University of Zurich[UZH]
URPP Equality of Opportunity

Trends in Worker Bargaining Power

Paolo Mengano

Equality of Opportunity Research Series #25
May 2023

URPP Equality of Opportunity

URPP Equality of Opportunity Discussion Paper Series No. 25, May 2023

Trends in Worker Bargaining Power

Paolo Mengano
University of Zurich
paolo.mengano@econ.uzh.ch

Trends in Worker Bargaining Power

Paolo Mengano*

May 30, 2023

Abstract

This paper investigates worker bargaining power evolution over the last decades and its consequences on the American and French labor markets. I use a framework where wages and marginal productivity of labor are linked by a negotiation process, allowing the bargaining power of the parties involved to vary over time. I uncover a sizable disproportion between employees and employers in salary negotiation by estimating an average worker bargaining power of 17% in the U.S. and 25% in France. However, these average estimates mask an aggregate declining trend in both countries since the 90s. Worker bargaining power followed a hump-shaped trend in the U.S. over the last 60 years, peaking in the 80s and then halving until nowadays. In France, it has also been declining steadily over the last 30 years. These patterns help explain the low unemployment and wage growth over the last decades: firms exploited the low level of worker bargaining power to hire an inefficiently high number of employees. I propose marginal wage and profit taxes to restore labor market efficiency. Technological advancement, regulation, trade, and outsourcing seem to play a minor role in the decline of bargaining power. Gender and occupation differences are crucial, with male employees and those performing non-routine abstract jobs experiencing the most significant erosion of bargaining power.

*Department of Economics, University of Zurich. Email: paolo.mengano@econ.uzh.ch. I am grateful to my advisors Nir Jaimovich, Greg Crawford, Florian Scheuer, and Alessandro Ferrari for their guidance and encouragement on this project. I also thank Marlon Azinovic, Nick Bloom, Lorenzo Casaburi, Rafael Dix-Carneiro, David Dorn, David Hemous, Pete Klenow, Vardges Levonyan, Luigi Pistaferri, Julian Schärer, Samuel Skoda, Simon Zuzek, Josef Zweimüller, and participants at seminars at the University of Zurich, Collège de France, Econ GSW, and Stanford for helpful discussions and feedback. I thank Maarten De Ridder, Basile Grassi, Mathilde Le Moigne, Isabelle Mejean and Giovanni Morzenti for help with the French data and Matthias Mertens for sharing his codes. This work was supported by the University Research Priority Program "URPP Equality of Opportunity" of the University of Zurich. Access to some confidential data, on which this work is based, was made possible within a secure environment provided by CASD – Centre d'accès sécurisé aux données (Ref. 10.34724/CASD).

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 employer-employee and firm level panel 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. I show that a decrease in bargaining power leads to a new equilibrium with lower unemployment and labor share, and I quantify that the observed changes in worker bargaining power can account for the recent dynamics of the American and French economies. 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., 2021). 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 yearly 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

[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.

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.

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.

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, 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, 2022), 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 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., 2022, Crivellaro, 2014). Additionally, following recent evidence

[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*.

of job polarization (Jaimovich et al., 2020, Patel, 2021), I classify workers based on their occupation and study how each occupation-specific marginal productivity transmits to its relative wage. I find 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.[4] This finding is consistent with the declining college wage premium in France and could be one of the driving phenomena (Crivellaro, 2014). Finally, I find that employees working at firms with university graduate managers experienced a steeper decrease in their bargaining power (Acemoglu et al., 2022).

Finally, I use the model to analyze the labor market's efficiency by comparing the decentralized equilibrium with a constrained efficient one. First, I solve the problem of a social planner facing the same search frictions in the labor market. 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).[5,6] 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. Recent work estimates the elasticity of matches to vacancies in a range between 0.2 and 0.5 (Petrongolo and Pissarides, 2001, Brügemann, 2008, Lange and Papageorgiou, 2020). My estimates of firm bargaining power exceed this range at any point in time, implying that firms do not internalize the frictions in the labor market in their behavior. Using the estimates of worker bargaining power, we can learn how far we are from the efficient equilibrium and how this inefficiency propagates to the labor market. 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 disproportion between employers and employees in the wage negotiation process, such taxes have to be very high, with the wage and profit tax starting at 50% and 80%, respectively. Moreover, being complementary, I show how any linear combination of the two works as well.

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

[4] de Almeida Vilares and Reis (2022) finds similar results in Portugal.

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

[6] 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.

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] Moreover, I find that changes in labor force composition are the main candidates for such a decline.[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 (2020), with papers providing new empirical insights (Azar et al., 2022, Goolsbee and Syverson, 2019, Dube et al., 2020)[12], the-

[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)

[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 and Salvanes (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. (2022) 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. (2018) studies rent-sharing evolution on a selected sample of British firms and industry data in the U.S. and European countries.

[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, 2021). 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.

oretical frameworks (Berger et al., 2021, Jarosch et al., 2021) and quantification of efficiency losses (Azkarate-Askasua and Zerecero, 2022, 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. (2020) 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 Vilares and Reis (2022) builds a dynamic search-and-matching model and estimates it on Portuguese data. My results align with all this evidence, finding a large decline in worker bargaining power in the U.S. and France. In addition, the strand of this literature that builds on insight from the industrial organization has focused on estimating firm-level markdowns. These indicators are the ratio of the marginal value employees generate at a firm over their compensation, and estimating this marginal value is empirically challenging. Prime examples are Yeh et al. (2022) and Traina (2021) in the U.S., Mertens (2022) in Germany, and Wong (2021) in France. I incorporate these methods in a structural analysis that allows me to identify worker bargaining power and its evolution over time.

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 used and Section 4 shows the estimation framework for measuring worker bargaining power. Section 5 presents the main results of the paper, i.e. the estimates of bargaining power, and Section 6 provides several extensions and robustness to the baseline framework. Section 7 discusses the implication for the total economy of changing values of bargaining power with a focus on unemployment, wages, labor share, and policy interventions. Section 8 provides suggestive evidence on what the causes for the decline in bargaining power could be. Finally, Section 9 provides some concluding remarks.

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 my analysis. Firms are heterogeneous in their total factor productivity (TFP) and need labor inputs to produce. Due to market frictions, 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

Each firm maximizes profits and its problem can be formulated as:

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

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 or keep 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 are risk neutral and can be either employed (E) or unemployed (U). The respective Bellman values are:

$$E_t = w_t + \beta \mathbb{E}[(1-s)E_{t+1} + sU_{t+1}] \tag{2}$$
$$U_t = b + \beta \mathbb{E}[p(\theta_t)E_{t+1} + (1-p(\theta_t))U_{t+1}] \tag{3}$$

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. A matching function governs meeting probabilities and wages are negotiated upon meeting.

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

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

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

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. In equilibrium, it must be that V = 0, meaning that the marginal cost of opening a vacancy must equal the expected value it will generate. Else, firms will continue opening new vacancies and capture more profits. The resulting free entry condition can be expressed as:

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

Wages

Once a match occurs, the wage is negotiated between the firm and the newly hired worker according to the Nash bargaining protocol, the most common wage negotiation protocol in the literature. It envisages that the surplus generated by a match is divided among the parties according to their relative bargaining power. More specifically, wages are determined as:

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

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

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

This well-known result from DMP models with Nash bargaining states that three components determine wages: 1) productivity (MPN), 2) worker outside option (b), and 3) market conditions ($\theta\kappa$) weighted by the bargaining power of workers and firms. [13]

3 Data

For the estimation of bargaining power, I use data for two countries: the U.S. and France. The data source for the U.S. is Compustat, whereas I combine several administrative datasets for France. In Appendix C, I describe in more detail the sample construction, choice of variables, data preparation, and include summary statistics about the sample of the analysis.

3.1 The U.S.

To describe the U.S. labor market for the longest possible period, I use firm-level data from S&P's Compustat. This database offers financial information on the universe of publicly listed firms in the U.S. from 1960 to 2019. Information includes revenues, physical capital, intermediate inputs, number of employees, and labor costs. The complete list of variables used and some descriptive statistics are presented in Appendix C. One important limitation of this database for my study is that firms are not requested to report wages; thus, only a subsample does it. Hence, I focus my analysis on the manufacturing industry, the sector with the best coverage of wage information. The financial sector is another industry for which I have enough wage information to estimate bargaining power, which is, however, unsuitable for the production function estimation.[14]

[13] In appendix F I show that when firms internalize the effect that a new hire has on the rest of the workforce, equation 8 includes an additional term representing the changes in the total wage-bill (Equation F.2)

[14] I report estimates of bargaining power in the financial industry in Appendix H. However, I do not include it in the main text for concerns related to the production function already stated above.

3.2 France

I complement U.S. data with administrative data at the firm and worker levels in France. In particular, I rely on linked employer-employee data to compute job- and firm-level outcomes. Then I use survey information on technology and prices in robustness and extensions exercises. This combination allows me to comprehensively and extensively represent the French economy with information on workers and firms.

Firm information comes from the FICUS/FARE database, which provides financial information on the universe of French firms. FICUS and FARE cover the period 1994-2007 and 2008-2019, respectively, and are based on firms' annual tax filing documents. It includes firm revenues, value added, fixed assets, industry classification, etc.

Employee information comes from the DADS database, an administrative database of matched employer-employee data based on mandatory earning information that employers must provide about their establishment and employees annually. It covers the entire workforce of the universe of private employers from 1993 to 2019. It provides information on each employee's wage, the number of hours worked, type of contract, occupation, geographical location, and unique plant and firm identifiers for each job performed annually. Such employee/job data are anonymized, and it is not possible to track workers for more than two consecutive years; thus, there is no information about their education or job tenure.

I merge these data sources to create a matched employer-employee dataset covering 26 years. In Appendix C, I describe the sample construction, choice of variables, and data preparation in more detail. The resulting sample includes almost 9 million firm-year observations and 227 million employee/job-year observations.

I also use several additional data sources in robustness exercises. First, DADS data include as well a worker panel version. Such panel focuses only on workers born in October of an even year until 2001 and in October of every year starting in 2002. Hence, it covers around 4% of the total workforce until 2001 and 8% afterward. I cannot use this data for my main analysis as I need a comprehensive representation of the total workforce to describe the evolution of worker bargaining power. However, I use it in a series of robustness exercises to include worker experience and ability as it provides information for a representative subsample of the population. Second, I also use information from the Annual Production Survey (Enquête Annuelle de Production, EAP). This survey includes product-level revenues and quantity for all manufacturing firms with at least 20 employees or €5 million of revenues. Following De Ridder et al. (2021), I use this information to compute firm-level prices as described in Appendix C to show how using expenditure data rather than quantities does not generate bias in my setting in Appendix D (De Loecker et al., 2016). Third, I use a firm-level survey with detailed purchases of intermediates at the firm level (Enquête annuelle d'entreprise dans l'industrie, EAE). Firms report expenditures on *external workers*, i.e. employees of another firm, but that falls under a contracting agreement with the surveyed firm and are at least partially under the authority of the surveyed firm (Bilal and Lhuillier, 2021). I use such an expenditure as a measure for outsourcing. Finally, I use the Survey on Information Communication Technologies in businesses (TIC Entreprises). This survey reports information on ICT usage for a representative sample of firms with ten or more employees. I use this information in Section 8 to shed light on the role of technology for worker bargaining power.

In the remaining of the paper, I will focus mainly on the entire economy to unravel an aggregate trend and on the manufacturing industry to provide a consistent comparison to the U.S. results. Moreover, each analysis on worker-level information will solely focus on manufacturing for computational reasons. While Table A.2 provides estimates of bargaining power for other industries, I leave the analysis of the industry heterogeneity to future research.

Why two data sources? Access to two different data sources is an excellent advantage for analyzing worker bargaining power. I can leverage both of them to study its evolution in two of the major economies in the world, uncovering a common aggregate trend. In the U.S., the unique time coverage of firm-level data in Compustat allows me to go back in time and study changes over more than half a century. I can then compare the results to the French economy, for which I have extensive data coverage for the universe of firms and employees. Moreover, French data allow me to provide robustness to the methodology developed and to investigate heterogeneous aspects of bargaining power and worker characteristics to shed light on the sources of the estimated trends.

4 An Empirical Framework to Estimate Bargaining Power

This section introduces the methodology used to estimate worker bargaining power. The aim is to provide an econometric procedure to recover τ from Equation 8. However, estimating such an equation presents many challenges. First, the productivity of a worker is not directly observable; hence MPN must be estimated. Second, Equation 8 is an equilibrium equation, and as such, it inherently presents an endogeneity bias. Finally, information on unemployment benefits, vacancy costs, and market conditions are also unobservable, at least partially. In the following paragraphs, I will discuss how I deal with these issues.

4.1 Measuring Productivity

I need an indicator of how much value added is produced by an additional worker in each firm, i.e. the marginal productivity of labor, to have a measure of worker's productivity consistent with the framework described in Section 2. The marginal productivity of labor is:

$$\text{MPN}_{it} = \frac{\partial F(\cdot)}{\partial N_{it}} = \varepsilon_{Y,N}\frac{Y_{it}}{N_{it}} \tag{9}$$

Although Y and N can be found in the data, the output elasticity of labor, $\varepsilon_{Y,N}$ is unobservable, and its estimation raises several issues (Ackerberg et al., 2015). Most importantly, the simultaneity of the productivity realization and input choices makes it very challenging to identify the components of the firm production function individually. I adopt the control function or proxy approach initially proposed by Olley and Pakes (1996) to recover the output elasticities in the production function.[15] The intuition of this method is that idiosyncratic productivity is unobservable to the econometrician but observable to the firm. Starting from this idea, it is possible to use some other observable data with a few assumptions on firm behavior to control for unobservable TFP. Assuming that the latter follows a Markov process, it is possible to exploit such a process to estimate the output elasticities in the production function. I leave the details of this estimation procedure in Appendix D.

It is worth noticing that 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. Indeed, here I introduce a Cobb-Douglas production function with labor and capital. In Section 6, I further relax the function form implementing instead a Translog specification and I introduce intermediate inputs. Moreover, it is well-known that such a method – the control function approach for estimating production 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 my analysis in two ways. First, I add additional controls to proxy for such omitted information using structural assumptions (De Loecker et al., 2020, De Ridder, 2021, Chiavari, 2021). Second, I use price information from the EAP survey to estimate the production function on quantities (De Loecker et al., 2016, Mertens, 2022, De Ridder et al., 2021, Wong, 2021) finding an extremely high correlation between revenue and quantity estimates (Mairesse and Jaumandreu, 2005). I discuss in more detail both demand shifters and quantity estimates in Appendix D.

Finally, in this setting, I have worked under the assumption that firms do not have market power in product markets. If, on the other hand, they do, the productivity term in wage 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 rather than the output one. I

[15] 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.

discuss more on this and specifically 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, the estimation of Equation 8 presents two additional issues: i) the endogeneity bias stemming from the wage equation being an equilibrium condition and ii) the presence of unobservable terms such as worker outside option, the tightness ratio, and vacancy costs.

I address the former with an instrumental variable strategy. More specifically, I instrument current MPN with its lagged value. The relevance of lagged values as instruments for current levels is given by the serial correlation of productivity, which is already exploited in estimating the production function. Moreover, Equation 1 shows that the current realization of productivity is a function of its lagged value. The exclusion restriction, i.e. lagged productivity affecting wages only through current productivity, is guaranteed by two features of the framework described in Section 2. Namely, the timing of the hiring process and the static nature of the Nash bargaining protocol. Indeed, firms hire workers in the current period that start producing only in the next period and take market conditions ($\kappa\theta$) as given. Moreover, wages are renegotiated every period, thus, they reflect only today's productivity.

Finally, I include a set of sector times period fixed effects to account for worker outside options and labor market conditions. This implies 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. Even though both can vary over time, they cannot be different across workers/firms in a given period.[16] I will be unable to identify the outside option and labor market conditions. However, the combination of the IV strategy with fixed effects allows the estimation of the coefficient on the marginal productivity of labor, namely worker bargaining power. The target equation for my empirical analysis is then:

$$\omega_{ist} = \tau_{ST}\mathrm{MPN}_{ist} + \Upsilon_{ist} + \varepsilon_{ist} \tag{10}$$

where ω_{ist} represents wages and MPN_{ist} marginal productivity of labor of firm i in sector s in year t. Υ_{ist} is a set of fixed effects and ε 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. In Section 5, I show the results of this estimation both when bargaining power is fixed and when it varies over time.

[16] I relax this assumption and provide a number of extensions in Section 6 and 8.

Instrument Validity Timing and information assumptions guarantee the validity of the instruments in this setting. As discussed above, firms hiring in the current period and workers starting to produce in the following one and having firms taking θ as given ensures that the exclusion restriction holds. If that were not the case and lagged productivity were to affect current wages through another channel, the exclusion restriction would be violated. There is no formal test to understand what other channels might affect lagged productivity realization. Therefore I perform a robustness exercise with another instrument, implicitly allowing lagged productivity to affect current wages. I use current productivity shocks as instruments for current productivity (Chan et al., 2021). This directly follows from the structure of the stochastic process of TFP, which includes a persistent element and a temporary shock. Appendix E, shows the results of such an exercise in which I find similar results for bargaining power, thus, confirming the instrument's validity. To test the information assumption, I estimate the bargaining power only on very small firms, i.e. with less than ten employees. The rationale for that is that there might be strategic interactions in the labor markets that would make my estimate only a reduced-form result (Berger et al., 2021). Focusing on very small firms, I want to study a sample of firms whose hiring choices are unlikely to affect other participants in the labor markets. Table A.5 shows that the paper's main result, the trend discussed in the next Section, is robust to allowing for strategic interactions.

Worker Dimension In the empirical framework just described, there is minimal worker heterogeneity. As discussed above, all workers have the same outside option and face the same labor market conditions in a granular industry and period. Moreover, the variation in productivity comes from firm heterogeneity, and all workers are homogeneous. In the following Sections, I gradually relax these assumptions introducing a richer worker dimension. In Section 6 I introduce an occupation notion that allows productivity, outside option, and labor market conditions to vary across occupations. Moreover, I introduce granular worker/job information to be as flexible as possible in my estimation. Both of these exercises confirm an aggregate trend unaffected by worker heterogeneity. Finally, in Section 8 I investigate differences in bargaining power by worker types.

5 Constant vs Time-Varying Bargaining Power

This Section presents the main results of this paper. I start by estimating worker bargaining power keeping it constant throughout the whole period in order to provide a benchmark with the literature. This exercise is helpful as a validation of the entire procedure. Furthermore, it provides an average value that can give a sense of the magnitude of the relative power that workers and firms have and could be used in calibration exercises. Thereafter, I focus on the main contribution of this paper: estimating the trend in bargaining power in the U.S. and in France.

5.1 Constant Bargaining Power

Table 1 presents the result of estimating bargaining power from Equation 10 keeping it constant throughout the whole period.[17] The first column refers to the manufacturing industry in the US, and the second and third columns to the whole economy and manufacturing industry in France, respectively. Each specification includes sector times year fixed effects that, as mentioned in Section 4, capture time-varying worker outside option and labor market conditions for workers and firms. This implies that firms face the same labor market condition only within a narrowly defined industry in a given year. The same also holds for workers.

Table 1: Bargaining Power

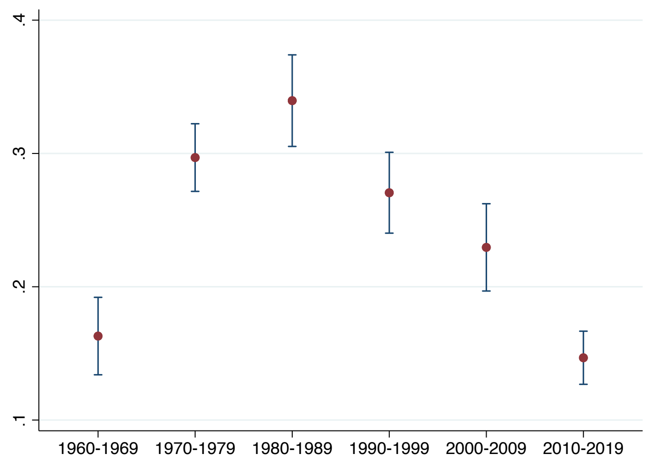
	USA	France	
	Manu	All	Manu
τ	0.17	0.21	0.25
	(0.01)	(0.001)	(0.002)
Ind x Year FE	Yes	Yes	Yes

Notes: This table shows estimates of *worker bargaining power*, defined as τ, the coefficient of productivity in Equation 10. T is defined as the entire period of analysis such that τ does not change over time. The sample in the analysis represents the manufacturing industry in the U.S. 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. Controls include time-varying 4-digit industry fixed effects.

It is evident that there is a stark disproportion in the relative importance that workers and firms have in the wage negotiation process, with firms having much larger importance than workers. In the US, workers have a bargaining power of only 17%. This number, although in line with the literature, is stunning by itself. It implies that only a minimal part of labor productivity is reflected in workers' compensation; thus, employers have bargaining power over wages almost five times higher than employees. Looking at it through the lens of the wage equation 8, that implies that wages are much closer to the outside option than to the marginal productivity of labor for given market conditions. Columns 2 and 3 show that bargaining power is higher in France than in the US, both in the total economy and manufacturing industry. Indeed, French firms seem to have a bargaining power of around four times higher than French employees. Interestingly, columns 2 and 3 also show that bargaining power is higher in manufacturing than in the general economy. In manufacturing, indeed, firm bargaining power is only three times higher than worker one, implying that the joint

[17] Table A.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 shows estimates of *worker bargaining power*, defined as τ, the coefficient of productivity in Equation 10. T is defined as a decade such that τ varies every ten years. The sample in the analysis represents the manufacturing industry in the U.S. from 1960 to 2019. Standard errors are clustered at the firm level. Controls include time-varying 4-digit industry fixed effects.

surplus is distributed more equally. However, the relationship is always disproportionately in favor of firms. It also means that there is an industry heterogeneity that masks important differences across firms and workers.

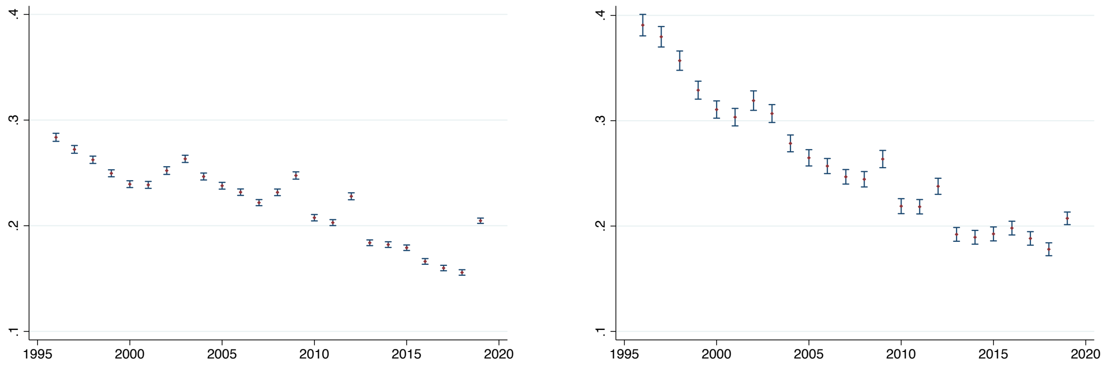
5.2 Trends in Bargaining Power

Figure 1 and Figure 2 present the main result of my paper: the evolution of bargaining power over time. While in France, bargaining power varies every year, in the US, I allow it to vary over each decade for data limitations. The figures then plot the coefficients with the corresponding 95% confidence intervals. The patterns are striking.

Figure 1 shows that bargaining power in the U.S. follows a hump-shaped trend starting at a very low level, around 16%, in the 60s and increases sharply over the following years reaching its peak in the 80s, at around 34%. Thereafter, it decreases steadily and almost linearly decade after decade until reaching its minimum, below 15%, during the period 2010-19. This figure is remarkable as it shows that the importance of employers and employees in the wage-setting process has changed substantially over time. The power that workers had in the 80s when negotiating their salary more than halved over the following years. That means that if productivity and labor market conditions were constant, wages would be much lower now than 40 years ago.

Figure 2, on the other hand, shows the evolution of bargaining power in France, highlighting a stark decline from 1995 to 2019. Such a pattern is common to the whole economy and the

Figure 2: Trends in Bargaining Power in France



(a) Whole Economy

(b) Manufacturing

Notes: This figure shows estimates of *worker bargaining power*, defined as τ, the coefficient of productivity in Equation 10. T is defined as a year such that τ varies yearly. The sample in the analysis represents 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. Controls include time-varying 4-digit industry fixed effects.

manufacturing industry.[18,19] Looking at Figure 2a, we can see that the bargaining power of French workers was around 30% in the mid-90s, and it decreased until reaching the lowest level in 2018 at around 15%. Hence, similarly to the US, it halved over two decades. Moreover, it seems to have experienced some fluctuations with a rebound in the early 2000s and around 2008. Both trends and levels align with the results that I find 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 the one in the whole economy, the levels are also, in this case, shifted upwards. Bargaining power in French manufacturing declined from 40% to around 20% over the 1995-2019 period.[20]

6 Extensions and Robustness

I now introduce several extensions to the baseline framework introduced in Section 2 and 4 for estimating worker bargaining power. Such exercises are meant to show the robustness of the patterns described in Section 5 to alternative frameworks. More specifically, I discuss

[18]This paper focuses on investigating the evolution of worker bargaining power in the entire economy and in manufacturing. Table A.2 compares worker bargaining power across industries finding that it has declined almost everywhere. The analysis of the industry breakdown is left for future research.

[19]Table A.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.

[20]Table A.4 shows estimation of worker bargaining power in the French manufacturing industry on the sample of firms for which output prices are available. It is clear that the possible output price bias typical of the markup literature does not transmit to this setting (see Bond et al. (2021) and De Loecker et al. (2016) for an extensive discussion of the problems of estimating markups in the absence of output prices and Kirov, Mengano and Traina (2022) for a solution).

how introducing a richer notion of competition in the output market changes my estimates of bargaining power in line with recent evidence (De Loecker et al., 2020). Thereafter, I leverage the employee information to further discuss the role of worker heterogeneity and estimate bargaining power in a context with heterogeneous workers. Finally, I introduce worker sorting into the framework and analyze how the results change. Appendix F shows estimates of bargaining power with different production technologies and technical changes, with firms internalizing the effect of a new hire on the total wage-bill and discussing the role of production function estimation. The main results of this paper, i.e. the hump-shaped trend in the U.S. and the stark decline in France in worker bargaining power, are robust to all these different specifications.

6.1 The Role of Markups

The framework introduced so far in Section 2 does not include imperfections in output markets and considers firms being price-takers. A number of recent papers document, however, that product market concentration has been increasing, and firms can exert market power in the output markets (De Loecker et al., 2020, Autor et al., 2020, Eggertsson et al., 2018). In addition, evidence shows that such markups are very heterogeneous across firms. Here I discuss how the presence of markups changes the framework described to measure bargaining power, the estimation strategy, and the resulting estimates of bargaining power.

With price-setting power, firm's profit maximization would necessarily include as well firm prices. Hence, the firm problem becomes

$$\begin{aligned} \Pi_{it} &= \max_{v_{it}} \ \pi_{it} + \beta\mathbb{E}[\Pi_{it+1}] \\ &= \max_{v_{it}} P_{it}F(A_{it}, N_{it}) - N_{it}w_{it} - \kappa_t v_{it} + \beta\mathbb{E}[\Pi_{it+1}] \end{aligned} \tag{11}$$

Hence, the value of a filled vacancy becomes

$$J_{it} = \mathrm{MRPN}_{it} - w_{it} + \beta\mathbb{E}[sV_{it+1} + (1-s)J_{it+1}] \tag{12}$$

where MRPN indicate the marginal revenue productivity of the worker at firm i. We can now find the following expression for wages using the same derivations as in Appendix B.1

$$w = \tau\mathrm{MRPN} + (1-\tau)b + \tau\kappa\theta \tag{13}$$

The intuition behind the equation is that firms are able to internalize the elasticity of demand and charge a price above their marginal costs. This, in turn, implies that the value generated by a new hire is not only his marginal product but rather his marginal revenue product. The latter is a combination of worker productivity and the ability of the firm to exert market power in the output markets, thus generating value above the marginal cost. Hence, the difference between the wage equation estimated in Section 5 and this one is that now an indicator of the marginal revenue productivity rather than of physical productivity of a worker is needed.

6.1.1 Measuring Marginal Revenue Productivity

The framework described in the previous paragraph and summarized in equation 13 poses the additional challenge of measuring the marginal revenue productivity of a worker. To do so, I need to estimate the revenue function of a firm rather than its production function. That implies that I need to take a stand on the functional form of the inverse demand a firm faces. Bond et al. (2021) and De Ridder et al. (2021) show that if the latter takes a convenient log-linear form, as for example in the CES case with $p_{it} = \eta^{-1} y_{it} + \zeta_{it}$, I can use the same machinery described in Section 4 to estimate the revenue function. That is the case, for example, also in De Loecker (2011). More specifically, this would allow markups to vary at the same level of the production function. If I were to estimate common elasticities within a sector, then that would imply the firms in that sector would have the same degree of market power, thus the same markups. Estimating time-varying elasticities would then allow markups to vary over time as well. Hence, under these admittedly restricted assumptions, Figure 1 and Figure 2 can be interpreted as showing bargaining power in a setting with imperfect competition in the product market with markups heterogeneous across industries and markups constant over time. In addition, Figure F.1 shows these estimates allowing markups to vary over time.

The recent evidence on market concentration in the US, however, highlights a vast heterogeneity of product market power across firms. Motivated by this, I derive a formula for MRPN that can be estimated on the data in Appendix B.2:

$$\mathrm{MRPN}_i = \frac{\varepsilon_{Y,N}}{\mu_i} \frac{R_i}{N_i} \tag{14}$$

with μ being firm i's markup.[21] Using the markup formula derived by the static cost minimization problem of the firm as in De Loecker and Warzynski (2012), it is possible to measure markups from production data. More specifically, markups can be expressed as the product of the output elasticity of a variable input and the inverse revenue share of such an input

$$\mu_i = \varepsilon_{Y,V} \frac{R_i}{P^V V_i} \tag{15}$$

Introducing this formula in Equation 14, the marginal revenue productivity of labor can be

[21] All the equations describe static relations; therefore, I omit time subscripts for clarity.

expressed as the output elasticity of labor divided by the output elasticity of a variable input multiplied by the expenditure in that variable input divided by labor

$$\text{MRPN}_i = \frac{\varepsilon_{Y,N}}{\varepsilon_{Y,V}} \frac{P^V V_i}{N_i} \tag{16}$$

In order to measure MRPN, I estimate a revenue function with three inputs, i.e. labor, capital, and intermediate inputs, with the latter being the flexible input.[22] I then use the estimated elasticities to construct MRPN using Equation 16 and, finally, I use the identification strategy described in Section 4 to estimate worker bargaining power in the presence of heterogeneous markups using Equation 13. Figure 3 shows estimates of bargaining power in the presence of product market power. As opposed to the interpretation of Figure 1 and Figure 2a with bargaining power and product market imperfections, the underlying estimation Figure 3a does not impose additional assumptions and allows firms to have heterogeneous markups. The first two panels show estimates of bargaining power in the U.S. and France with constant output elasticities. The last two panels, on the other hand, include time-varying elasticities.

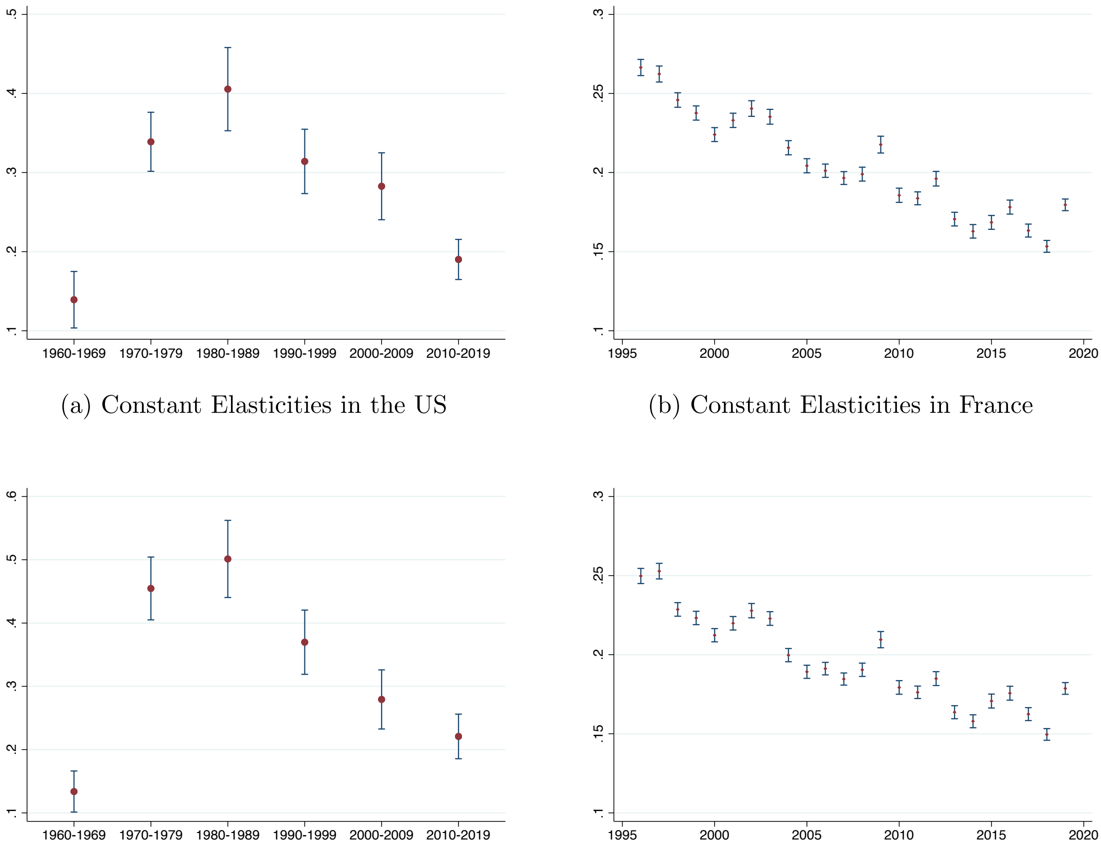
The patterns displayed for bargaining power are in line with the ones in the benchmark case shown in Figure 1 and Figure 2a. Bargaining power followed a hump-shaped trend in the U.S. over the last 60 years, whereas it has steadily decreased in France since the mid-90s. The levels are, however, different from the benchmark case shown in the previous Section. Interestingly, the difference is asymmetric for the U.S. and France. I find a higher level in the U.S. against a lower one in France. That is true both in the case of constant and time-varying elasticities.

6.2 The Role of Worker Heterogeneity

So far, I have limited worker heterogeneity to vary only across sectors and periods; hence most of the variation was on the firm side. Now, I discuss how I incorporate additional layers of heterogeneity in the worker dimension in the analysis. I proceed in two different ways. First, I start by introducing occupation heterogeneity in the estimation procedure. More specifically, I allow each job to have different productivity based on its occupation. Building on this insight, I leverage granular job-level information to express every hour worked in efficiency units. This allows accounting for changes in occupation composition within a firm's production process. Second, I complement my analysis with extensive worker heterogeneity in both outside options and labor market conditions. Drawing on rich employer-employee data, I allow for heterogeneity along with age, gender, location, and type of contracts. I

[22]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.

Figure 3: Bargaining Power with Product Market Imperfections



(a) Constant Elasticities in the US

(b) Constant Elasticities in France

(c) Time-varying Elasticities in the US

(d) Time-varying Elasticities in France

Notes: This figure shows estimates of *worker bargaining power*, defined as τ, the coefficient of revenue productivity in Equation 13. Production function estimates are constant in panel a and b, and estimates on a rolling basis in panel c and d. T is defined as a decade such that τ varies every ten years (panel a and c) and as a year such that τ varies yearly (panel b and d). The sample in the analysis represents the manufacturing industry in the U.S. from 1960 to 2019 (panel a and c), and the manufacturing industry in France from 1994 to 2019 (panel b and d). Standard errors are clustered at the firm level. Controls include time-varying 4-digit industry fixed effects.

discuss this in detail in the following paragraphs.

6.2.1 Occupation Composition

Many papers have documented changes in occupational composition in the economy (Jaimovich and Siu, 2020, Patel, 2021). It is, therefore, likely that the set of occupations performed within each firm has also evolved and that the role of each of these occupations has changed. To account for this, I complement my estimation with an analysis of the importance of each occupation. Hence, I first create an indicator measuring occupation-specific components. After that, I use this information in estimating bargaining power to account for occupation heterogeneity in two steps. First, I use the occupation-specific component to express hours worked in efficiency units and then use this information in both the production function and bargaining power estimation.[23]

In practice, I use worker-job data to run a pseudo-Mincer equation on wages of the form:

$$\ln w^o_{jit} = \alpha^o_t + \psi_{i(j,i)t} + X_{jt}\Gamma_t + \varepsilon_{jit} \tag{17}$$

in which w^o_{jit} is the wage of worker j in occupation o at firm i in period t, α^o_t are time-varying occupation fixed effects for occupation o, $\psi_{i(j,i)t}$ are time-varying firm fixed effects for firm i when worker j works there, X_{jt} includes a number of worker-level control and finally ε_{jit} is an idiosyncratic shock. The α^o_t is the information I am interested in and represent differences between occupations. While there is not a clear interpretation as in a benchmark two-way fixed effect wage regression model (AKM, hereafter - Abowd et al., 1999, Bonhomme et al., 2022), they do capture all the differences that there can be between occupations, such as abilities, wage premia, average unobserved worker skills. I do not make inference about what they represent, but I use them in my estimation strategy to weigh different workers performing different job occupations. Time-varying firm effects are essential to be coherent with the rest of the analysis as they represent differential effects that each firm has on its wages. I allow them to have time variation in line with changes in bargaining power over time or any other firm-specific characteristic. The vector of controls includes a polynomial in age plus location, gender, and type of contract dummies.[24]

To recover occupation fixed effects, I estimate Equation 17 on employee-job data.[25] Figure 4 shows the estimated time-varying fixed effects by 2-digit occupations. As an illustrative example, the occupation fixed effects of business heads of large businesses are always higher than the fixed effects of a low-skill craftsman.[26]

Armed with these α^o_t, I use them to construct a measure of firm workforce expressed in efficiency units. I do so by weighting each worker with the fixed effect of the occupation they

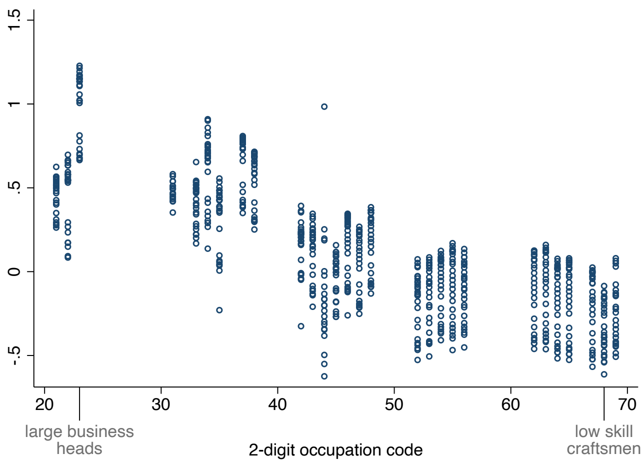
[23]It is worth mentioning that a few recent papers have combined the proxy method for estimating production function with the two-way fixed effects of workers and firms proposed by Abowd et al. (1999) to allow for worker-specific productivity (Lochner and Schulz, 2022, Chan et al., 2021, Wong, 2021). 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.

[24]In the next Section, I provide a thorough description of the rationale for each of these controls.

[25]For computation ease, I run the estimation on a random subsample of workers, including 20% of the total workforce. Table C.5 in the Appendix shows the representativeness of such subsample vis-á-vis the total workforce.

[26]Figure A.1 in the Appendix shows how such a measure of occupation fixed effects compares with average worker fixed effects by occupation. The latter results in estimating an AKM model on the panel version of the French employee data and averaging the resulting worker abilities by occupation. The correlation is 96.24%. While it is not possible to interpret the occupation fixed effects only as occupation abilities, such a high correlation is a reassuring signal on the result of this procedure.

Figure 4: Occupation Fixed Effects



Notes: This figure plots the occupation fixed effects estimated from equation 17. Each occupation is defined at the 2-digit level and within occupation variation reflects changes over time. The sample in the analysis represents a 20% random subsample of the total workforce in France from 1960 to 2019 (more details on its representativeness in table C.5).

perform:

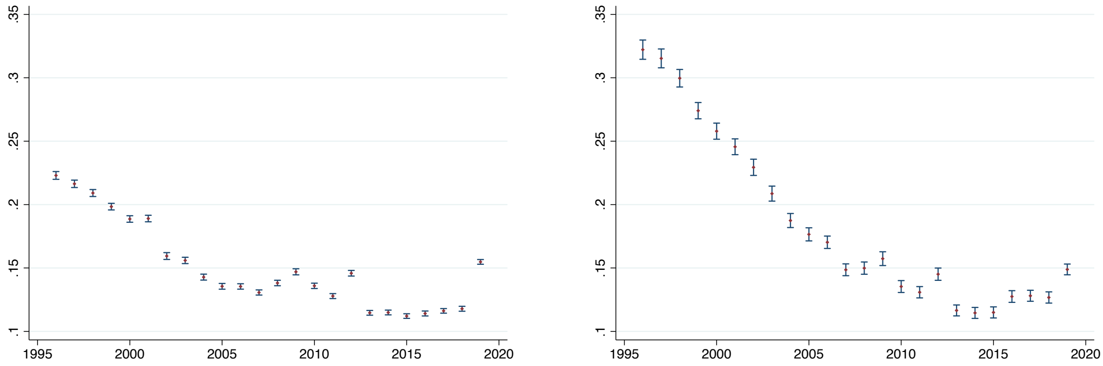
$$\tilde{H}_{it} = \sum_{j} \exp(\alpha_t^o) h_{ijt}^o$$

with h_{jit}^o being the hours worked by employee j at firm i in occupation o and $\tilde{H}_{it}$ firm i's workforce expressed in efficiency units. I then ran the estimation procedure described in the previous Sections, adding the controls used in Equation 17. Namely, I estimate firm production function using this new measure of the workforce; after that, I construct an indicator of marginal productivity of (efficiency) labor and finally look at its relation with wages.[27]

Figure 5 shows the results of this estimation accounting for changes in occupational composition. It is clear that the downward trend depicted in Figure 2 is robust to changes in occupational composition and that the importance of workers in the wage negotiation process has drastically decreased. However, the evolution of bargaining power over time differs from the one estimated, considering all workers to be homogeneous, and the decline is more pronounced in the first half of the period analyzed. That holds for both the total economy and manufacturing. Moreover, it seems that in the last years, the decline has plateaued, even showing signs of recovery. That is also present when estimating heterogeneous bargaining power in the following Sections. Another significant difference with Figure 2a is that the

[27] I need to correct wages as well for the occupation fixed effects. I do so by dividing total wages by the hours worked expressed in efficiency unit. This correction leaves me with an hourly wage for efficient hours.

Figure 5: Bargaining Power Accounting for Occupational Composition



(a) Total Economy

(b) Manufacturing

Notes: This figure shows estimates of *worker bargaining power*, defined as τ, the coefficient of productivity in Equation 10. In this figure, productivity and wages are expressed in efficiency units as they take into account the occupation fixed effects estimated from equation 17. T is defined as a year such that τ varies yearly. The sample in the analysis represents 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. Controls include time-varying 4-digit industry fixed effects.

rebound in bargaining power around 2003 disappears when accounting for the compositional difference. This indicates that it could be caused by changes in composition that can be connected to occupations' role in the production process, something addressed more in Section 8.

6.2.2 Worker-level Analysis

In the previous Section, I introduced a novel method to control for changes in occupational composition. That might indeed be useful to account for changes in occupation. However, there might be more worker heterogeneity regarding outside options and labor market conditions that are not controlled for. To incorporate such additional heterogeneity, I use a rich set of information at the worker-job level to include a more informative notion of outside options and labor market conditions for workers in my analysis. Indeed, in Equation 10 so far, all workers are assumed to have the same outside option in a period within a narrowly defined sector. Leveraging employee-employer matched data, I extend Equation 10 to a version that allows including worker information:

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

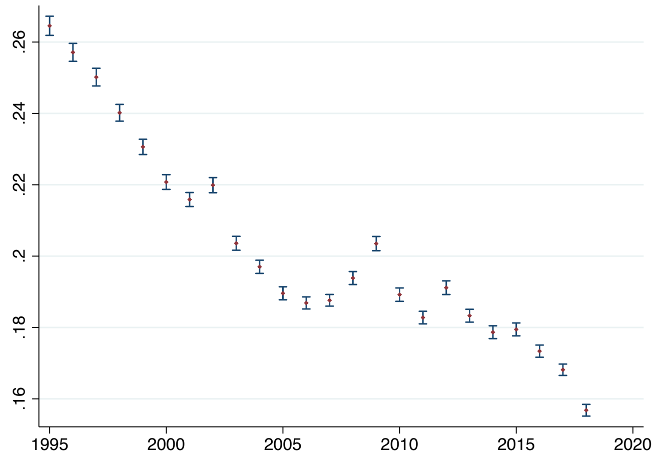
with w_{jist} being the wage of worker j at firm i in sector s at time t and X_{jst} a vector of worker j characteristics. The latter includes a polynomial in age plus dummies for location, gender, occupation, and type of contract. Given the presence of time dummies, I use a third-order expansion of age standardized at 40 to identify the age effect (Card et al., 2018). I do not include the linear term for collinearity with time fixed effects. Controlling for age captures the non-linear effect of age on the outside option and labor market conditions. It is indeed likely that younger workers face different labor market conditions than experienced ones. Along these lines, regional dummies are used to control for different conditions across local labor markets. This is building on the insight from recent literature documenting that firm wage-setting ability is related to local labor markets and might stem from location preferences (Berger et al., 2021, Yeh et al., 2022). Gender dummies are also included to control for differences between male and female employees. Also, in this case, a large amount of literature has provided evidence of the presence of gender discrimination hence that male and female workers might face different labor market conditions (Biasi and Sarsons, 2022, Roussille, 2022). Finally, workers may face different labor market conditions depending on their occupation and contract. For this reason, I include dummies for 2-digit occupation codes and fixed vs permanent contracts. I will return on the occupation in Section 8. Given that the main focus of my analysis is on the trend of bargaining power over time, I interact each piece of information with time-varying coefficients to capture potential changes over time.

Figure 6 shows the results of such estimation in manufacturing. Also, in this case, the declining trend in bargaining power is striking. It follows the same downward trend shown in Figure 2b decreasing starkly over the period considered. That implies that workers negotiating their wages in the 2010s have much lower bargaining power with respect to what they had in the mid-90s. This gives firms a stronger position and can explain the decrease in unemployment, as discussed in Section 7. As for the results incorporating occupational composition, most of the decline occurs in the first half of the period, and the decrease in bargaining power is milder in the second half. On the contrary, it does not show any sign of recovery.

6.3 The Role of Sorting

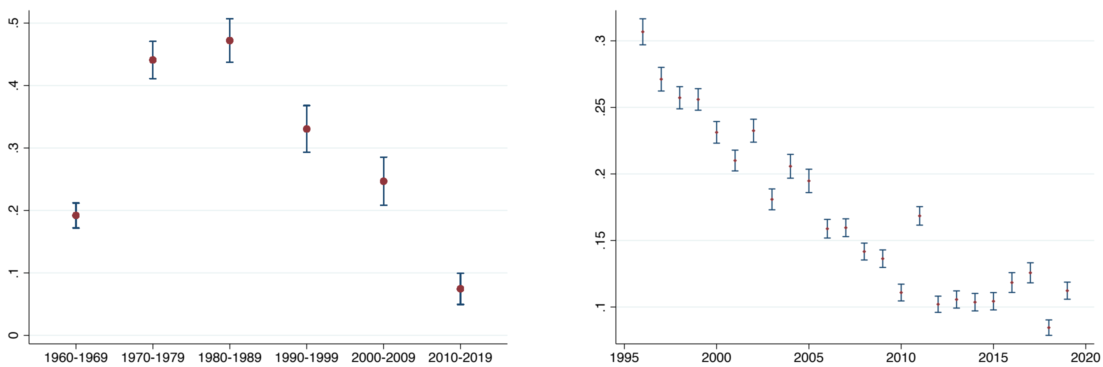
There is mounting evidence that high-wage workers are more likely to work in high-wage firms (Abowd et al., 1999, Bonhomme et al., 2022). The reason is that high-skill workers might benefit from working in an environment that is more productive and where other high-skill employees work. In this sense, sorting implies that different workers sort into specific firms. This generates a positive correlation between workers' and firms' characteristics, and such a correlation might generate a positive bias in the estimates of bargaining power. In order to tackle this issue and to understand how sorting would change the trends depicted in 1 and 2b, I estimate equation 10 in first difference to partial out any permanent worker and firm component that might enter in the empirical specification.

Figure 6: Bargaining Power with Worker Heterogeneity in Manufacturing



Notes: This figure shows estimates of *worker bargaining power*, defined as τ, the coefficient of productivity in Equation 18. T is defined as a year such that τ varies yearly. The sample in the analysis represents the manufacturing industry in France from 1994 to 2019. Standard errors are clustered at the firm level. Controls include time-varying 4-digit industry fixed effects, a polynomial in age and dummies for location, gender, occupation, and type of contract. All worker information are interacted with period dummies.

Figure 7: Bargaining Power with Worker Sorting



(a) US

(b) France

Notes: This figure shows estimates of *worker bargaining power*, defined as τ, the coefficient of productivity in Equation 10. In this figure, productivity and wages are expressed in first difference to partial out any permanent characteristics that might lead to sorting. T is defined as a decade such that τ varies every ten years (panel a) and as a year such that τ varies yearly (panel b). The sample in the analysis represents the manufacturing industry in the U.S. from 1960 to 2019 (panel a), and the manufacturing industry in France from 1994 to 2019 (panel b). Standard errors are clustered at the firm level. Controls include time-varying 4-digit industry fixed effects.

Figure 7 shows the results of estimating bargaining power accounting for sorting. As expected, the levels in France are lower than in Figure 2b, showing a positive bias due to sorting. Surprisingly, the opposite is true for the US. However, the trends depicted in the two figures are the same as in the baseline specification.

7 Implications for the Economy

The previous Sections show how bargaining power has changed for U.S. and French workers in recent decades. Interestingly, U.S. workers experienced a rise in their importance in the wage negotiation process from the 1960s to the 1980s. After that, it decreased steadily until reaching the trough in the 2010s. French workers experienced the same decline in bargaining power since the mid-1990s. With this new evidence, I use the theoretical framework discussed in Section 2 to shed light on what we can learn from such changes. More specifically, I start by analyzing the effects of declining bargaining power on the economy, focusing on the evolution of unemployment and wages. Thereafter, I study the efficiency of the labor market and propose policy interventions.

7.1 Unemployment and Wages

I study the effects of the changes in bargaining power documented in Section 5 on unemployment and wages in the U.S. economy using the model described in Section 2. In particular, I calibrate the model to the period with the highest bargaining power and then analyze the new equilibrium after an exogenous change in bargaining power. Here, I report results for the benchmark version of a DMP model abstracting from firm size and idiosyncratic productivity to focus solely on the implications of changes in bargaining power. Appendix J includes additional details on the model's solution, calibration results for the complete model, and extensions with imperfect competition in output markets. Before turning to the quantitative exercise, I discuss the mechanisms in action when bargaining power decreases in Figure 8. From equation 8, it is straightforward to see that wages decrease, getting closer to the worker outside option, keeping everything else constant. As a result of such a decline, firms face an environment with lower labor costs. Thus, they want to hire more and post new job vacancies. Unemployment decreases. The increase in vacancies, however, exacerbates the congestion externalities generated by search frictions. Indeed, the increase in vacancies posted lowers the probability of each vacancy being filled as the number of unemployed workers per vacancy decreases. Therefore, firms have to post more vacancies increasingly to continue hiring, which generates the shape of the response as bargaining power decreases. However, this externality effect is not strong enough to overturn the decrease in wages and unemployment, as shown in Figure 8.

Figure 8: Responses to Changes in Bargaining Power

7.2 Model Calibration

I now provide a quantitative assessment of the effects of the estimated changes in bargaining power by focusing on the periods with the highest and the lowest worker bargaining power. Those are the 80s and the 2010s in the US, and 1995 and 2018 in France, respectively. I calibrate the model to the economy in the period with the highest bargaining power and then change its value to the lowest one to compare the two steady states. This experiment sheds light on the effects of declining worker bargaining power in the economy, keeping everything else constant. Table 2 shows the external parameters and their sources. The model period

Table 2: External parameters

Parameter	US		France	
	Value	*Source*	*Value*	*Source*
Productivity (z)	1	normalization	1	normalization
Discount factor (β)	0.9967	4% annual interest	0.9967	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)

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. I use the average monthly separation rate in JOLTS over the period 2001-19, 0.036, and take the average value in Hairault et al. (2015) for France, 1.7%, consistent with a more dynamic labor market in the US. I fix the vacancy cost, κ, to 0.9, the equivalent of a one-month pay. Finally, I assume that the matching function is of the form $M(v,u) = A^z v^\alpha u^{1-\alpha}$ and I set the elasticity of matches to vacancies to 0.22 in the U.S. as estimated in Lange and Papageorgiou (2020) for normal times. In France, I set the elasticity to 0.5 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 (7.3) in the U.S. finding A^z = 0.46. In France, I calibrate it to match the average monthly unemployment rate in 1995 (11.8) and find $A^z = 0.19$.

7.3 Implications for the Total Economy

With the parametrization described above, I solve for the steady state values of unemployment and wages in the 80s in the U.S. and 1995 in France.[28] Then, I switch the bargaining value to its highest value and analyze the new steady states. Table 3 shows the equilibrium objects of the model. In both panels, columns 2 and 3 report the values of unemployment and wages in the initial steady states and after the change in bargaining power. Wages and labor share are normalized to 1 in the initial steady state. Columns 4 and 5 show the counterpart in the data.[29] The model predicts that both unemployment and wages decrease significantly following the decline in worker bargaining power described in Figure 8. Given that everything else, including productivity, is constant in this specification, the effect on wages is almost mechanical as a lower bargaining power brings wages closer to their lower bound, namely the worker outside option. However, this mapping is confounded by firms' endogenous response to wage changes. They indeed open more job vacancies in response to a cheaper labor environment generating a negative hiring externality – more vacancies competing for the same amount of unemployed workers – that counteracts the initial effect on wages. As predicted by the model, more open vacancies also lead to a decline in unemployment. Comparing the new steady states to the data, we can see that the estimated changes in bargaining power can fully explain the decrease in unemployment that took place both in the U.S. and in France, even with the stylized version of the model presented in Section 2. However, the data shows that wages have been rising rather than declining. The

[28] I leave the definition of a steady state in a DMP model in Appendix J.

[29] The source of this data is FRED, Federal Reserve Bank of St. Louis, except for wages in France that come from the OECD. I use the series UNRATE, COMPRNFB, and PRS85006173 for the US, and LRHUTTTTFRA156S, LABSHPFRA156NRUG, and Average Wages for France. I apply an HP filter to each series to recover the trend.

Table 3: Changes in Unemployment and Wages

Variable	Model		Data	
	80s	10s	80s	10s
Unemployment	7.3	6.1	7.3	6.3
Wages	1	0.91	1	1.35
Labor Share	1	0.91	1	0.91
Barg. Power	0.34	0.15	0.34	0.15

(a) US

Variable	Model		Data	
	95	18	95	18
Unemployment	11.3	9.0	11.3	8.7
Wages	1	0.96	1	1.27
Labor Share	1	0.96	1	0.99
Barg. Power	0.28	0.16	0.28	0.16

(b) France

reasons for this can be easily found in the very nature of the model I am using. It is a very stylized vision of reality that allows capturing the dynamics in the labor markets but not growth over time. For what concerns wages, indeed, the model does not include any change other than the bargaining power, so there is no reason why the economy should move over time. To account for this and validate the empirical exercise, I include the predicted changes in labor share. If the economy were constantly growing, there would be no reason to see a change in the share of income paid to labor. As seen in the Table, the model matches both qualitatively and quantitatively the changes in the labor share following a decline in worker bargaining power in the US. For France, on the other hand, that is not the case suggesting that such a stylized environment cannot fully account for its economic dynamics. In the next Section, I will discuss in more detail how I incorporate more elements in the analysis of the French labor markets and what we can learn from them.

7.4 Efficiency and Interventions

I use the bargaining power estimates to study the economy's efficiency level.[30] A well-known result in this class of models is that the solution to the social planner problem constrained by the random frictions in the labor market is equal to the decentralized one if the elasticity of the job filling rate with respect to the tightness ratio is equal to (the negative of) the bargaining power of the worker (Hosios, 1990). Namely,

$$\frac{q'\left(\theta^{ss}\right)\theta^{ss}}{q\left(\theta^{ss}\right)} = -\tau \tag{18}$$

Assuming a traditional Cobb-Douglas matching function like $M(v,u) = A^z v^\alpha u^{1-\alpha}$, then this would imply $1-\alpha = \tau$, with α being the elasticity of matches to vacancies. Petrongolo and Pissarides (2001) establish a plausible range for such elasticity of 0.3-0.5 with Brügemann (2008) refining it to 0.37-0.46. Recently, Lange and Papageorgiou (2020) finds a range of 0.15-0.3 using non-parametric techniques. These works clearly show that the decentralized

[30] I focus on the U.S. here and leave the analysis of France to Appendix I. The reason is that the elasticity of the filling rate is a crucial element in this case, and I have more evidence on that for the US.

Table 4: Interventions To Restore Efficiency

Variable	80s		10s	
Unemployment	7.3	10.4	6.1	10.4
Wages	0.92	0.98	0.84	0.98
Tax Rate	0	0.55	0	0.58

(a) Wage Tax

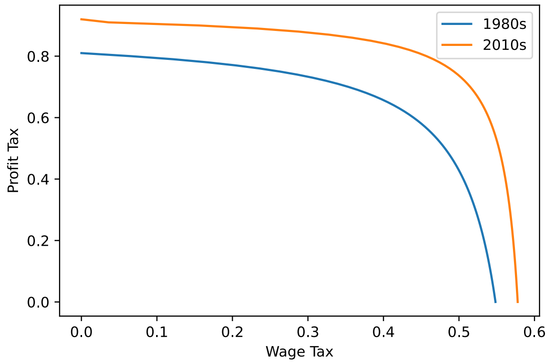
Variable	80s		10s	
Unemployment	7.3	10.4	6.1	10.4
Wages	0.92	0.89	0.84	0.77
Tax Rate	0	0.80	0	0.91

(b) Profit Tax

solution is not (constrained) efficient. The reason for this inefficiency is that each new vacancy and unemployed generate externalities on the rest of the labor market, endogenously affecting the rates at which meetings are determined. When the bargaining power is different from the elasticity of the matching function, then firms and the unemployed do not internalize such externalities. In a situation with bargaining power being lower than the elasticity of matches to vacancies, firms exploit the low labor cost environment by posting an excessive number of vacancies, i.e. over-hiring. It is easy to show that the efficient equilibrium would have a higher unemployment rate (10.4) for these market conditions.

In light of this, I propose two policy interventions to restore efficiency. Given that the inefficiency stems from the surplus sharing weights, I introduce a marginal tax on wages or profits. These instruments would have agents internalizing their congestion externalities. The intuition for these taxes is to increase the cost of labor, thus discouraging firms from over-hire and restoring the constrained equilibrium. The wage tax makes leisure more attractive for workers as unemployment benefits are not taxed. Hence, firms are forced to offer higher wages to their employees. On the other hand, profit tax acts directly on firms' profits by decreasing them. Table 4a and Table 4b show the taxes that would lead the decentralized equilibrium to an efficient outcome. Both Tables' second and fourth columns show the decentralized equilibrium again without any tax as in Table 3a. The third column of Table 4a shows the wage tax that leads the economy to reach the same level of unemployment as the constrained Social Planner in the 80s. As it can be seen, such a level is (much) higher than the decentralized one, thus reflecting the high inefficiency level that a low value of bargaining power generates in the labor market. The mechanism is such that, as described above, workers' earnings are being taxed; hence, firms are forced to offer higher wages. This disincentivizes firms from posting as many vacancies as before, thus, the unemployment rate increases. Although the tax rates are very high, implying that this stylized model needs additional features to provide quantitative insights and has to be interpreted with caution, it is worth noticing that the difference between the tax rate in the 80s and the one in the 10s (fifth column) is minimal. This emphasizes again the mechanisms through which the wage tax is working. It is indeed straightforward to see that it shows up in the wage equation as the denominator of the value of unemployment (b), *de facto* more than

Figure 9: Combinations of Wage and Profit Taxes



doubling it. Such a high outside option compresses the set of possible values for the wages that the workers would accept. However, the change is already so dramatic in the 80s that the further diminishing of worker bargaining power leads to a small change in the tax rate necessary to restore efficiency in the 10s. The profit taxes in Table 4b are even higher than the wage taxes in Table 4a. The mechanism, in this case, is that the profit tax diminishes profits directly. However, there is a more subtle feature. It is straightforward to see that, in this case, the profit tax would show up as the denominator of the market conditions in the wage equation. This term is not exogenous (like the outside option for the wage tax) and endogenously responds to taxes. Indeed, a higher tax leads to fewer vacancies, thus a lower tightness ratio. A lower tightness ratio, amplified after that by the tax, leads to lower wages counterbalancing the original scope of the profit tax. This results in very high profit taxes. Figure 9 characterizes all possible combinations of the two taxes introduced above for the 80s and the 2010s. The deteriorating bargaining power leads to increasingly stronger interventions necessary to restore (constrained) efficiency.

8 What Happened to Bargaining Power?

Section 5 uncovers an aggregate pattern in bargaining power that took place in the U.S. and France, and Section 6 provides an extensive number of tests and extensions confirming its robustness. In this Section, I investigate the causes of such decline by providing qualitative evidence for identifying the sources of variation behind the decline in worker bargaining power. With this aim, I differentiate firms and workers based on specific characteristics and estimate heterogeneous bargaining power. This exercise serves two purposes. The first is to investigate whether there is differential bargaining power across groups (e.g. gender). Hence, to learn about worker bargaining power heterogeneity in the economy. The second purpose, and the one most related to the main contribution of this paper, is to shed light on differential evolution across groups to identify where the variation originates.[31] I analyze a multitude of different culprits that could relate to worker bargaining power. I start by analyzing traditional market power causes, such as technology, competition, trade, and outsourcing. I estimate differential bargaining power and the contribution to the aggregate decline for each of them. After that, I focus on the working population's composition by focusing on gender, age, and occupation differences. Finally, I estimate differential bargaining power based on managers' educational backgrounds.

For each of these exercises, I specify an indicator variable, including information regarding the specific characteristic in analysis, and then I interact it with productivity and labor market conditions terms in the following specification at the firm-level:

$$\omega_{ist} = \tau_{CT}\text{MPN}_{ist} \times \mathbb{1}_{\text{CT}} + \Upsilon_{ist} \times \mathbb{1}_{\text{CT}} + \varepsilon_{ist} \tag{19}$$

or at the worker-level:

$$w_{jist} = \tau_{CT}\text{MPN}_{ist} \times \mathbb{1}_{\text{CT}} + X_{jst}\Gamma_t \times \mathbb{1}_{\text{CT}} + \Upsilon_{ist} \times \mathbb{1}_{\text{C}} + \varepsilon_{jist} \tag{20}$$

the indicator $\mathbb{1}_{\text{C}}$ divides the employees based on the characteristic C in analysis, e.g. gender. While interacting productivity by characteristics allows me to estimate type-specific bargaining power, it is crucial also to include type-specific controls. This indeed allows each subgroup to face differential labor market conditions and, as such, to identify the correct gradient of productivity to wages.

8.1 Technology

Technology advancements have long been considered the causes of rising inequality (Acemoglu and Restrepo, 2022) and the decoupling of productivity and wages (Traina, 2021). Moreover, French firms have increased their access to more advanced technology over the last 30 years. I, therefore, test the importance of technology adoption for the evolution of worker bargaining power. More specifically, I use survey data on ICT usage at the firm level to distinguish between firms that use ICT and firms that do not (Schivardi and Schmitz, 2020). Table 5 presents the results of this estimation. The first column shows that more technologically advanced firms, i.e. firms with ICT, exert higher bargaining power on their employees over the whole period. This result confirms the importance that technology plays in the negotiation dynamics between employers and employees. Columns 2 and 3 analyze the changes over time. In particular, column 2 shows the bargaining power level for the first half of the period of analysis and column 3 the second half.[32] It is straightforward that

[31] To perform this analysis, I complement the sample of analysis with information from additional data sources. See Section 3 for more details.

there is always a gap between the two types of firms, but the decline in bargaining power occurred for both of them. These findings suggest that although technological advancements might play a role in the negotiation dynamics, they do not seem to have contributed to the aggregate decline in France.

Table 5: Bargaining Power and ICT

Bargaining Power	All Period	2008-12	2013-19
Firms w/ ICT	0.27	0.31	0.25
	(.006)	(.011)	(.006)
Firms w/o ICT	0.29	0.34	0.27
	(.007)	(.011)	(.008)
Δ (Groups) ICT - $\neg$ICT	-0.02	-0.04	-0.01
	(.009)	(.016)	(.010)
Δ (Time) ICT		0	-0.05
		(.)	(.013)
Δ (Time) $\neg$ICT		0	-0.08
		(.)	(.014)
Share of Firms w/ ICT	0.46	0.43	0.49
Controls	Yes	Yes	Yes

Notes: This table shows estimates of *worker bargaining power*, defined as τ, the coefficient of productivity in Equation 19. The characteristic in consideration is ICT adoption, denoted by the use of ERP software. T is defined as the entire period of analysis such that τ does not change over time (column 1), and by splitting the period in half such that τ varies over time (columns 2 and 3). The sample in the analysis represents the manufacturing industry in France from 2008 to 2019. Standard errors are clustered at the firm level. Controls include time-varying 4-digit industry fixed effects interacted with ICT indicators to allow for differential market conditions for firms depending on ICT adoption.

8.2 Competition

Along with technology, competition regulation is considered the other traditional source of market power (Lancieri et al., 2022). In order to shed light on its contribution to changes in bargaining power, I use unique information on corporate groups. More specifically, the French Statistical Institute provides unique information on whether a legal entity belongs to a corporate group, and I use this information to proxy for the competition level they are facing (Acemoglu et al., 2020). Table 6 presents bargaining power differentiating along this dimension. As for technology, the first column shows that firms in corporate groups can exert higher bargaining power on their employees over the entire period. The following columns analyze such differences over different periods. They show that there always is a positive gap between the two types of firms, but, in this case, such a gap does not seem to change over time. This suggests that bargaining power has declined for workers employed at both banks, suggesting that competition regulation has played a minor role.

[32]ICT information is available only from 2008 to 2019, with gaps in 2016 and 2018.

Table 6: Bargaining Power and Corporate Groups

Bargaining Power	All Period	1999-03	2004-08	2015-19
Firms in Group	0.23	0.28	0.24	0.18
	(.003)	(.002)	(.002)	(.001)
Firms not in Group	0.28	0.32	0.26	0.20
	(.003)	(.002)	(.001)	(.001)
Δ (Groups) Group - $\neg$Group	-0.05	-0.05	-0.02	-0.02
	(.003)	(.003)	(.002)	(.002)
Δ (Time) Group		0	-0.03	-0.06
		(.)	(.003)	(.002)
Δ (Time) $\neg$Group		0	-0.07	-0.06
		(.)	(.002)	(0.002)
Share of Firms in Group	.27	.19	.23	.37
Controls	Yes	Yes	Yes	Yes

Notes: This table shows estimates of *worker bargaining power*, defined as τ, the coefficient of productivity in Equation 19. The characteristic in consideration is being in a corporate group. T is defined as the entire period of analysis such that τ does not change over time (column 1), and by splitting the period into thirds such that τ varies over time (columns 2, 3, and 4). The sample in the analysis represents the manufacturing industry in France from 1999 to 2019 (with gaps from 2008 to 2014). Standard errors are clustered at the firm level. Controls include time-varying 4-digit industry fixed effects interacted with corporate group indicators to allow for differential market conditions for firms conditional on being in a corporate group.

8.3 Trade

Access to international markets has been identified as a critical factor differentiating firms, their workforce, and the level of competition they face (Melitz, 2003, Autor et al., 2020, Acemoglu et al., 2016). Leveraging firm-level information on access to export, I estimate differential bargaining power for firms with access to international markets and firms with access only to domestic markets. Table 7 shows that firms with access to foreign markets exert a significantly higher bargaining power in the wage negotiation process. This implies that the degree of productivity transmitted to wages is lower, although the productivity level might be even higher. Table 7 also shows the evolution of such a gap from 1997 to 2007.[33] Even though workers at exporting firms always have lower bargaining power, the gap seems constant over time, meaning that bargaining power has declined for employees working at both firms. Thus, the contribution to the aggregate decline appears minimal in this case.

8.4 Outsourcing

Outsourcing, or "fissuring", is also an increasingly common activity in modern labor markets (Katz and Krueger, 2019). Recent evidence also shows that such increasing outsourcing of labor activities in France leads to an efficiency gain in terms of productivity but also a

[33] FICUS-FARE database includes information on revenues from exporting activities only until 2007. I use this to distinguish between exporting and non exporting firms.

Table 7: Bargaining Power and Access to Foreign Markets

Bargaining Power	All Period	1995-99	2000-03	2004-07
Exporting Firms	0.28	0.33	0.28	0.23
	(.003)	(.005)	(.005)	(.004)
Non Exporting Firms	0.31	0.37	0.31	0.26
	(.003)	(.005)	(.004)	(.004)
Δ (Groups) Exporting - Non Exporting	-0.03	-0.04	-0.03	-0.03
	(0.004)	(.007)	(.006)	(.006)
Δ (Time) Exporting		0	-0.05	-0.05
		(.)	(.005)	(.005)
Δ (Time) Non Exporting		0	-0.06	-0.05
		(.)	(.005)	(.004)
Share of Exporting Firms	.45	.45	.45	.46
Controls	Yes	Yes	Yes	Yes

Notes: This table shows estimates of *worker bargaining power*, defined as τ, the coefficient of productivity in Equation 19. The characteristic in consideration is being an exporter. T is defined as the entire period of analysis such that τ does not change over time (column 1), and by splitting the period into thirds such that τ varies over time (columns 2, 3, and 4). The sample in the analysis represents the manufacturing industry in France from 1995 to 2007. Standard errors are clustered at the firm level. Controls include time-varying 4-digit industry fixed effects interacted with exporting indicators to allow for differential market conditions for firms conditional on the exporting status.

contraction of the labor share Bilal and Lhuillier (2021). I use this result to test whether workers employed by firms engaging in outsourcing have lower bargaining power and if that might cause the aggregate decline. Table 8 confirms the hypothesis that workers employed by a firm engaging in outsourcing activities have lower bargaining power. Interestingly, however, in this case, the gap is constant over time, suggesting that outsourcing does not play a significant role in the decline of worker bargaining power.

8.5 Managers

Recent evidence identifies managers as a critical determinant for firm market power (Acemoglu et al., 2022, Bao et al., 2022). In line with this, I test this hypothesis in France using the information on managers' education. In particular, I test whether workers employed at a firm with a university-graduated manager have different bargaining power than other workers.[34,35] Table 9 presents the results of such estimation. Worker bargaining power is lower when managers have a university degree. The difference is that bargaining power has

[34]To construct a measure of education for the manager, I use demographic information from the panel version of the DADS data. As explained in Section 3, this covers only 8% of the total workforce. I link it to my sample of analysis and drop all firms for which this information covers less than 20% of the workforce. Moreover, differently than Acemoglu et al. (2022), I do not observe the degree topic in the data. Therefore, I study the difference in bargaining power differentiating firms on having a manager with a university degree or not.

[35]In Appendix A I repeat the same exercise but 1) considering only the education of the highest paid manager, or 2) considering whether more than half of managers have a university degree.

Table 8: Bargaining Power and Outsourcing

Bargaining Power	All Period	1995-99	2000-03	2004-07
Outsourcing Firm	0.30	0.35	0.30	0.26
	(.005)	(.007)	(.006)	(.006)
Not Outsourcing Firms	0.37	0.45	0.38	0.32
	(.008)	(.012)	(.011)	(.009)
Δ (Groups) Outsourcing - Non Outsourcing	-0.07	-0.10	-0.08	-0.05
	(.008)	(.013)	(.012)	(.011)
Δ (Time) Outsourcing		0	-0.05	-0.03
		(.)	(.007)	(.006)
Δ (Time) Not Outsourcing		0	-0.08	-0.06
		(.)	(.013)	(.012)
Share of Outsourcing Firms	.72	.69	.70	.74
Controls	Yes	Yes	Yes	Yes

Notes: This table shows estimates of *worker bargaining power*, defined as τ, the coefficient of productivity in Equation 19. The characteristic in consideration is outsourcing labor services denoted by firms hiring "external workers'. T is defined as the entire period of analysis such that τ does not change over time (column 1), and by splitting the period into thirds such that τ varies over time (columns 2, 3, and 4). The sample in the analysis represents the manufacturing industry in France from 1995 to 2007. Standard errors are clustered at the firm level. Controls include time-varying 4-digit industry fixed effects interacted with outsourcing indicators to allow for differential market conditions for firms conditional on the outsourcing status.

changed greatly over time, with workers employed at a firm with a university-graduated manager experiencing a large erosion of their bargaining power. At the same time, other employees did not see any change in their bargaining power. Therefore, it seems that managers' role has played an important role in the decline of worker bargaining power.

8.6 Gender and Age

I now turn to the analysis of bargaining power by worker characteristics. Empirical evidence shows that labor market conditions faced by workers are different according to their gender and age profile (Biasi and Sarsons, 2022, Chan et al., 2021). Indeed, gender discrimination is a well-documented phenomenon, as well as the lifetime dynamics of earnings profiles. To unravel whether bargaining power is heterogeneous along these lines, I use the information at the employee/job level to estimate it, differentiating by worker type according to equation 20. I start by dividing workers by gender and estimating the bargaining power of male and female employees. In doing so, I introduce type-specific controls to allow for gender-specific outside options and labor market conditions. This ensures that the bargaining power estimates do not mechanically identify mere level differences, e.g. the so-called wage gender gap. On the other hand, the (marginal) productivity is the same for both types of workers, so the necessary condition for identifying bargaining power is that men and women do not differ in productivity at the firm-level within the narrow cell defined by the fixed effects.

Table 9: Bargaining Power and Managers

Bargaining Power	All Period	2002-10	2011-19
Firms w/ Manager with Degree	0.26	0.29	0.23
	(.008)	(.014)	(.013)
Firms w/o Manager with Degree	0.28	0.29	0.28
	(.008)	(.013)	(.013)
Δ (Groups) Manager - $\neg$Manager	-0.02	-0.00	-0.04
	(.008)	(.012)	(.010)
Δ (Time) Manager		0	-0.06
		(.)	(.002)
Δ (Time) $\neg$Manager		0	-0.01
		(.)	(.016)
Share of Firms with Manager with Degree	.36	.33	.39
Controls	Yes	Yes	Yes

Notes: This table shows estimates of *worker bargaining power*, defined as τ, the coefficient of productivity in Equation 19. The characteristic in consideration is the presence of a manager with a university degree. T is defined as the entire period of analysis such that τ does not change over time (column 1), and by splitting the period in half such that τ varies over time (columns 2, and 3). The sample in the analysis represents the manufacturing industry in France from 2002 to 2019. Standard errors are clustered at the firm level. Controls include time-varying 4-digit industry fixed effects interacted with manager indicators to allow for differential market conditions for firms conditional on the presence of a manager with a university degree.

This exercise allows us to measure the difference in bargaining power by gender and to study its evolution over time. Table 10 shows the result of such estimation.[36] The first striking result is that the bargaining power of male workers always lies above female workers. Indeed, column 1 shows the difference throughout the entire period, which is large and statistically significant. These results are consistent with recent papers showing that women are less inclined to negotiate their salary, contributing to the gender wage gap (Biasi and Sarsons, 2022, Roussille, 2022). I call this phenomenon the *gender bargaining power gap*. Table 10, moreover, uncovers an additional interesting fact. Such a gap has been shrinking over time, and, surprisingly, this is due to the decrease in male employees' bargaining power rather than the increase in female employees' one.

I perform the same analysis by age profile. The goal is to identify differences along employees' life cycles in the wage negotiation process and to understand how they have evolved. To do so, I differentiate workers into three age brackets and estimate bargaining power according to the specification in equation 20. Table 11 shows the results of such estimation. Also, in this case, it is possible to see a clear ranking of types throughout the whole period. Young workers have the lowest level of bargaining power, and their importance in the wage negotiation process is very little. Moreover, such importance has been decreasing drastically over the

[36] I report gender differences keeping the bargaining power constant throughout the whole period in Appendix A.

Table 10: Bargaining Power and Gender

Bargaining Power	All Period	1996-03	2004-10	2011-18
Male Employees	0.24	0.28	0.23	0.21
	(.002)	(.003)	(.003)	(.003)
Female Employees	0.10	0.10	0.09	0.11
	(.002)	(.004)	(.004)	(.004)
Δ (Groups) Male - Female	0.14	0.18	0.14	0.10
	(.001)	(.001)	(.001	(.001
Δ (Time) Male		0	-0.05	-0.02
		(.)	(.001)	(.001)
Δ (Time) Female		0	-0.01	0.02
		(.)	(.005)	(.001)
Controls	Yes	Yes	Yes	Yes

Notes: This table shows estimates of *worker bargaining power*, defined as τ, the coefficient of productivity in Equation 20. The characteristic in consideration is gender. T is defined as the entire period of analysis such that τ does not change over time (column 1), and by splitting the period into thirds such that τ varies over time (columns 2, 3, and 4). The sample in the analysis represents the manufacturing industry in France from 1995 to 2018. Standard errors are clustered at the firm level. Controls include a polynomial in age and dummies for 4-digit industry, location, occupation, and type of contract. All controls are interacted with period dummies and with gender indicators to allow for differential market conditions for firms and workers conditional on gender.

last 25 years. Middle age and old workers have a similar bargaining level, averaging around 30%. In the first half of the period analyzed, both types of workers experienced a comparable decline in bargaining power. Indeed, from 1996 to 2010, all workers experienced a declining bargaining power. Interestingly, the bargaining power of the middle age workers plateaued, and it did not decrease further. On the contrary, older workers saw their negotiation power decreasing. It is clear from this table that young workers are very disadvantaged in the labor market with respect to the rest of the population. Moreover, such a disadvantage has been worsening over the last two decades.

8.7 Occupation's Automability

The U.S. and France both experienced job polarization, meaning the disappearance of easily automatable jobs, the so-called routine jobs, in favor of jobs that are more difficult to perform by machinery and robots, non-routine jobs (Jaimovich et al., 2020, Patel, 2021). As a primary candidate for changing dynamics in the bargaining setting, I incorporate this into the analysis to understand its relevance to the decline in bargaining power. So far, all estimates of bargaining power assume that workers are equally productive within a firm; hence, there is no distinction between different occupations. To credibly study the evolution of bargaining power for different occupations, I allow workers to have heterogeneous productivity levels. I start by classifying workers into different types and specifying a firm production function that takes as arguments different labor inputs. More specifically, I classify workers into

Table 11: Bargaining Power and Age

Bargaining Power	All Period	1997-03	2004-10	2011-18
Older Age (49-65)	0.32	0.41	0.31	0.27
	(.002)	(.004)	(.004)	(.004)
Medium Age (33-48)	0.24	0.28	0.23	0.22
	(.002)	(.004)	(.004)	(.003)
Younger Age (16-32)	0.05	0.08	0.05	0.03
	(.002)	(.004)	(.004)	(.004)
Δ (Groups) Older - Medium	0.08	0.13	0.08	0.05
	(.001)	(.001)	(.001)	(.001)
Δ (Groups) Medium - Younger	0.20	0.21	0.19	0.20
	(.001)	(.001)	(.001)	(.001)
Δ (Time) Older Age		0	-0.09	-0.04
		(.)	(.001)	(.001)
Δ (Time) Medium Age		0	-0.05	-0.01
		(.)	(.001)	(.001)
Δ (Time) Younger Age		0	-0.03	-0.02
		(.)	(.001)	(.001)
Controls	Yes	Yes	Yes	Yes

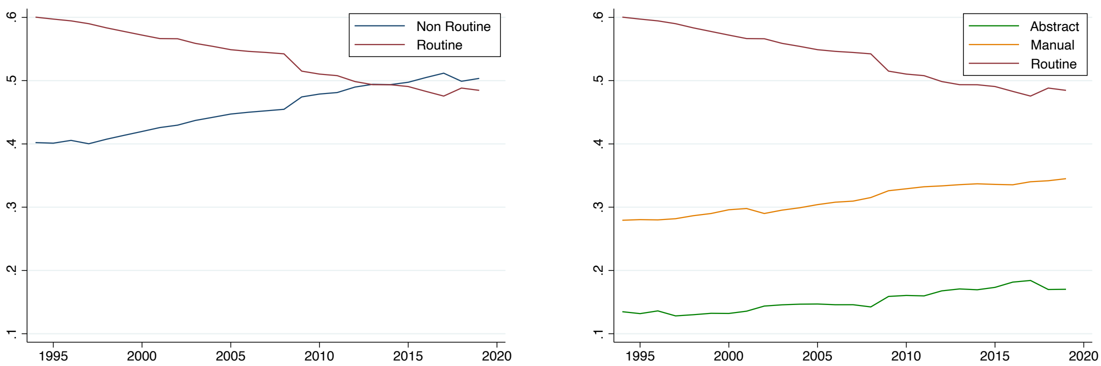
Notes: This table shows estimates of *worker bargaining power*, defined as τ, the coefficient of productivity in Equation 20. The characteristic in consideration is age profile. T is defined as the entire period of analysis such that τ does not change over time (column 1), and by splitting the period into thirds such that τ varies over time (columns 2, 3, and 4). The sample in the analysis represents the manufacturing industry in France from 1996 to 2018. Standard errors are clustered at the firm level. Controls include dummies for 4-digit industry, location, occupation, and type of contract. All controls are interacted with period dummies and with age indicators to allow for differential market conditions for firms and workers conditional on the age profile.

routine and non-routine jobs following the classification proposed by Albertini et al. (2017), which studies the same data source I am using.[37] After that, I split non-routine workers into abstract and manual (omitting the "non-routine" term). This classification speaks directly to the job polarization in France (Patel, 2021) and sheds light on a factor that has not been considered in the literature, differential market power by worker type. As in the previous Section, I allow labor market conditions to vary by worker type. Figure 10 displays the evolution of employment shares by worker type in my sample of analysis. The share of routine jobs has declined steadily since the mid-90s, whereas the employment share of abstract and manual occupations has grown, similar to what happened in the US. First, I specify a firm production function that takes as arguments different types of labor, namely $F(A, R, N, K)$ or $F(A, R, AB, M, K)$ with R, N, AB and M being routine, non-routine, abstract and manual workers, respectively. Then, I estimate it following the procedure described in Section 4, hence recovering different output elasticity for each type of worker. Finally, I construct a

[37] In Appendix C I show the mapping from education to occupation finding that abstract occupations are performed mainly by higher educated workers, routine by medium-educated ones, and manual by the least educated ones.

type-specific indicator of marginal productivity of labor at the firm level and look at its relation to wages. While I estimate the different elasticities jointly, I estimate the bargaining power for each worker type separately. This allows for having different productivities and type-specific controls, meaning that each worker type faces specific conditions in the labor market.

Figure 10: Job Polarization in France



(a) Routine and Non-Routine

(b) Abstract, Manual, and Routine

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

Table 12 shows the estimates of bargaining power for each of these worker types. The first panel includes workers classified into routine and non-routine jobs whereas the second panel further differentiates non-routine occupations into abstract and manual. The resulting differences in bargaining power are astonishing. Non-routine workers have a much higher bargaining power than routine workers. Throughout the whole time, the value is always almost double. Surprisingly however non-routine workers experienced a large decline in their bargaining power. Until the early 2010s, the only workers whose bargaining power decreased were the abstract ones, whereas routine workers saw no changes at all. After that point, routine workers saw their bargaining power starting to decline as well. When digging deeper into worker heterogeneity in the second panel, it is possible to see that all the decline in non-routine workers' bargaining power is due entirely to abstract occupations. Indeed, they were (and still are) the ones with the highest bargaining power at the beginning of the period and experienced a significant deterioration in their bargaining position. On the other hand, manual workers did not see any change in their bargaining power throughout the whole period.

Table 12: Bargaining Power and Job Polarization

Bargaining Power	All Period	1996-03	2004-10	2011-18
Non Routine (NR)	0.21	0.29	0.18	0.15
	(.002)	(.003)	(.003)	(.003)
Routine (R)	0.10	0.12	0.11	0.09
	(.002)	(.002)	(.002)	(.002)
Δ (Groups) NR - R	0.11	0.17	0.07	0.07
	(.001)	(.001)	(.001)	(.001)
Δ (Time) Non Routine		0	-0.12	-0.02
		(.)	(.003)	(.001)
Δ (Time) Routine		0	-0.01	-0.02
		(.)	(.007)	(.007)
Abstract (A)	0.23	0.32	0.24	0.18
	(.002)	(.004)	(.004)	(.004)
Routine (R)	0.10	0.12	0.11	0.09
	(.002)	(.004)	(.004)	(.003)
Manual (M)	0.07	0.07	0.07	0.06
	(.002)	(.004)	(.004)	(.004)
Δ (Groups) A - R	0.13	0.20	0.13	0.09
	(.001)	(.001)	(.001)	(.001)
Δ (Groups) R - M	0.04	0.06	0.04	0.02
	(.001)	(.001)	(.001)	(.001)
Δ (Time) Abstract		0	-0.08	-0.06
		(.)	(.001)	(.001)
Δ (Time) Routine		0	-0.01	-0.02
		(.)	(.007)	(.007)
Δ (Time) Manual		0	-0.00	-0.00
		(.)	(.001)	(.001)
Controls	Yes	Yes	Yes	Yes

Notes: This table shows estimates of *worker bargaining power*, defined as τ, the coefficient of productivity in Equation 20. The characteristic in consideration is occupation type. T is defined as the entire period of analysis such that τ does not change over time (column 1), and by splitting the period into thirds such that τ varies over time (columns 2, 3, and 4). The sample in the analysis represents the manufacturing industry in France from 1996 to 2018. Standard errors are clustered at the firm level. Controls include a polynomial in age and dummies for 4-digit industry, location, and type of contract. All controls are interacted with period dummies and with occupation indicators to allow for differential market conditions for firms and workers conditional on the job performed.

8.8 Taking Stock: What Happened to Bargaining Power?

In this Section I provide suggestive evidence for the reasons behind the decline in worker bargaining power. I start by looking at firm characteristic exploring traditional sources of market power such as technology, competition, trade, and outsourcing. Suggestive evidence shed light on heterogeneity in bargaining power along these dimensions. Indeed, employees at more technologically advanced or facing less competition or exporting or outsourcing firms have a lower bargaining power than other firms. However, each of these element does not seem to contribute to the dynamics of worker bargaining power over time. In line with recent evidence, I find that managers' education is a key element and that it seems to have played an important role for the decline in worker bargaining power in France. Thereafter, I analyze worker characteristics by differentiating employees by gender, age, and occupation. I find a large *gender bargaining power gap*, i.e. male employees having a much higher bargaining power than female ones. Surprisingly such gap shrinks over time with the erosion of male employees' bargaining power and female employees seeing their one staying flat or increasing if anything. Different age profiles, on the other hand, do not seem to play a role in the evolution over time. Finally, I look at difference by occupation and detect very heterogeneous patterns with high skill workers seeing their bargaining power declining and low skill workers having a constant (or slightly decreasing) importance.

9 Conclusions

This paper proposes a novel measure of worker bargaining power that combines macroeconomic theory and empirical tools. I uncover a common phenomenon in the U.S. and France: a substantial aggregate decline in worker bargaining power over the last 30 years. Using modern techniques to estimate firm production function, I show that this finding is robust to incorporating technical change, imperfect competition in the output market, and a more sophisticated version of wage negotiation. In addition, leveraging employer-employee matched data, I show that this phenomenon is also present when controlling for occupational composition, worker heterogeneity, and sorting. Building on this result, I analyze the economy's responses to worker bargaining power changes finding that its decline leads to a new steady state with a lower unemployment rate and labor share. I quantify that it can help account for the recent macroeconomic situations in the U.S. and France.

These findings are important not only for understanding the dynamics of the wage negotiation process but also for policy purposes. I show that the inefficiently low worker bargaining power exacerbates the congestion externalities in the labor markets. Indeed, firms post an inefficiently excessive amount of job vacancies taking advantage of their importance in the wage negotiation process. This excessive job posting lowers the probability of finding a worker due to the presence of search frictions in the labor market, thus, generating negative congestion externalities on all firms. Therefore, I propose two complementary policy interventions to restore the labor markets' efficiency, profit, and wage marginal taxes.

Finally, I investigate the potential causes of such a decline in bargaining power. In particular, I collect evidence in favor of what the economic literature has considered traditional sources of market power, such as technology, competition, trade, and outsourcing. Interestingly, I find that the aggregate decline in bargaining power does not correlate with any of these factors, suggesting that all of them play only a minor to no role in this regard. Shifting the focus then on the characteristics of the workforce, I uncover a significant *gender bargaining power gap*. Male employees have a much higher bargaining power than female ones. However, this distance has reduced over time, in line with evidence of the gender gap in France. Surprisingly, the reduction of the *gender bargaining power gap* is due to the erosion of male employees' bargaining gap rather than to an improvement of women's negotiation position. Finally, I analyze the bargaining gap along different occupations, grouping them along the degree of automability. Evidence shows that the decline was concentrated in non-routine abstract occupations, jobs performed by high-skill workers. This also confirms the decline in 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.

References

Abowd, John M., Francis Kramarz, and David N. Margolis, "High wage workers and high wage firms," *Econometrica*, 1999, *67* (2), 251–333. 6, 23, 26

Acemoglu, Daron, Alex He, and Daniel le Maire, "Eclipse of Rent-Sharing: The Effects of Managers' Business Education on Wages and the Labor Share in the Us and Denmark," *NBER Working Papers*, 2022. 5, 37

_ **and Pascual Restrepo**, "Tasks, Automation, and the Rise in Us Wage Inequality," *Econometrica*, 2022. 34

_ **, Claire Lelarge, and Pascual Restrepo**, "Competing with Robots: Firm-Level Evidence from France," *AEA Papers and Proceedings*, 2020, *110*, 383–388. 35

_ **, David Autor, David Dorn, Gordon H Hanson, and Brendan Price**, "Import Competition and the Great US Employment Sag of the 2000s," *Journal of Labor Economics*, 2016, *34* (1). 36

Ackerberg, Daniel A., Kevin Caves, and Garth Frazer, "Identification Properties of Recent Production Function Estimators," *Econometrica*, 2015, *83* (6), 2411 – 2451. 13, 72

Albertini, Julien, Jean Olivier Hairault, Francois Langot, and Thepthida Sopraseuth, "A Tale of Two Countries A Story of the French and US Polarization," *IZA Discussion Paper*, 2017, (11013). 41, 42

Arellano, Manuel and Stephen Bond, "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies*, 1991, *58* (2), 277–297. 72

Autor, David, David Dorn, and Gordon Hanson, "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 2013, *103* (6), 2121–2168. 4

_ , _ , Lawrence F Katz, Christina Patterson, and John Van Reenen, "The Fall of the Labor Share and the Rise of Superstar Firms," *Quarterly Journal of Economics*, 2020, *135* (2), 645–709. 4, 19, 36

Azar, José, Steven T. Berry, and Ioana Elena Marinescu, "Estimating Labor Market Power," *NBER Working Paper*, 2022, (30365). 6

Azkarate-Askasua, Miren and Miguel Zerecero, "The Aggregate Effects of Labor Market Concentration," *Working Paper*, 2022. 7

Bagger, Jesper, Bent Jesper Christensen, and Dale T. Mortensen, "Productivity and Wage Dispersion: Heterogeneity or Misallocation?," *Working Paper*, 2014. 6

Bao, Renjie, Jan De Loecker, and Jan Eeckhout, "Are Managers Paid for Market Power?," *Working Paper*, 2022. 37

Barth, Erling, Alex Bryson, James C Davis, and Richard Freeman, "It's Where You Work: Increases in the Dispersion of Earnings across Establishments and Individuals in the United States," *Journal of Labor Economics*, 2016, *34* (2), S67 – S97. 6

Bell, Brian, Paweł Bukowski, and Stephen J. Machin, "Rent Sharing and Inclusive Growth," *Working Paper*, 2018. 6

Berger, David W., Kyle Herkenhoff, and Simon Mongey, "Labor Market Power," *American Economic Review*, 2021, *112* (4), 1147–93. 7, 15, 26

Berman, Nicolas, Philippe Martin, and Thierry Mayer, "How do different exporters react to exchange rate changes?," *Quarterly Journal of Economics*, 2012, *127* (1), 437–492. 6

Biasi, Barbara and Heather Sarsons, "Flexible Wages, Bargaining, and the Gender Gap," *The Quarterly Journal of Economics*, 2022, *137* (1), 215–266. 4, 26, 38, 39

Bilal, Adrien and Hugo Lhuillier, "Outsourcing, Inequality and Aggregate Output," *NBER Working Paper*, 2021, (29348). 4, 12, 37

Blanchflower, David G, Andrew J Oswald, and Peter Sanfey, "Wages, Profits, and Rent-Sharing," *Quarterly Journal of Economics*, 1996, *111* (1), 227 – 251. 6

Blundell, Richard and Stephen Bond, "Initial conditions and moment restrictions in dynamic panel data models," *Journal of Econometrics*, 1998, *87* (1), 115–143. 72

— **and Steve Bond**, "GMM Estimation With Persistent Panel Data: An Application to Production Functions," *Econometric Reviews*, 2000, *19*, 321–340. 72

Bond, Steve, Arshia Hashemi, Greg Kaplan, and Piotr Zoch, "Some unpleasant markup arithmetic: Production function elasticities and their estimation from production data," *Journal of Monetary Economics*, 2021, *121*, 1–14. 3, 13, 18, 20, 21, 67

Bonhomme, Stephane, Kerstin Holzheu, Thibaut Lamadon, Elena Manresa, Magne Mogstad, and Bradley Setzler, "How Much Should We Trust Estimates of Firm Effects and Worker Sorting?," *Journal of Labor Economics*, 2022. 23, 26, 73

Brügemann, Björn, "What Elasticity of the Matching Function is consistent with US Aggregate Labor Market Data?," *Working Paper*, 2008. 5, 31

Burstein, Ariel Tomas, Vasco M. Carvalho, and Basile Grassi, "Bottom-Up Markup Fluctuations," *Working Paper*, 2020. 60

Cacciatore, Matteo and Fabio Ghironi, "Trade, Unemployment, and Monetary Policy," *Journal of International Economics*, 2021, *132*. 6

Cahuc, Pierre and Thomas Le Barbanchon, "Labor market policy evaluation in equilibrium: Some lessons of the job search and matching model," *Labour Economics*, 2010, *17* (1), 196–205. 30

— **, Francois Marque, and Etienne Wasmer**, "A theory of wages and labor demand with intra-firm bargaining and matching frictions," *International Economic Review*, 2008, *49* (3), 943–972. 70

Card, David, Ana Rute Cardoso, and Patrick Kline, "Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women," *The Quarterly Journal of Economics*, 2016, *131* (2), 633 – 686. 4, 6

— **, — , Joerg Heining, and Patrick Kline**, "Firms and Labor Market Inequality Evidence and Some Theory," *Journal of Labor Economics*, 2018, *36* (S1), S13 – S70. 5, 6, 26

Chan, Mons, Sergio Salgado, and Ming Xu, "Heterogeneous Passthrough from TFP to Wages," *Working Paper*, 2021. 6, 15, 23, 38

Chiavari, Andrea, "The Macroeconomics of Rising Returns to Scale: Customers Acquisition, Markups, and Dynamism Preliminary," *Working Paper*, 2021. 13

Crivellaro, Elena, "The college wage premium over time: Trends in Europe in the last 15 years," *Working Paper, Ca' Foscari University of Venice*, 2014, (03), 287–328. 4, 5

Dalvit, Nicolò, "Aggregate Uncertainty and the Micro-Dynamics of Firms," *Working Paper*, 2021. 59

de Almeida Vilares, Hugo and Hugo Reis, "A Saga of Wage Resilience : Like a Bridge over Troubled Water," *Working Paper*, 2022. 5, 7

De Loecker, Jan, "Recovering markups from production data," *International Journal of Industrial Organization*, 2011, *29*, 350–355. 20

— **and Chad Syverson**, "An Industrial Organization Perspective on Productivity," *NBER Working Papers*, 2021, (29229), 1–114. 72

— **and Frederic Warzynski**, "Markups and Firm-Level Export Status," *American Economic Review*, 2012, *102* (6), 2437–2471. 20

— **, Jan Eeckhout, and Gabriel Unger**, "The Rise of Market Power and the Macroeconomic Implications," *The Quarterly Journal ofEconomics*, 2020, *135* (2), 561 – 644. 3, 13, 19, 66, 69, 79

— **, Pinelopi K. Goldberg, Amit K. Khandelwal, and Nina Pavcnik**, "Prices, Markups, and Trade Reform," *Econometrica*, 2016, *84* (2), 445–510. 3, 11, 13, 18, 21, 66, 67

De Ridder, Maarten, "Market Power and Innovation in the Intangible Economy," *Working Paper*, 2021. 13

— **, Basile Grassi, and Giovanni Morzenti**, "The Hitchhiker's Guide to Markup Estimation," *Working Paper*, 2021. 3, 11, 13, 20, 60, 63

Demirer, Mert, "Production Function Estimation with Factor-Augmenting Technology: An Application to Markups," *Working Paper*, 2022. 58

Diamond, Peter A., "Wage Determination and Efficiency in Search Equilibrium," *The Review of Economic Studies*, 1982, *49* (2), 217. 2, 7

Dix-Carneiro, Rafael, Pinelopi Koujianou Goldberg, Costas Meghir, and Gabriel Ulyssea, "Trade and Informality in the Presence of Labor Market Frictions and Regulations," *Working Paper*, 2021. 6

Drautzburg, Thorsten, Jesús Fernández-Villaverde, and Pablo Guerrón-Quintana, "Bargaining shocks and aggregate fluctuations," *Journal of Economic Dynamics and Control*, 2021, *127*, 104121. 7

Dube, Arindrajit, Jeff Jacobs, Suresh Naidu, and Siddharth Suri, "Monopsony in Online Labor Markets," *American Economic Review: Insights*, 2020, *2* (1), 33–46. 6

Eggertsson, Gauti B, Jacob A Robbins, and Ella Getz Wold, "Kaldor and Piketty's Facts: The Rise of Monopoly Power in the United States," *NBER Working Paper*, 2018, (24287). 19

Estevao, Marcello and Stacey Tevlin, "Do firms share their success with workers? The response of wages to product market conditions," *Economica*, 2003, *70* (280), 597–617. 6

Fakhfakh, Fathi and Felix FitzRoy, "Basic wages and firm characteristics: Rent sharing in French manufacturing," *Labour*, 2004, *18* (4), 615–631. 6

Gandhi, Amit, Salvador Navarro, and David A. Rivers, "On the Identification of Gross Output Production Functions," *Journal of Political Economy*, 2020, *128* (8), 2973–3016. 13

Goldberg, Pinelopi Koujianou and Rebecca Hellerstein, "A Structural Approach to Identifying the Sources of Local Currency Price Stability," *Review of Economic Studies*, 2013, *80* (1), 175–210. 6

Goolsbee, Austan and Chad Syverson, "Monopsony Power in Higher Education: A Tale of Two Tracks," *NBER Working Paper*, 2019, (26070). 6

Gorodnichenko, Yuriy and Oleksandr Talavera, "Price Setting in Online Markets: Basic Facts, International Comparisons, and Cross-Border Integration," *American Economic Review*, 2017, *107* (1), 249–282. 6

Greenspon, Jacob, Anna Stansbury, and Larry Summers, "Productivity and Pay in the US and Canada," *NBER Working Paper*, 2021, (29548). 2

Guiso, Luigi and Luigi Pistaferri, "The insurance role of the firm," *The Geneva Risk and Insurance Review*, 2020, *45*, 1–23. 5

_ , _ , and Fabiano Schivardi, "Insurance within the Firm," *Journal of Political Economy*, 2005, *113* (5). 6

Hairault, Jean Olivier, Thomas Le Barbanchon, and Thepthida Sopraseuth, "The cyclicality of the separation and job finding rates in France," *European Economic Review*, 2015, *76*, 60–84. 29, 30

Hosios, Arthur J., "On the efficiency of matching and related models of search and unemployment," *Review of Economic Studies*, 1990, *57* (2), 279–298. 5, 31

Jäger, Simon, Benjamin Schoefer, Samuel G. Young, and Josef Zweimüller, "Wages and the Value of Nonemployment," *Quarterly Journal of Economics*, 2020, *135* (4), 1905–1963. 6

Jaimovich, Nir and Henry E. Siu, "Job polarization and jobless recoveries," *Review of Economics and Statistics*, 2020, *102* (1), 129–147. 22

_ , Itay Saporta-Eksten, Henry Siu, and Yaniv Yedid-Levi, "The Macroeconomics of Automation: Data, Theory, and Policy Analysis," *CEPR Discussion Paper*, 2020, (14362). 5, 40

_ , _ , _ , and _ , "The macroeconomics of automation: Data, theory, and policy analysis," *Journal of Monetary Economics*, 2021, *122*, 1–16. 6

Jarosch, Gregor, Jan Sebastian Nimczik, and Isaac Sorkin, "Granular Search, Market Structure, and Wages," *NBER working paper*, 2021, (26239). 7

Karabarbounis, Loukas and Brent Neiman, "The Global Decline of the Labor Share," *The Quarterly Journal of Economics*, 2014, pp. 61 – 103. 2

Katz, Lawrence F. and Alan B. Krueger, "The Rise and Nature of Alternative Work Arrangements in the United States, 1995-2015," *ILR Review*, 2019, *72* (2), 382–416. 36

Keller, Wolfgang and Stephen R. Yeaple, "Multinational enterprises, international trade, and productivity growth: Firm level evidence from the United States," *Review of Economics and Statistics*, 2009, *91* (4), 821–831. 58

Kirov, Ivan, Paolo Mengano, and James Traina, "Measuring Markups with Revenue Data," *Working Paper*, 2022. 18, 67

Kline, Patrick, Neviana Petkova, Heidi Williams, and Owen ZIdar, "Who Profits from Patents? Rent-Sharing at Innovative Firms," *Quarterly Journal of Economics*, 2019, *134* (3), 1343–1404. 6

Krueger, Alan B, "Reflections on Dwindling Worker Bargaining Power and Monetary Policy," in "Luncheon Address at the Jackson Hole Economic Symposium" 2018. 7

Lancieri, Filippo, Eric Posner, and Luigi Zingales, "The Political Economy of the Decline of Antitrust Enforcement in the United States," *NBER Working Paper*, 2022, (30326). 35

Lange, Fabian and Theodore Papageorgiou, "Beyond Cobb-Douglas: Flexibly Estimating Matching Functions with Unobserved Matching Efficiency Fabian," *NBER Working Paper*, 2020, pp. 1–37. 5, 30, 31

Leduc, Sylvain and Zheng Liu, "Robots or Workers ? A Macro Analysis of Automation and Labor Markets," *Federal Reserve Bank of San Francisco, Working Paper Series*, 2022. 4

Levinsohn, James and Amil Petrin, "Estimating production functions using inputs to control for unobservables," *Review of Economic Studies*, 2003, *70* (2), 317–341. 13

Lochner, Benjamin and Bastian Schulz, "Firm Productivity, Wages, and Sorting," *Journal of Labor Economics*, 2022, pp. 1–31. 6, 23

Lombardi, Marco J., Marianna Riggi, and Eliana Viviano, "Bargaining power and the Phillips curve: a micro-macro analysis," *Bank of Italy, Working Paper*, 2020, (1302), 1–28. 7

Mairesse, Jacques and Jordi Jaumandreu, "Panel-data estimates of the production function and the revenue function: What difference does it make?," *Scandinavian Journal of Economics*, 2005, *107* (4), 651–672. 13, 67

Manning, Alan, "Monopsony in Labor Markets: A Review," *ILR Review*, 2020, (X), 1–24. 6

Margolis, David N and Kjell G Salvanes, "Do Firms Really Share Rents with Their Workers?," *IZA Discussion Paper*, 2001, (330). 6

Melitz, Marc J, "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 2003, *71* (6), 1695–1725. 36

Mertens, Matthias, "Micro - Mechanisms Behind Declining Labor Shares : Rising Market Power and Changing Modes of Production," *International Journal of Industrial Organization*, 2022, *81*. 7, 13, 66, 67, 69

Mortensen, Dale, "Property Rights and Efficiency in Mating , Racing , and Related Games," *The American Economic Review*, 1982, *72* (5), 968–979. 2, 7

Olley, G. Steven and Ariel Pakes, "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 1996, *64* (6), 1263–1297. 3, 13, 72

Palladino, Marco Guido, Alexandra Roulet, and Mark Stabile, "Understanding the role of firms in the gender wage gap over time , over the life cycle , and across worker types," *Working Paper*, 2022. 4

Patel, Assem, "The role of firms in shaping job polarization," *Working Paper*, 2021. 5, 22, 40, 41

Petrongolo, Barbara and Christopher A Pissarides, "Looking into the Black Box: A Survey of the Matching Function," *Journal of Economic Literature*, 2001, *XXXIX*, 390–431. 5, 31

Pissarides, Christopher A, "Short-Run Equilibrium Dynamics of Unemployment, Vacancies, and Real Wages," *American Economic Review*, 1985, *75* (4), 676–690. 2, 7

Ratner, David and Jae Sim, "Who Killed the Phillips Curve? A Murder Mystery," *Finance and Economics Discussion Series*, 2022, (028), 1–36. 7

Roussille, Nina, "The Central Role of the Ask Gap in Gender Pay Inequality," *Working Paper*, 2022. 4, 26, 39

Schivardi, Fabiano and Tom Schmitz, "The IT revolution and Southern Europe's two lost decades," *Journal of the European Economic Association*, 2020, *18* (5), 2441–2486. 4, 34, 63

Schubert, Gregor, Anna Stansbury, and Bledi Taska, "Employer Concentration and Outside Options," *Working Paper*, 2022. 6

Shimer, Robert, "The Cyclical Behavior of Equilibrium Unemployment and Vacancies," *American Economic Review*, 2005, *95* (1), 25–49. 29, 30

Sokolova, Anna and Todd Sorensen, "Monopsony in Labor Markets: A Meta-Analysis," *ILR Review*, 2021, *74* (1), 27–55. 6

Song, Jae, David J Price, Fatih Guevenen, Nicholas Bloom, Till von Wachter, David J. Prince, Fatih Guevenen, Nicholas Bloom, and Till von Wachter, "Firming Up Inequality," *The Quarterly Journal ofEconomics*, 2019, *134* (1), 1 – 50. 73, 74

Stansbury, Anna and Lawrence H Summers, "The Declining Worker Power Hypothesis: An Explanation for the Recent Evolution of the American Economy," *NBER Working Paper*, 2020, (27193). 7

Stole, Lars A and Jeffrey Zwiebel, "Intra-firm Bargaining under Non-binding Contracts," *Review of Economic Studies*, 1996, *63*, 375–410. 70

Traina, James, "Labor Market Power and Technological Change in US Manufacturing," *Working Paper*, 2021. 4, 7, 34, 69

Trottner, Fabian, "Misallocations in Monopsonistic Labor Markets," *Working Paper*, 2022. 7

Wang, Yifei, Toni M. Whited, Yufeng Wu, and Kairong Xiao, "Bank Market Power and Monetary Policy Transmission: Evidence from a Structural Estimation," *Journal of Finance*, 2021. 69

Weyl, E. Glen and Michal Fabinger, "Pass-Through as an Economic Tool: Principles of Incidence under Imperfect Competition," *Journal of Political Economy*, 2013, *121* (3), 528–583. 6

Wong, Horng Chern, "Understanding High Wage and Low Wage," *Working Paper*, 2021. 6, 7, 13, 23

Yeh, Chen, Claudia Macaluso, and Brad Hershbein, "Monopsony in the U.S. Labor Market," *American Economic Review*, 2022. 7, 26

A Additional Figures and Tables

Table A.1: Bargaining Power: First Stage

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

Table A.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: Worker bargaining power is defined as τ, the coefficient of productivity in Equation 10. Standard errors are clustered at the firm level. Controls include time-varying 4-digit industry fixed effects. The estimation is performed separately for each industry, but jointly for the different years. Representativeness denotes the value added (VA) or employment (EMP) share in the sample.

Table A.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: Worker bargaining power is defined as τ, the coefficient of productivity in Equation 10. Standard errors are clustered at the firm level. Controls include time-varying 4-digit industry fixed effects. The estimation is performed separately for each subindustry, but jointly for the different years. Representativeness denotes the value added (VA) or employment (EMP) share in the sample.

Table A.4: 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

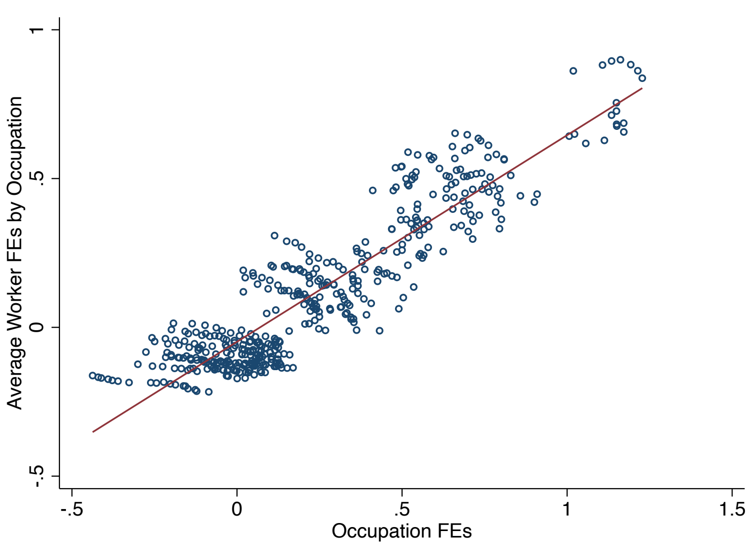
Notes: Worker bargaining power is defined as τ, the coefficient of productivity in Equation 10. Standard errors are clustered at the firm level. Controls include time-varying 4-digit industry fixed effects. The rows report bargaining power estimates based on different productivity measures. Revenues and Quantities denote whether production function was performed on revenues on or physical quantities. CD and T denote whether the production function is a Cobb-Douglas or a Translog (more details in Appendix C and D).

Table A.5: 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: Worker bargaining power is defined as τ, the coefficient of productivity in Equation 10. Standard errors are clustered at the firm level. Controls include time-varying 4-digit industry fixed effects interacted with size indicators to allow for differential market conditions for firms of different sizes.

Figure A.1: Correlation Between Occupation FEs and AKM FEs



Notes: This figure shows the correlation between worker fixed effects averaged across occupations (y-axis) and occupation fixed effects (x-axis). Worker fixed effects are the results of a twoway fixed effect regression of log wages on worker and firm fixed effects controlling for observable characteristics. The data used are from Panel DADS which include the sample of employees born in October from 2002 and occupations are defined at the 2-digit level. Occupation plots fixed effects are estimated from equation 17 on a 20% random subsample of the total workforce in France from 1960 to 2019 (more details on its representativeness in table C.5).

B Derivations

B.1 Wage Equation

Losing the subscripts and denoting by the "prime notation" a next period's variable, I derive the Nash product for the wage and find the bilateral efficiency condition.

$$\tau J = (1-\tau)(E-U)$$

Such condition states that in a match the surplus is shared such that the firm value multiplied by worker bargaining power must be equalized to the worker value multiplied by firm bargaining value. It thus shows how the surplus is shared among the parts.
Plugging in the Bellman values, wages can be expressed as

$$w = \tau \text{MPN} + (1-\tau)b + \tau\beta(1-s)\mathbb{E}[J'] - (1-\tau)\beta(1-s-p(\theta))\mathbb{E}[E'-U']$$

and using the bilateral efficiency condition

$$w = \tau \text{MPN} + (1-\tau)b + \tau\beta p(\theta)\mathbb{E}[J']$$

At this point, I can use 1) the relation between job finding probability and job filling probability and 2) the free entry condition to get to the final expression for wages shown in Equation 8.

B.2 Marginal Revenue Productivity of Labor

To derive a formula for MRPN, I start by deriving the revenue function by labor

$$\frac{\partial R}{\partial N} = \frac{\partial P}{\partial Y}\frac{\partial Y}{\partial N}Y + \frac{\partial Y}{\partial N}P = \left(\frac{\partial P}{\partial Y}Y + P\right)\frac{\partial Y}{\partial N} = \left(\frac{\partial P}{\partial Y}\frac{Y}{P} + 1\right)\frac{\partial Y}{\partial N}P \tag{B.1}$$

this equation shows the difference of value that a worker generates in an environment with market power in contrast to the one described in Section 2. In this case, indeed, the marginal revenue productivity, $\frac{\partial R}{\partial X}$ is a combination of the physical marginal productivity, $\frac{\partial Y}{\partial N}$, the demand elasticity, $\left(\frac{\partial P}{\partial Y}\frac{Y}{P} + 1\right)$, and prices.

I can use the profit maximization problem to show that the additional terms in the marginal revenue productivity can be summarized by firm markup. Let's start indeed from the static profit maximization problem

$$\max_{Y} R - C(Y)$$

and derive by quantity

$$\begin{aligned} &\frac{\partial P}{\partial Y}Y + P = C'(Y) \\ &\left(\frac{\partial P}{\partial Y}\frac{Y}{P} + 1\right)P = C'(Y) \Rightarrow \left(\frac{\partial P}{\partial Y}\frac{Y}{P} + 1\right) = \frac{C'(Y)}{P} = \frac{1}{\mu} \end{aligned} \tag{B.2}$$

where μ, firm markup, is defined as the ratio of price over marginal costs. I can now substitute markup in Equation B.1 and express marginal revenue productivity as in Equation 14.

B.3 Wages in Multi-Worker Negotiation

In order to solve Equation F.2, I re-write it as an ordinal differential equation

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

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. However, I do not need to keep track of it as it will simplify in the next step. Indeed, by using the product rule, I can express Equation B.3 as

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

Plugging in the values of the function

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

Finally, solving the second integral gives Equation F.3.

C Data

In this Section, I provide further details on the sample construction, variable choice and data treatment as well as an overview of the representativeness of my sample.

C.1 The US

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 with 2012 as benchmark year from the Bureau of Economic Analysis. Table C.1 shows the list of variables used. Table C.2 presents summary statistics of firms in the sample. 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

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

Revenues and Capital are expressed in USD millions;
Number of Employees and Wages in thousands of workers and USD, respectively

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 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 track the workforce of each firm over time. Thus it is possible to have worker-job information on wages, hours worked, etc. as well as to understand the evolution of the workforce at each firm from one year to the other.

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,

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	

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., 2021). 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. More specifically, I use gross output deflators for revenues, value added deflators for value added and wages, capital deflators for capital and intermediate input deflators for materials.[38]

Representativeness and Industry Composition

The final sample I use for my analysis covers XX% of total value added and XX% of total employment on average in every year. Table C.4 shows summary statistics for my sample of analysis. Finally in Figure C.1, I show the industry composition in the sample and a comparison with CompNet, a micro-founded database, in which information on the French economy are available over the period 2004-18.[39] Panels C.1a and C.1b show the industry

[38] 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.

[39] More information on CompNet can be found in www.comp-net.org

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

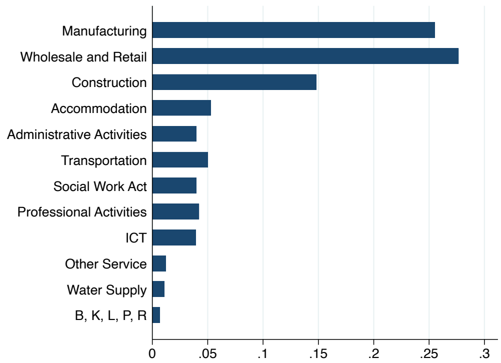
(b) Workers

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

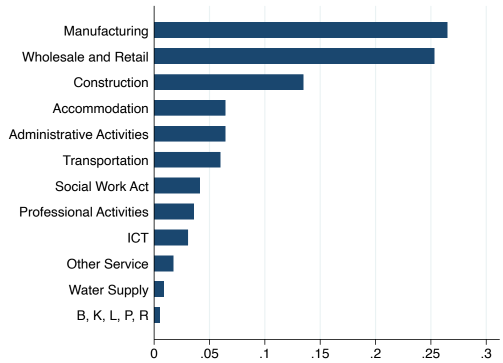
Notes: this Table shows summary statistics for firms and employees in the sample of analysis. All variables are real. Values for firms are in thousands of Euros, values for employees are in Euros.

composition in my sample pooled over the entire period, highlighting that manufacturing and Wholesale and Retail sectors account for half of the total economic activities. Panels C.1c and C.1d show the industry composition in CompNet for comparison revealing a similar industry composition.

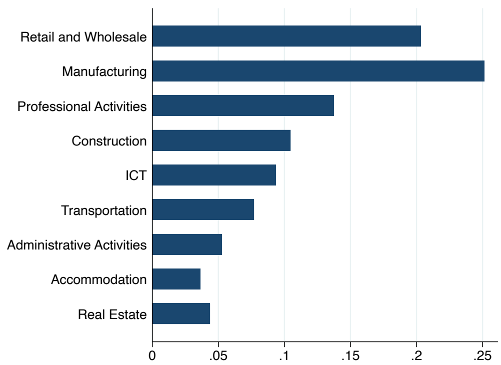
Figure C.1: Industry composition



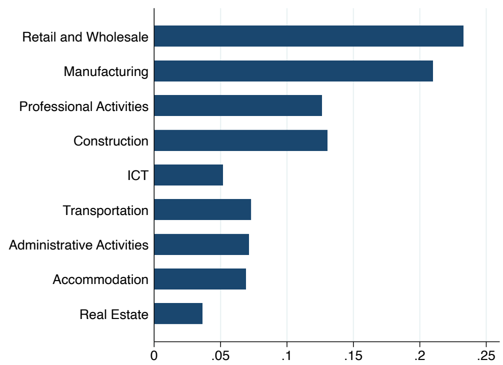
(a) Value Added



(b) Employment



(c) Value Added in CompNet (2004-18)



(d) Employment in CompNet (2004-18)

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.

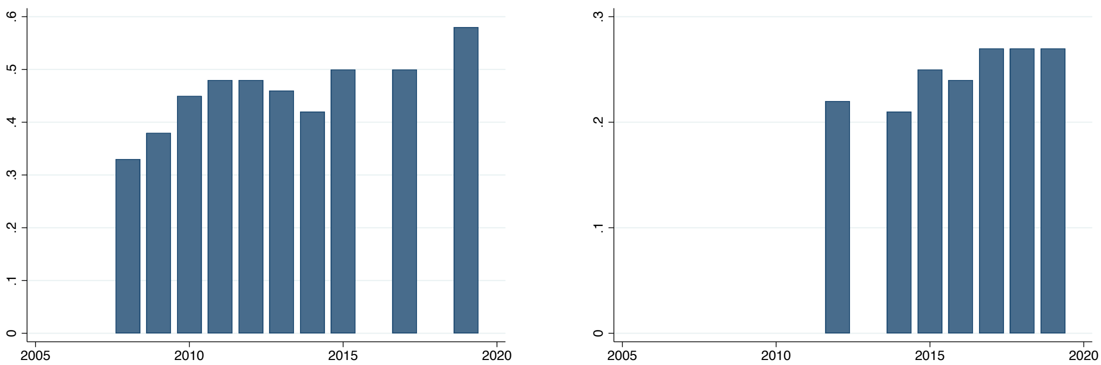
Additional Sources: Product-level Information

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. (2021). 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. Table C.2 below shows the share of ICT usage per the available years.

Figure C.2: Share of firms adopting ICT



(a) ERP

(b) 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.

Table C.5: Employee-job Subsample Representativeness

	Total Sample	20% Subsample
Gender composition		
Woman	39.5%	39.5%
Occupation composition		
Abstract	15.3%	15.3%
Routine	53.5%	53.5%
Manual	31.3%	31.3%
Age composition		
16-33	35.9%	35.9%
34-51	47.9%	47.9%
52-70	16.2%	16.2%
Region composition		
Île-de-France	26.3%	26.3%
Others	73.7%	73.7%
Wage	15.5	15.5

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. Hence, I use the input demand function for material as a proxy 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. $\omega = m^{-1}(m, \Lambda)$.[40] 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. 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 D.4 and 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

[40]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.

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.

D.1.1 Common Prices and Demand Shifters

In order to recover physical quantities, I use deflators to purge prices from revenues and input expenditures. This is a good 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.[41] In this case, the error term would include both the measurement error term as well as the omitted output and input price (De Loecker et al., 2016). 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.1.2 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.[42] I follow Mertens (2022) and De Loecker et al. (2016) and estimate

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

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

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).[43]

I find that the results are extremely similar (Mairesse and Jaumandreu, 2005). Below I show the comparison between elasticities estimated on revenues and input expenditure data and the ones estimated on physical quantities and controlling for omitted input prices. I find a cross-industry correlation of elasticities of labor and materials in the Cobb-Douglas specification of 93% and 96%, respectively. In the translog case, I find within-industry correlations of 93% for the labor elasticity and of 87% for the materials one.

Table A.4 shows the results of estimating worker bargaining power on productivity measures based on revenue or physical quantity data. I focus on the sample of firms for which output prices are available in the French manufacturing industry. It is clear that the possible output price bias typical of the markup literature does not transmit to this setting (see Bond et al. (2021) and De Loecker et al. (2016) for an extensive discussion of the problems of estimating markups in the absence of output prices and Kirov, Mengano and Traina (2022) for a solution).

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

[43] 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).

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)
Tau	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: Worker bargaining power is defined as τ, the coefficient of productivity in Equation 10. Standard errors are clustered at the firm-level. Column 1 reports benchmark estimation from Table 1. Column 2 estimation with productivity shocks; Column 3 with a third-order polynomial approximation of a Markov process; Column 4 - 6 using second, third and forth lags as instruments, respectively.

Table E.2: Alternative Instruments in France

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tau	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: Worker bargaining power is defined as τ, the coefficient of productivity in Equation 10. Standard errors are clustered at the firm-level. Column 1 reports benchmark estimation from Table 1. Column 2 estimation with productivity shocks; Column 3 with a third-order polynomial approximation of a Markov process; Column 4 - 6 using second, third and forth lags as instruments, respectively. Column 7 reports the estimate of bargaining power in the benchmark case performed on employees data. With respect to the other columns, it includes as well nonlinear controls for age, gender, location, occupations and contracts. 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 (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.

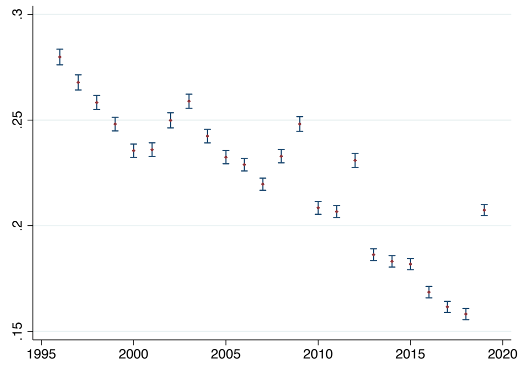
Alternative Production Functions

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, Wang et al., 2021, 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.

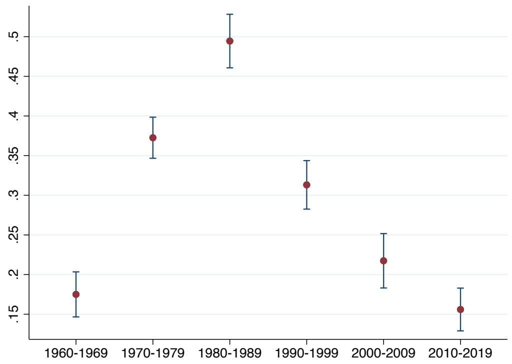
The last two panels in Figure F.1 show the results of this exercise. More specifically, Figure F.1c shows the estimated values of bargaining power over time in the U.S. with marginal productivity of labor resulting from a translog production function and Figure F.1d shows the same in France. In both 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

Figure F.1: Bargaining Power with Alternative Production Technologies

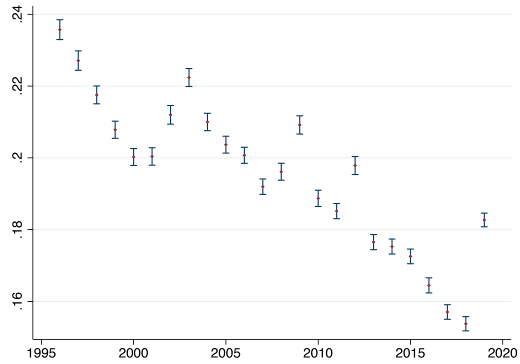
(a) Technical Change in the US



(b) Technical Change in France



(c) Translog in the US



(d) Translog in France

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 show in this Section that incorporating such feature in my analysis changes only marginally the level of the estimates of the bargaining power leaving my main result, the trend in bargaining power, unaltered.

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 solve the differential equation in Appendix B.3 and arrive to this intermediate result:

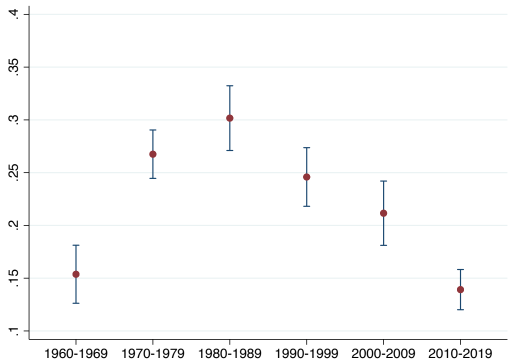
$$wN^{\frac{1}{\tau}} = \int \frac{MPN}{N^{1-\frac{1}{\tau}}}dN + [(1-\tau)b + \tau\theta\kappa]N^{\frac{1}{\tau}} + C \tag{F.3}$$

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

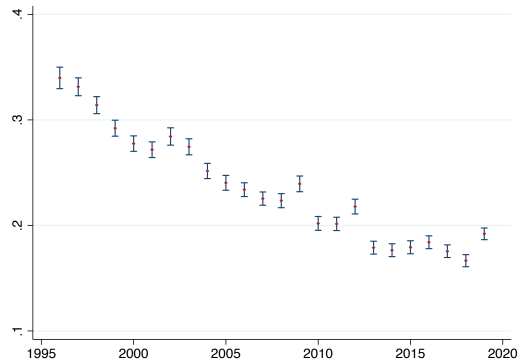
$$w = \frac{1}{(\varepsilon_{Y,N} + \frac{1}{\tau} - 1)}\text{MPN} + (1-\tau)b + \tau\theta\kappa \tag{F.4}$$

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.4 by the ratio of the bargaining power parameter and the coefficient of the marginal productivity of labor.

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



(a) US



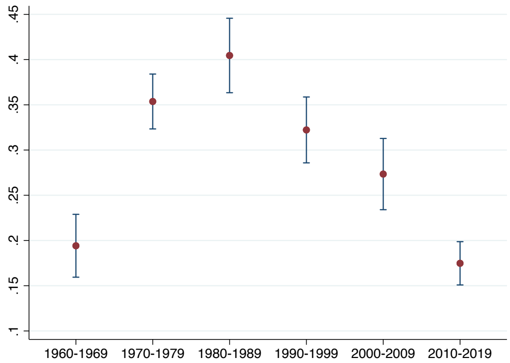
(b) France

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 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.

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



(a) US

(b) France

G Sorting in France

Furthermore, Song et al. (2019) and Bonhomme et al. (2022) show that the extent of worker sorting into firms has increased in recent periods in the US. That might be one of the reason why we see lower bargaining power over time. I analyze what happened in France following the approach of Song et al. (2019). I first decompose the earning variance into the within- and between- component to shed light on how these elements have changed over time. Then I estimate an AKM model over two different time periods and compare the covariance term between worker and firm fixed effects to analyze the changes in worker sorting.

Figure G.1: Decomposition of Variance of Log Hourly Earnings

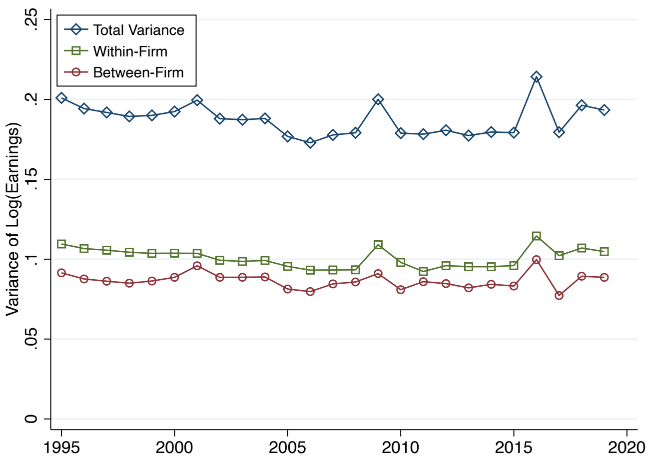


Table G.1: Sorting in France

	2002-10	2011-19
Cov(WFE,FFE)	0.013	0.0092

Figure G.1 shows the evolution over time of the variance of log hourly earnings.[44] This analysis allows to study the volution of the variance of (log) hourly earnings over time and to shed light on the importance of within and between firm factors. From the figure, it is clear that there is no increase in earnings variance in contrast to the evidence in the US. Moreover, it is possible to see that the between and within factors have a very similar importance in determining the total variance and their relative importance did not vary over the period analyzed. Also this is in contract with the U.S. where Song et al. (2019) finds that the within-factor alone account for around two thirds of the total variance. This result suggests that there is no change in sorting over the period analyzed.

I use the panel version of the employee data to formally test for changes in sorting over time. Namely, focusing on the period after 2001 for which I have information on 8 % ot the total workforce, I estimate two AKM models for each half of the period. Thereafter, I compare the covariance between firm and worker fixed effect, a indicator of the degree of sorting in the market. Table G.1 shows the values of the covariance term in the period 2002-2010 and in 2011-19. Although there is clear evidence of limited mobility bias, there is no sign of increasing sorting. Contrarily to the US, the covariance term has decreased suggesting that workers are spreading more evenly across the entire population of firms.

H Finance

In this Section, I present the results of my estimation procedure for listed firms in Finance. Due to data availability, I perform the analysis over the period 1999-2019 and focus on firms with more than 10 employees.

As already anticipated in Section 5, an intermediate step for such estimation consists in estimating firm production function. With this aim, it is necessary to take a stand on its functional form and I assume it is a Cobb-Douglas or a Translog function that takes as inputs number of employees and physical capital. While this might be a good representation for manufacturing, it is clearly not appropriate for financial firms. Hence, I report here the results for completeness but the reader should keep this caveat in mind.

[44] I follow the variance decomposition of Song et al. (2019): $\text{var}(y^{j,i}) = \text{var}_i(\bar{y}^i_t) + \sum_i \text{emp}_i \times \text{var}_j(y^{j,i}|i \in j)$. This formula decomposes the variance of (log) hourly earnings into the first term that reflect the variance of firm average earnings plus the employment-weighted mean of within-firm dispersion in employee earnings, with emp_i denoting firm j's employment share

Table H.1: Bargaining Power

	(1)	(2)	(3)
Tau	0.055***	0.228***	0.197***
	(0.001)	(0.003)	(0.002)
Year FE	Yes	Yes	Yes
Industry FE	No	Yes	Yes
Industry x Year FE	No	No	Yes

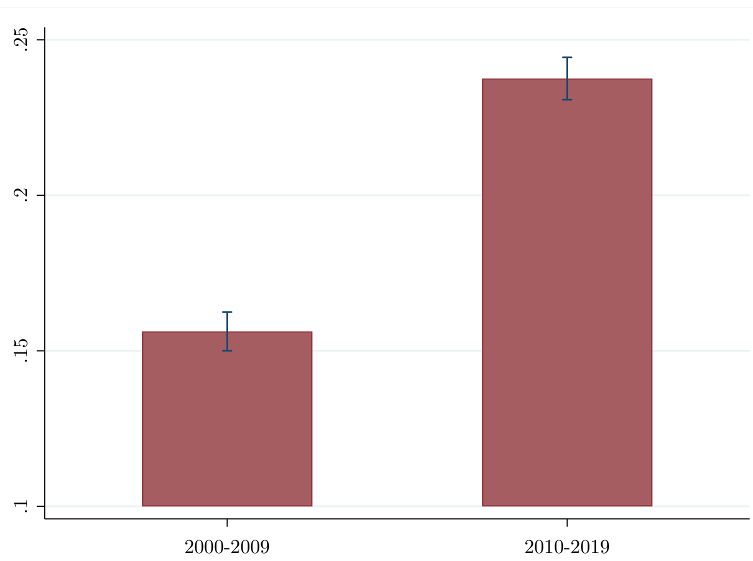
Bootstrapped standard errors in parentheses, * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Industry FE are specified at the 4-digit level.

Bargaining Power

Table H.1 shows the estimation results keeping bargaining power constant over the whole period. The value that I find is surprisingly similar to the one in manufacturing shown in Section 5. However, the importance of industry heterogeneity is remarkable. Indeed, the change in the estimated parameter τ is tremendous when introducing industry fixed effects in column 2 and industry times year fixed effects in column 3. Such heterogeneity, that is captured in my empirical framework but is not present in my theoretical analysis, seems to have an important role in the Finance industry and clearly deserves more research.

Figure H.1 shows the trends in worker bargaining power over the last two decades. Although it is comparable in magnitude to the one in manufacturing, the trend is completely reversed with respect to that industry. Indeed, it start at around 15% in the early 2000s to arrive to a value of almost 25% in the last decade. A possible explanation might be a structural change following the financial crisis. New regulations or different business activities could have indeed increased the importance of workers in the wage setting process.

Figure H.1: Trends in Bargaining Power in the Finance Industry



I Efficiency in France

J Model Solution and Calibration

The model analyzed in Section 7 does not envisage productivity heterogeneity across firms nor a notion of firm size as each active firm hires only one worker. Therefore, 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: $\kappa = \beta q(\theta^{SS})J^{SS}$
2. the wage equation: $\omega^{SS} = \tau z + (1-\tau)b + \tau\kappa\theta^{SS}$
3. the unemployment equation: $u^{SS} = (1 - p(\theta^{SS}))u^{SS} + s(1 - u^{SS})$

The zero profit condition, introduced in Section 2.3 comes from the fact that there is a continuum of firms ready to enter in the market. Hence, it guarantees that the cost of entry (LHS) is equal to the benefits (RHS). The wages equation is also derived in Section 2.3 and describes the solution to the Nash bargaining game in steady state. Finally, the unemployment equation characterizes the law of motion for unemployment and is defines as the sum of the unemployed that do not match with any vacancy and the outflow from employment (workers whose job is destroyed).

J.1 Multi-Worker Framework

I repeat the quantitative exercise done in Section 7.1 with the model introduced in Section 2. In this case, firms have an idiosyncratic productivity and can choose their size, meaning they can hire more than just one employee. Moreover, firms produce with a Cobb-Douglas production function with labor and materials as inputs. For computational ease, I abstract from capital, which would represent another fixed input in this framework, and introduce a flexible input, materials, which is inelastically supplied at a fixed cost. It is straightforward to see that all the derivations in Section 2 remain the same.

A competitive equilibrium in this framework is a collection of wages (ω), tightness ratio (θ), firm input demands (labor, n, vacancies, v, and materials, m), and unemployment (u), such that:

1. firms maximize profits (and in particular the zero profit condition for vacancy creation is satisfied)
2. workers maximize utility
3. wages satisfy the Nash bargaining problem
4. labor market clears

The difference with respect to the equilibrium conditions for the model in which each active firm corresponds to a single worker is that both zero profit conditions and wage equation must be satisfied for each firm in the market. Moreover, having a workforce, now firms internalize the effect that hiring an additional employee has on the existing wage-bill. This consists of a combination of changes in marginal productivity and in tightness ratio. As a result (and with a standard parametrization), firms will choose a workforce size that allows them to minimize labor costs in addition, of course, to maximize profits..

To calibrate the steady state, I need three additional parameters, namely the two output elasticities and the price of materials. I set the labor elasticity to .6, the material elasticity to .3 and normalize the price of materials to 1. Table J.1 shows the steady state in the multi-worker framework using the same calibration of the simplified model presented in Section 7.1 and the additional parameters just described. The first column shows the steady state in the 80s and the second one the new steady state once I change the bargaining value to the one of the 10s.

The results are very much in line with what I find with the simplified version of the model.[45] Unemployment decreases and the tightness ratio increases as a consequence of the lower

[45] Unemployment is no longer a targeted moment in this setting and thus it is not surprising that it does not match exactly the data

Table J.1: Model Predictions and Data

Variable	Model		Data	
	80s	10s	80s	10s
Unemployment (u)	6.6	6.1	7.3	6.3
Wages (ω)	1	0.79	1	1.35
Labor Share	1	0.79	1	0.91

labor cost environment. The magnitude of the change in unemployment however is only half of the one in the benchmark model (0.5pp vs 1.2pp). This is resulting from the mechanism described above. Indeed, in a setting in which firms can hire multiple worker, they internalize the effect that hiring an additional worker has on the existing wage-bill. As a consequence, firms hire more workers in order to reduce wages and minimize the cost of labor. As a result, a change in the bargaining power has more mitigated effect in this framework as wages are already more compressed towards workers' outside options.

J.2 Multi-Worker Framework With Product Market Power

Finally, I study the implications for the total economy of changes in bargaining power in a setting where firms have product market power.

I introduce monopolistic competition to the multi-worker setting described above. The economy is then constructed by a continuum of sectors producing intermediate products and a final good sector bundling them together to produce a consumption good.

The final good sector bundles products from intermediate sectors with a CES production function governed by an elasticity of substitution, ε:

$$\max_{y_j} \quad P\left(\int_0^1 y_j^{\frac{\varepsilon-1}{\varepsilon}} \mathrm{d}j\right)^{\frac{\varepsilon}{\varepsilon-1}} - \int_0^1 p_j y_j \mathrm{d}j$$

Each firm in the intermediate sector maximizes profits subject to the demand of its product from the final sector in addition to the constrains that were already valid in the multi-worker framework described in the previous Section:[46]

$$\max_{y_{j,t},p_{j,t},v_{j,t},m_{j,t}} \quad \mathbb{E}_0\left[\sum_{t=0}^{\infty}\beta^t\left(p_{j,t}y_{j,t} - w_{j,t}n_{j,t} - \kappa v_{j,t} - p^M m_{j,t}\right)\right]$$

$$\text{s.t.} \qquad y_{j,t} = \left(\frac{p_{j,t}}{P_t}\right)^{-\varepsilon} Y_t$$

[46]This includes the law of motion of employment, the idiosyncratic productivity process and the production function specification.

A competitive equilibrium in this framework is a collection of final good price (P) and quantity (Y), intermediate good prices (p_j) and quantities (q_j), wages (ω_j), tightness ratio (θ), firm input demands (labor, n_j, vacancies, v_j, and materials, m_j), and unemployment (u), such that:

1. firms maximize profits (and in particular the zero profit condition for vacancy creation is satisfied)
2. workers maximize utility
3. wages satisfy the Nash bargaining problem
4. final good market clears
5. labor market clears

To calibrate the steady state, in addition to the parametrization used in the previous Section, I need a value of the elasticity of substitution, ε. I set $\varepsilon = 5.75$ to match the markup measured in De Loecker et al. (2020) in the 1980, 1.21. Table J.2 shows the steady state in this framework. The first column shows the steady state in the 80s and the second one the new steady state once I change the bargaining value to the one of the 10s.

Table J.2: Model Predictions and Data

Variable	Model		Data	
	80s	10s	80s	10s
Unemployment (u)	7.7	6.7	7.3	6.3
Wages (ω)	1	0.88	1	1.35
Labor Share	1	0.88	1	0.91

Also in this case, the results are in line with the benchmark version of the model presented in Section 7.1. Unemployment decreases and the tightness ratio increases following the decline in worker bargaining power. Moreover, wages decrease and so does the labor share. It is interesting to see that the unemployment level in steady state is higher than in the case without market power. Intuitively, firms have higher profits due to their monopolistic competition and hence will produce less and hire less workers.