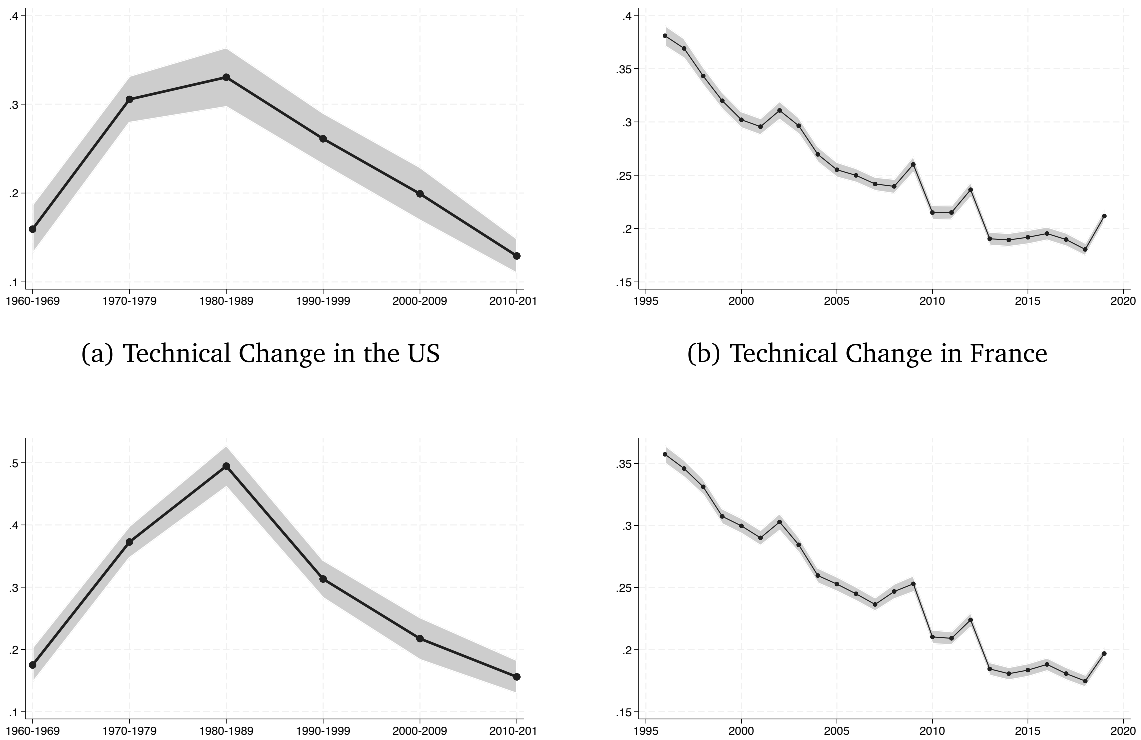
F.1 The Role of Alternative Production Technologies

The baseline analysis in Section 5 works under the assumption that firms produce according to a Cobb-Douglas production function with constant output elasticities. In this Section, I advance on this exploring first the idea that technical change could lead to changes in output elasticities over time and, second, relaxing the functional form specification and thus allowing for a more general production function.

Technical Change

Following De Loecker et al. (2020), I allow output elasticities to vary over time by estimating firm production function on 7-year rolling windows. This is such that firm can change the way they combine inputs over time in order to produce output as a result of technical change

Figure F.1: Bargaining Power with Alternative Production Technologies



(a) Technical Change in the US

(b) Technical Change in France

(c) Translog in the US

(d) Translog in France

Notes: This figure presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (9). The sample covers the manufacturing industry in the U.S. from 1960 to 2019 and the manufacturing industry in France from 1994 to 2019. Standard errors are clustered at the firm level. All regressions include fixed effects for 4-digit industries interacted with year indicators. In Panels (a) and (b), the production function is allowed to change over time and is estimated using rolling windows. In Panels (c) and (d), a translog specification is used, which is a flexible production function with firm-specific elasticities.

(among other potential explanations). The first two panels in Figure F.1 show the results of this exercise. More specifically, Figure F.1a shows the evolution of bargaining power in the U.S. when the marginal productivity of labor includes time-varying output elasticities. And Figure F.1b shows the evolution in France. In both cases, the results are not different from the ones in the previous Section in terms of levels and trends. This means that changes in the way input are mixed at the firm level do not affect the estimates of bargaining power.

Alternative Production Functions

Now, I relax the Cobb-Douglas production function used in Section 4 and assume that firms produce according to a more flexible translog production function. In this case the output elasticity of labor is firm- and time-specific but is governed by a set of common parameters (Mertens, 2022, Wong, 2023, Kirov and Traina, 2021). This allows to include further heterogeneity across firms as well as more flexibility in the way physical inputs are combined. The procedure for estimating the parameters of the production function is the same discussed in Section 4.

The last two panels in Figure F.1 show the results of this exercise. More specifically,

Figure F.1c shows the estimated values of bargaining power over time in the U.S. with marginal productivity of labor resulting from a translog production function and Figure F.1d shows the same in France. In both cases the levels of bargaining power vary but the trend, the main contribution of this paper, is preserved. In the US, it can be seen that the trend is very similar to the one in the benchmark case shown in Figure 1 with bargaining power following a hump-shaped evolution starting at a very low level in the 60s, reaching its peak in the 80s and finally arriving to its lowest level in the 2010s. The levels, on the other hand, are all shift upwards and the difference is most notably in the central part of the period analyzed. Indeed, bargaining power reaches .5 in the 80s with this specification. In France as well the trend is virtually the same as in Figure 2a however there is less variation over time. The distribution is more compact. Bargaining power starts at around 25% and then follows the same trend as in Figure 2a arriving as well to 15%.

There is no test to understand which functional form fits better the data and hence is not possible to identify which of the two I use in this paper is more realistic. What is clear, however, is that the main contribution of this paper, the trend of bargaining power, holds with both specifications.

F.2 The Role of Multi-Workers Negotiations

The surplus that a firm receives from hiring a new worker, as described in Section 2, consists of the difference between his marginal productivity and wage plus the continuation value. Stole and Zwiebel (1996) and Cahuc et al. (2008), among others, argue that firms internalize the effect that a new hire would have on the wages of the existing workforce already in the negotiation process. Such effect indeed changes the value that a worker generates at a firm and needs to be accounted for in the wage negotiation process. I incorporate this additional layer in the analysis and show that the main result,i.e., the trend in bargaining power, is unaffected.

Starting from the firm problem described in Section 2, I define the marginal profitability of hiring a new worker, *J*, as the derivative of the firm problem with respect to labor:

$$J_{it} = \frac{\partial \Pi_{it}}{\partial N_{it}} = \frac{\partial F(\cdot)}{\partial N_{it}} - w_{it} - N_{it}\frac{\partial w_{it}}{\partial N_{it}} + \beta(1-s)\mathbb{E}[J_{it+1}] \tag{F.1}$$

with $N\frac{\partial w}{\partial N}$ representing the changes in wages of the existing workforce. In this setting indeed all workers are identical and wages can always be renegotiated so all the employees of a firm are paid the same amount. Including this in the Nash negotiation leads to the new equilibrium equation for wages:

$$w = \tau\left(\text{MPN} - N\frac{\partial w}{\partial N}\right) + (1-\tau)b + \tau\theta\kappa \tag{F.2}$$

Hiring a new worker has two effects for a firm. First, it increases the production, thus the revenues, and that is represented by the first term in parenthesis as in the standard framework discussed in Section 2. Second, it has an effect on the wage-bill that constitutes the second term in parenthesis.

I follow the steps in Cahuc et al. (2008) to solve Equation (F.2). Specifically, I re-write it as an ordinal differential equation:

$$w'(N) + p(N)w = q(N), \tag{F.3}$$

where $w'(N) = \frac{\partial w}{\partial N}$, $p(N) = \frac{1}{\tau N}$, $q(N) = \frac{\text{MPN}}{N} + \frac{D}{\tau N}$ and $D = (1-\tau)b + \tau\theta\kappa$. At this point, I define the auxiliary function $\mu(N)$, such that $p(N) = \frac{\mu(N)'}{\mu(N)}$. Substituting the value of $p(N)$, I can find the value of $\mu(N)$:

$$(\ln(\mu(N)))' = \frac{1}{\tau N} \;\rightarrow\; \ln(\mu(N)) = \frac{1}{\tau}\int \frac{1}{N}\mathrm{d}N + C \;\rightarrow\; \mu(N) = N^{\frac{1}{\tau}}\mathrm{e}^{C},$$

with C being a constant of integration that changes at each step—I do not keep track of it as it will simplify in the next step. By using the product rule, I can express Equation (F.3) as:

$$\big(w'(N)\mu(N)\big)' = q(N)\mu(N). \tag{F.4}$$

Plugging in the values of the function:

$$wN^{\frac{1}{\tau}} = \int \frac{\text{MPN}}{N^{1-\frac{1}{\tau}}}\mathrm{d}N + D\int \frac{1}{\tau N^{1-\frac{1}{\tau}}}\mathrm{d}N + C \tag{F.5}$$

Finally, solving the second integral gives:

$$wN^{\frac{1}{\tau}} = \int \frac{MPN}{N^{1-\frac{1}{\tau}}}dN + [(1-\tau)b + \tau\theta\kappa]N^{\frac{1}{\tau}} + C \tag{F.6}$$

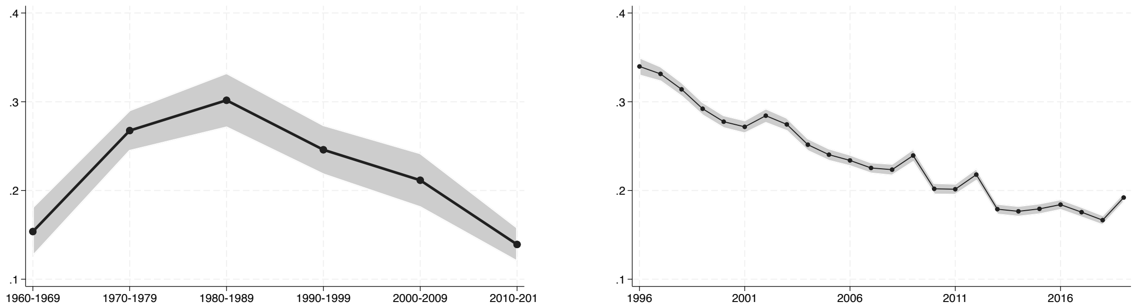
with C being an unknown constant of integration. At this stage, I need to take two additional assumptions for finding a closed form solution. Namely, 1) a functional form for firm production function; and, 2) a bound for the limiting behavior of wages. I choose to use Cobb-Douglas specification and that the limit of the labor cost is zero when the workforce tends to zero, $\lim_{N\to 0} Nw = 0$. The former allows me to solve the integral and the latter is necessary to find that C must be equal to 0. Hence, the final solution is:

$$w = \frac{1}{(\varepsilon_{Y,N} + \frac{1}{\tau} - 1)}\text{MPN} + (1-\tau)b + \tau\theta\kappa. \tag{F.7}$$

When bringing this to the data, the only free parameter in the coefficient of MPN is τ because the output elasticity is already estimated with the control function approach as described in Section 4. To do inference, I adjust the standard errors obtained in the estimation of Equation (F.7) by the ratio of the bargaining power parameter and the coefficient of the marginal productivity of labor.

Figure F.2 shows the estimation results of bargaining power in the presence of multi-worker bargaining. The evolution of bargaining power is the same as in my benchmark results (Figure 1 and Figure 2a) and only the level is slightly shifted downward. This, as

Figure F.2: Bargaining Power with Multi-worker Bargaining



(a) US (b) France

Notes: This figure presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (F.7). The sample covers the manufacturing industry in the U.S. from 1960 to 2019 and the manufacturing industry in France from 1994 to 2019. Standard errors are clustered at the firm level. All regressions include fixed effects for 4-digit industries interacted with year indicators.

explained above, is due to the higher benefits that a worker brings to his employer that are not reflected in his compensation.

F.3 The Role of Production Function Estimation

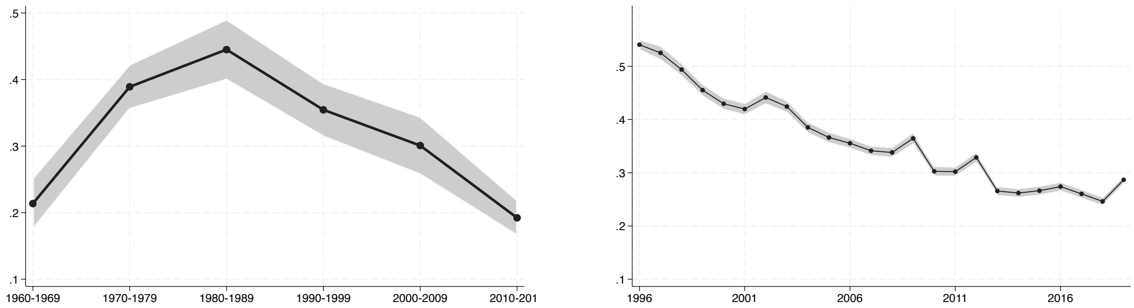
The pioneering idea of controlling for unobserved productivity by using the outcome of firms' behavior and to exploit the stochastic process of TFP to estimate production function proposed by Olley and Pakes (1996) started a vast and active literature on the topic (see Ackerberg et al. (2015) for a review). Being a structural method however it relies on two critical assumptions, namely that firm productivity is the only unobservable variable to the econometrician and that input demand is monotonic in productivity. It is not possible, and would anyway be beyond the scope of the paper, to verify such assumptions. To understand how the results depend on the elasticities estimated in such a way, I estimate worker bargaining power using a different set of output elasticities. I indeed estimate the production function of a firm using a dynamic panel method (Arellano and Bond, 1991, Blundell and Bond, 1998, 2000), what is considered the reduced-form alternative to the control function approach (Ackerberg et al., 2015, De Loecker and Syverson, 2021). The main differences with respect to the proxy approach are that the serial correlation in productivity is linear and the missing treatment of selection over time. Figure F.3 shows the estimates of bargaining power using such elasticities. Also in this case, the main result of the paper, the hump-shaped trend in bargaining power in the U.S. and the stark decline in France, is confirmed.

G Model Solution and Calibration

The steady state equilibrium is defined as a triple of unemployment, wage and tightness ratio (u, ω, θ) that satisfies:

1. the zero profit condition: Equation (6);

Figure F.3: Bargaining Power with Reduced-Form Elasticites of the Production Function



(a) US (b) France

Notes: This figure presents estimates of worker bargaining power (τ), defined as the coefficient on productivity in Equation (9). The sample covers the manufacturing industry in the U.S. from 1960 to 2019 and the manufacturing industry in France from 1994 to 2019. Standard errors are clustered at the firm level. All regressions include fixed effects for 4-digit industries interacted with year indicators. Elasticities of the production function are estimated using the dynamic panel method (Blundell and Bond, 2000).

2. the wage equation: Equation (8);

3. the unemployment equation: $u^{SS} = (1 - p(\theta^{SS}))u^{SS} + s(1 - u^{SS})$.

The zero profit condition allows firms to enter the market as long as there are profits to extract, until the cost of entry (LHS) is equal to the benefits (RHS). The wages equation describes the solution to the Nash bargaining game in steady state. Finally, the unemployment equation characterizes the law of motion for unemployment, where future unemployment results from unmatched unemployed and the outflow from employment.

G.1 Model Calibration

The model is calibrated to match the period with the highest worker bargaining power, the 80s in the U.S., and 1995 in France. Table G.1 summarizes the external parameters and their sources.

The model period is a month. I normalize the productivity of a match to 1 and then use a discount factor of 0.9967 to reflect a 4% annual interest rate. The bargaining value is the highest estimate for both countries, namely 0.34 in the 80s in the U.S. and 0.28 in 1995 in France. The outside option is 0.4 in the U.S. (Shimer, 2005) and 0.6 in France (Cahuc and Le Barbanchon, 2010), consistent with a more institutionalized environment in Europe. The separation rate is the monthly average in JOLTS over the period 2001-19, 0.036, for the U.S. and the average value in Hairault et al. (2015) for France, 0.017. These values show a more dynamic labor market in the U.S. The vacancy cost, κ, is set to 0.9, the equivalent of a one-month pay. Finally, the matching function is of the form $M(v, u) = A^z v^\alpha u^{1-\alpha}$ and with the elasticity of matches to vacancies of 0.22 in the U.S. as estimated in Lange and Papageorgiou (2020) for normal times, and of 0.5 in France following Cahuc and Le Barbanchon (2010).

I am left with one free parameter, the efficiency of the matching function, A^z. I calibrate it to match the average monthly unemployment rate during the 80s (7.5) in the U.S. finding

Table G.1: External parameters

Parameter	US		France	
	Value	*Source*	*Value*	*Source*
Productivity (z)	1	normalization	1	normalization
Discount factor (β)	0.9966	4% annual interest	0.9964	4% annual interest
Bargaining power (τ)	0.34	own estimation	0.28	own estimation
Outside option (b)	0.4	Shimer (2005)	0.6	Cahuc and Le Barbanchon (2010)
Separation rate (s)	0.036	JOLTS	0.017	Hairault et al. (2015)
Matching elasticity (α)	0.22	Lange and Papageorgiou (2020)	0.5	Cahuc and Le Barbanchon (2010)

Notes: This table summarizes the external calibration parameters for the US and France.

$A^z = 0.44$. In France, I calibrate it to match the average monthly unemployment rate in 1995 (11.8) and find $A^z = 0.19$.