Are Managers Paid for Market Power?

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Abstract

To answer the question whether managers are paid for market power, we propose a theory of executive compensation in an economy where firms have market power, and the market for managers is competitive. We identify two distinct channels that contribute to manager pay in the model: market power and firm size. Both increase the profitability of the firm, which makes managers more valuable as it increases their marginal product. Using data on executive compensation from Compustat, we quantitatively analyze how market power affects Manager Pay and how it changes over time. We attribute on average 45.8% of Manager Pay to market power, from 38.0% in 1994 to 48.8% in 2019. Over this period, market power accounts for 57.8% of growth. We also find there is a lot of heterogeneity within the distribution of managers. For the top managers, 80.3% of their pay in 2019 is due to market power. Top managers are hired disproportionately by firms with market power, and they get rewarded for it, increasingly so.

Keywords. Market Power. Manager Pay. Executive Compensation. Markups. Reallocation. Superstars.

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1 Introduction

In the last four decades, inequality has increased dramatically, mainly driven by the increase in top incomes.[1] Among the top incomes earners, many of them are managers.[2] Managers do things differently than production and service workers. Most notably, successful managers render other workers more productive and firms pay a premium to hire those successful managers. And when firms become larger and more profitable, the impact of managers becomes more valuable to the firm, as every single decision now has far-reaching implications. Because their salaries are determined in a competitive labor market, this leads to higher pay for managers. This has been the seminal insight of Gabaix and Landier (2008) and Terviö (2008): the rise of the size of firms can explain why Manager Pay increased so much.

Yet, it remains an open question what determines the size and productivity of the firm. In this paper, we build on the insights from this literature by shedding new light on the origins of firm productivity and firm size. In particular, we focus on the role of market power. The recent literature documents that in the last four decades, there has been a rise in market power,[3] and this evolution coincides remarkably with the rise in Manager Pay (see Figure 1 below; in what follows, we use Manager and CEO interchangedly). Pay was relatively stable until the 1980s, when it started to rise sharply, a pattern similar to that of markups. So we ask whether managers are paid for market power.

Firms with market power also tend to be larger, and it is predominantly large superstar firms that exert market power: firms that have market power and have higher markups tend to obtain a larger market share. Of course, firms are also large because they have superior technologies.[4] The fact that market power and firm size correlate poses a serious challenge to tease out the role of each in determining the pay of managers. The correlation between markups and manager pay therefore does not elucidate our understanding of the causal determinants, due to, amongst other, reverse causality and omitted-variable bias.

In this paper, we propose a model that decomposes the origins of Manager Pay that are due to market power and those due to firm size. Do firms with market power pay managers more because those managers make firms sell more, or produce more efficiently? Because they generate more profits? Do managers extract some of the rents that market power creates? To analyze the contribution of market power to Manager Pay and the underlying mechanism, we start from the premise that productivity

[1] See Piketty and Saez (2003, 2006) and Atkinson, Piketty, and Saez (2011).

[2] Overall, about one fifth of the workforce has a managerial position (Santamarıa, 2018). Of course, not all managers are top earners, but one of the main determinants of higher wages is whether a worker supervises other workers. Because there are hierarchies, the managers of managers supervise most workers and hence become the top earners.

[3] See amongst others Grullon, Larkin, and Michaely (2016); Gutiérrez and Philippon (2017); De Loecker et al. (2020).

[4] One of the robust drivers of the rise in market power is the reallocation of market share towards more efficient firms that have high markups. See Autor, Dorn, Katz, Patterson, and Van Reenen (2020) and De Loecker et al. (2020).

and firm size are not determined in a competitive vacuum. Instead, firms exert market power in the goods market and managers who are hired in a competitive labor market contribute to their firm's productivity.

Our main findings derive from the fact that we are able to decompose Manager Pay into two channels: firm size and market power. Using data on executive compensation from Compustat between 1994 and 2019, we quantitatively analyze how market power affects Manager Pay and how it changes over time. We attribute on average 45.8% of Manager Pay to market power, the remainder is due to firm size. Over time, 57.8% of the growth in pay is due to market power. We also find there is a lot of heterogeneity within the distribution of managers. For the top managers in 2019, 80.3% of their pay is due to market power, and so is nearly all their growth since 1994. For the lower ranked managers, pay and growth of pay is determined mainly by firm size. Our main conclusion is that top managers are hired disproportionately by firms with market power, and they get rewarded for it. And while our focus due to data availability is on CEOs, the same logic applies to all managers who supervise other workers and other professions where sorting is a key determinant. And because one fifth of the workers supervise other workers, these findings have macroeconomic implications, not least of course for the top percentiles of the income distribution.

We build a model with a small number of competitors, in an economy with many of these small markets as in Atkeson and Burstein (2008). The main determinants of market power in these small, oligopolistic markets is the market structure (the number of firms in each market) and the distribution of productivities of the competitors. As in standard oligopolistic markets, the fewer the number of firms, or the more dispersed the productivities, the more market power. But market power is not equally distributed. The more productive firms compete by setting lower prices, which yields a higher market share and hence a larger firm. But those productive firms do not pass on all their productivity gains to the customer, so they set higher markups and generate more profits.

And here comes in the role of the manager. The manager raises the productivity of the firm in the sense of Lucas (1978) span of control. Generally, better managers have a larger span of control and optimally hire more production workers. As in the canonical matching model of Gabaix and Landier (2008) and Terviö (2008), total factor productivity is determined by the complementary inputs of the manager ability and the firm type. In a competitive labor market therefore, there is sorting between heterogeneous firms who compete for managers of heterogeneous ability. The match value of a matched pair is naturally determined by the profits the pair generates in their market. And profits depend on market power and firm size, and each in turn depends on the primitives of the model: the production technology, firm type, manager ability and market structure. Each of these jointly determines market power and firms size, and we can decompose how they determine profits and therefore Manager Pay.

While market power is determined by an amalgam of different factors, one of the main insights we gain is that the technology, and especially the differences in total factor productivity (TFP) between firms in the same market, determines market power. Even if the number of firms is small, when firms are identical in TFP, they have identical profits and market shares. Instead, when one firm has higher TFP, it achieves higher profits, and it obtains a larger market share. In the limit, as one firms is a lot more productive than all competitors in the market, it effectively behaves as a monopolist and obtains a market share close to one. And here the sorting of managers to firms plays a key role. As top managers join top firms and less talented managers lead low productivity firms, assortative matching increases the gap in productivity. An increase in the productivity difference is socially desirable in part, because it increases reallocation towards more productive firms who produce more of the output. But due to market power, the bigger gap also leads to an increase in market power: the high productivity firm faces less competition and passes on less of the productivity gains to the customer. This therefore leads to higher deadweight loss.

Related Literature. Our work builds on a large literature of prior work. The starting point is the body of work that introduces matching of managers of heterogeneous ability to firms of different size. This approach can explain why, in a competitive labor market, managers receive superstar pay and why it has increased so much in recent decades. See Gabaix and Landier (2008) and Terviö (2008), and also Edmans and Gabaix (2016) and Edmans, Gabaix, and Jenter (2017), for comprehensive surveys of the literature. For further evidence documenting the firm size hypothesis and its effect on compensation see also Frydman and Saks (2010), Gabaix, Landier, and Sauvagnat (2014) and Green, Heywood, and Theodoropoulos (2021).

There is also a growing literature documenting the rise of superstar firms and the effect this has on the capital and labor shares: Autor, Dorn, Katz, Patterson, and Van Reenen (2020), Barkai (2019), Hartman-Glaser, Lustig, and Zhang (2016), Kehrig and Vincent (2017). Much of this literature highlights the role of market power, and the reallocation of market share towards high markup firms. Firms that are large also tend to have high markups (Edmond, Midrigan, and Xu (2019); Grassi (2017); De Loecker et al. (2021)).

Our paper bridges these literatures on firm size and Manager Pay on the one hand, and firm size and market power on the other. We model market power in the tradition of the general equilibrium model of Atkeson and Burstein (2008), which allows for endogenous markups, a flexible market structure and firm heterogeneity. The theoretical novelty is to add a two-sided matching framework to this model with oligopolistic competition and endogenous markups in general equilibrium. Our analysis framework is also related to Jung and Subramanian (2017, 2021), who check the relationship between CEO compensation and product market competition. While their works are built on Dixit and Stiglitz (1977) with exogenous markups, we contribute in a new perspective that managers are paid because they allow firms to exert larger market power. In this world with externalities, the matching problem is very different from the competitive (or monopolistically competitive) setting. Chade and Eeckhout (2020) show that there can be multiple equilibria, that equilibrium and optimal allocation may involve randomization, and that the equilibrium is typically inefficient. Moreover, there exist no algorithms that find these allocations in polynomial time. We propose an approximate matching algorithm to find the equilibrium solution.

Our work complements the work that studies the effect of product market competition on incentive provision and optimal incentive contracts, which are absent in our model (Schmidt, 1997; Aggarwal and Samwick, 1999; Raith, 2003; Falato and Kadyrzhanova, 2012; Antón, Ederer, Giné, and Schmalz, 2021). Key in our setup with matching are endogenous markups and our ultimate objective is to estimate the technology and the market structure and to measure the contribution of market power to Manager Pay.

Finally, there is also a growing literature linking economy-wide inequality to market power. Using micro data from the US Census, Deb et al. (2020a) document the effect of market power on the skill premium and the wage level of all workers. And Kaplan and Zoch (2020) analyze the productivity of different occupations and the effect of markups.

In the next section, we describe the data and perform a preliminary analysis on the correlation between pay and market power. In Section 3 we propose a theory that captures the mechanism that drives manager pay by market power and firm size, and derive analytical results for its properties. In Section 4, we quantify the model. We present our main results in Section 5. Finally, Section 6 concludes.

2 Data and Preliminary Analysis

Data. We use data from Compustat throughout the paper.[5] The North America Fundamentals Annual data set (1950–2019) contains information on firm-level financial statements, including measures of sales, input expenditure, and industry classifications. We drop the finance, insurance, and real estate sectors (SIC between 6000 and 6799). The ExecuComp data set (1992–2019) has measures for Manager Pay. We use the variable TDC1 for Manager Pay, which include salary, bonus, restricted stock grants,

[5]The Compustat Data has been used extensively in the literature related to executive compensation, for example, Gabaix and Landier (2008), which makes our results comparable with the literature.

and value of option grants.[6] Although the ExecuComp data starts in 1992, we observe a substantial difference with the samples in 1992 and 1993, so our analysis will be carried out during the period 1994 to 2019.[7] Finally, all the nominal variables are deflated by dollars in 2019. Appendix A.1 provides more details of the firm-level panel data used in our reduced-form and structural analysis.

Markups are a key component in our analysis. Because they are not directly observable in the data, we estimate firm-level markups using the production approach (see De Loecker et al. (2020)).[8]

Correlation between markups and executive salaries. We begin our analysis by looking at the correlation between Manager Pay and markups. As we have mentioned in the introduction, Figure 1.A depicts the evolution over time of average Manager Pay (in 2019 USD) and average markups, and shows that the increase in Manager Pay correlates with the rise of markups. From 1994 to 2019, the average CEO salary more than doubled from \$3.34 to \$6.96 million, while the average markup also increased from 1.53 to 1.78. In Figure 1.B, we show the same series for markups for a longer time period (starting in 1955). Instead, for executive compensation, in the right panel we use data from Frydman and Saks (2010) who have constructed a longer time series dating back to pre-WWII and running until 2005. The Frydman and Saks (2010) measure of Manager Pay shows barely any increase between 1936 and the late 1970s, after which there is a sharp increase. The year 1980 is also when markups start to increase. Casual empiricism shows that there is a positive correlation between the markup and Manager Pay between 1955 and 2005.

Given the positive correlation between markups and executive compensation, we further analyze this relation including covariates X about the firm characteristics (number of employees, sales, and variable and fixed costs) as well as year and firm fixed effects. We are typically interested in the regression with interactions between year dummies and markup:

$$\log \text{Manager Pay}_{it} = \sum_t \beta_t \left(\log \text{Markup}_{it} \times \text{Year}_t\right) + X_{it} + \alpha_i + \gamma_t + e_{it}, \tag{1}$$

where i and t represent for firm and year, respectively. We have to assume that the residual term, e_{it}, is independent from markups after controlling the covariates X and fixed effects α_i and γ_t. Figure

[6]The difference between TDC1 and the alternative measure TDC2 measures is that TDC1 includes the value of options at the time the options are awarded while TDC2 includes the value of options at the time they are exercised. Our quantitive results are robust with both definitions.

[7]Details are documented in Figure A.1 of Appendix A.3, which is also mentioned in Terviö (2008).

[8]The recent work by Bond, Hashemi, Kaplan, and Zoch (2021), Traina (2018), Basu (2019) and Syverson (2019) has brought to the attention of the research community important methodological aspects of production function estimation, which directly affect the markup estimates when using the production approach. Most notably, estimates are biased due to endogeneity (first addressed by Olley and Pakes (1996) using the control function approach) and omitted price bias (first pointed out by Klette and Griliches (1996)). In our estimation, we control for these biases using the techniques laid out in this literature. For a detailed discussion, see Appendix A in De Loecker et al. (2020).

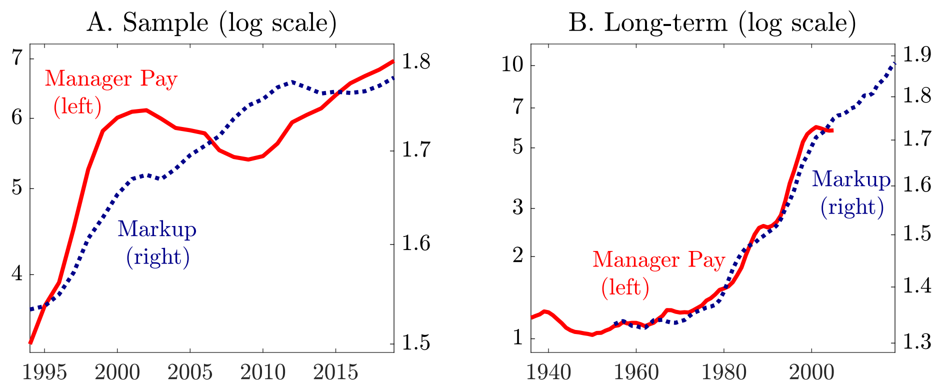


Figure 1: The evolution of Manager Pay and markups

Notes: Panel A plots the average executive compensation and average markup from ExecuComp sample. Panel B shows the long-term evolution of manager pay and markups, where the red line is the median manager pay among top firms constructed by Frydman and Saks (2010) and the blue, dotted line is the average markup from Compustat sample. All of them are plotted in 2019 million dollars, in log scale, and in five-year centered moving average.

2 shows the evolution of manager pay elasticity of markup, β_t, across time. Overall, this elasticity is significantly positive, indicating that a higher markup will contribute to higher Manager Pay. Moreover, we see an increase in the importance of market power. In 2019, a one percent increase in the firm level markup increases Manager Pay by 0.41 percent, which is 70.1% larger than the effect in 1994. Below, we confirm this increasingly important role of market power in our structural analysis. Additional regression results with different specifications are reported in Appendix A.2.

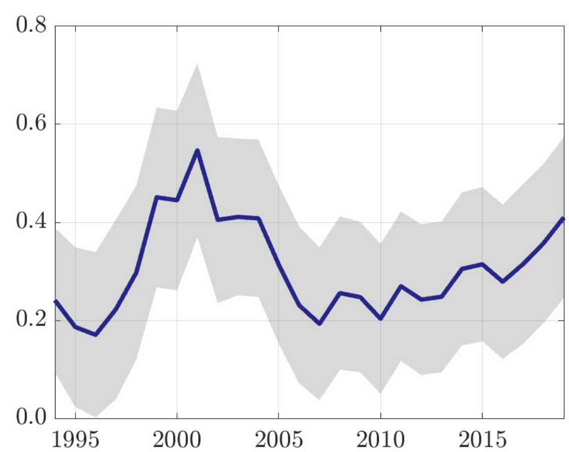


Figure 2: The elasticity of markups on Manager Pay over time

Notes: This figure reports the coefficients β_t in regression specification (1) across year. The 95% confidence interval (CI), which is constructed with robust standard errors under heteroscedasticity, is indicated by the shaded area.

While these regression results give an indication of the correlation between market power and managers' pay, they do not inform us about causality. We are faced with a number of serious identification problems, including reverse causality and omitted-variable bias. The limited availability of data makes it extremely difficult to uncover a clean causal relationship behind the correlations we observe. Therefore, in the remainder of this paper we propose a theory that can explain the relation between market power and executive compensation. Then we structurally estimate the model using the data that we have analyzed in this section.

3 Model

We build a model of the macroeconomy where firms have market power, and each firm hires a manager. The imperfect competition is modeled in the fashion of Atkeson and Burstein (2008), while the allocation of managers to firms is within a Becker (1973) matching framework in the spirit Gabaix and Landier (2008) and Terviö (2008).

3.1 Setup

Environment. The general equilibrium economy is populated by representative households and heterogeneous firms. A continuum of identical households consume goods, and they supply unskilled labor and managers. All surpluses generated in the economy revert to the households. The measure of firms is equal to M. The measure of households is normalized to one, and contains a large measure of identical production workers and a measure M of heterogeneous managers whose ability is indexed by x with distribution $F(x)$.[9] The market structure contains a continuum of markets with measure J, each indexed by $j \in [0, J]$. Each market j contains a finite number of I_j firms, where I_j varies by market j.[10] A single firm produces a single good. We use the subscript ij to index firm i in market j.

There are two stages. In stage 1, firms and managers match and the type of the manager and the type of the firm will contribute to total factor productivity. In stage 2, households choose their consumption bundles and make their labor supply decisions, and firms compete by choosing their production allocations.

Preferences. Households have preferences for consumption of all goods, within and between markets. The utility of consumption is represented by the double-nested Constant Elasticity of Substitution (CES) aggregator. The finite number of I_j goods are substitutes with elasticity η, and the elasticity of substitution between markets is θ. We assume $\eta > \theta > 1$, indicating that households are more willing

[9]The fact that the measure of managers equals the measure of firms is without loss of generality. A variation of the model can have occupational choice between becoming a manager and a production worker and where the number of managers is determined endogenously.

[10]The measure J is endogenous, which is determined by $M = J \times \mathbb{E}(I_j)$.

to substitute goods within a market (say Pepsi vs. Coke) than across markets (soft drinks vs. cars). The CES aggregates are defined as:

$$C = \left[\int_0^J J^{-\frac{1}{\theta}} c_j^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} \quad \text{and} \quad c_j = \left[\sum_{i=1}^{I_j} I_j^{-\frac{1}{\eta}} c_{ij}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}},$$

where c_{ij} is the consumption of good ij, c_j is the consumption aggregate of market j, and C is the economy-wide aggregate of consumption. Following De Loecker et al. (2021), we normalize the utility by the number of varieties to neutralize the love of variety effect, both within market j with size I_j and between markets with measure J.[11] We represent the household's preferences with the following utility function over the consumption bundle $\{c_{ij}\}$ that aggregates to C, and the supply of labor L:

$$U(C, L) = C - \overline{\varphi}^{-\frac{1}{\varphi}} \frac{L^{1+\frac{1}{\varphi}}}{1+\frac{1}{\varphi}}, \tag{2}$$

where utility is linear utility over aggregate consumption, and there is a constant elasticity disutility of labor with elasticity φ and intercept $\overline{\varphi}$. We further assume without loss that the manager's labor is supplied inelastically at zero cost.

Prices of the final consumption goods are denoted by p_{ij}, wages for production labor by W, salaries for managers by $\omega(x)$, and profits by π_{ij}. Manager salaries aggregate economy-wide to Ω and profits to Π, of which each household receives an equal share. Households face a budget constraints, where their spending on goods cannot exceed the income consisting of wage bill WL, executive salaries Ω, and dividends Π. We can thus summarize the household problem as follows:

$$\max_{\{c_{ij}\}, L} U(C, L) \quad , \quad \text{s.t.} \quad \int_0^J \left(\sum_{i=1}^{I_j} p_{ij} c_{ij} \right) dj \leq WL + \Omega + \Pi. \tag{3}$$

An important feature here is that all output produced is equal to the total income of the households. Therefore, all the value general by the allocation of this economy stays in the economy.

Technology. Firms differ in two dimensions. First, each firm has its own type z_{ij}, where $z_{ij} \sim G(z_{ij})$. Second, there is a productivity A_j that commonly affects all firms in the same market, which captures technology differences across markets, with $A_j \sim H(A_j)$. Denoting the ability of the manager who

[11] The love of variety adjustment ensures the households' preferences remain fixed when the market structure changes over time. This assumption is not crucial to any of our results.

matches with firm ij as x_{ij}, the firm-specific Total Factor Productivity (TFP) A_{ij} is defined as:

$$A_{ij} = A_j \left[\alpha x_{ij}^{\gamma} + (1-\alpha) z_{ij}^{\gamma}\right]^{\frac{1}{\gamma}}. \tag{4}$$

Both the manager ability x_{ij} and the firm type z_{ij} determine the TFP of the firm, while A_j is a market-level Hicks-neutral technology. The share α measures the importance of the manager relative to the firm type. The expression (4) allows for a CES functional form where γ is the constant elasticity of substitution between manager ability and firm type. We assume $\gamma < 1$, which means that managers and firms are complementary. This CES functional form allows for a flexible specification of the TFP technology. For example, when $\gamma = 0$, the expression (4) is the Cobb-Douglas function similar to Gabaix and Landier (2008). It turns out that this flexible CES setup plays an important role in matching the model to the data.

Given the firm's TFP A_{ij}, the technology that determines the quantity of output y_{ij} as a function of inputs of production labor is linear:

$$y_{ij} = A_{ij} l_{ij}. \tag{5}$$

This is a standard production technology except that now TFP is a combination of firm type and manager ability, so it can likewise be interpreted as a model span of control as in Lucas (1978).

Timing. All types realize at the outset: $\{x, z_{ij}, A_j\}$. There are two stages. In stage 1, each firm hires one manager in a frictionless market with payoffs under perfectly transferable utility (TU). The salary $\omega(x)$ denotes the compensation function of manager type x. Therefore, the profit maximization problem for firm ij at this stage is:

$$\max_{x_{ij}} \pi_{ij} = \widetilde{\pi}_{ij}(A_{ij}|A_{-ij}) - \omega\left(x_{ij}\right), \tag{6}$$

where $\widetilde{\pi}_{ij}$ is the firm's gross profit coming from the next period. We use the '$\sim$' to distinguish between gross profits $\widetilde{\pi}$ before paying the manager compensation, and net profits π after paying the manager compensation. Note that there is an externality in the problem (6), that the profit of the firm ij depends not only on its own TFP A_{ij} but also on the productivity of its competitors, A_{-ij}.[12] In general, for a treatment of matching games in the presence of externalities, see Chade and Eeckhout (2020).

Once managers of type x and firms of type z_{ij} in markets A_j have matched, the firm's TFP A_{ij} is common knowledge to all in the economy. In stage 2, firms then Cournot compete in quantity y_{ij} with

[12] Competition only occurs within each market. As there is a continuum of markets, a single firm cannot influence the aggregates of the entire economy. Therefore, there is no externality between markets.

their rivals in the same market.[13] The firms make production decisions to maximize gross profits:

$$\max_{l_{ij}} \widetilde{\pi}_{ij} = p_{ij} y_{ij} - W l_{ij}, \tag{7}$$

subject to the production technology (5) and (4). This is a problem with strategic interaction within each market j through the Cournot game, so y_{ij} depends on y_{-ij}. As we have described above, in the first period matching problem, the gross profits is then further partitioned into executive salaries, ω_{ij}, and net profits, π_{ij}.

Equilibrium. We can now define the equilibrium of this economy in the two subgames, as first, a compensation function $\omega(x)$ that specifies the salary for all managers and an assignment function Γ of manager abilities to firm productivities that is measure preserving and that maximizes (6) of the matching game, taking as given the stage two subgame, which includes prices p_{ij}, the wage W, and employment l_{ij} that solve (7) for all firms.

3.2 Solution

We solve the model backwards. In stage 2, we solve the canonical Atkeson and Burstein (2008) taking as given the TFP A_{ij} which depends on the allocation Γ determined in stage 1. The manager's compensation is sunk, so it does not enter as a choice in this subgame.

Stage 2. Production with Market Power. We first write down the solution to the household problem in Lemma 1 and then solve the firm's profit maximization problem. Market clearing closes the economy.

Lemma 1 (Household Solution) *The solution to the household problem* (3) *yields:*

(a) Goods demand function:

$$y_{ij} = \frac{1}{J}\frac{1}{I_j}\left(\frac{p_{ij}}{p_j}\right)^{-\eta}\left(\frac{p_j}{P}\right)^{-\theta} Y,$$

where

$$p_j := \left[\frac{1}{I_j}\sum_{i=1}^{I_j} p_{ij}^{1-\eta}\right]^{\frac{1}{1-\eta}} \quad \textit{and} \quad P := \left[\frac{1}{J}\int_0^J p_j^{1-\theta} dj\right]^{\frac{1}{1-\theta}}.$$

(b) Labor supply function:

$$L = \overline{\varphi} W^{\varphi}.$$

[13] Cournot competition is not the crucial assumption. All of our results extend when the firms Bertrand compete on price.

Proof. See Appendix B.1. ■

We now turn to the firm's optimal production decision. The profit maximization problem (7) yields the first order condition:

$$p_{ij}(y_{ij})\left[1+\frac{dp_{ij}}{dy_{ij}}\frac{y_{ij}}{p_{ij}}\right]\frac{dy_{ij}}{dl_{ij}}=W \quad \Leftrightarrow \quad p_{ij}\underbrace{\left(1+\varepsilon^{P}_{ij}\right)}_{\mu_{ij}^{-1}}A_{ij}=W. \tag{8}$$

The markup μ_{ij} is defined as the ratio of the output price p_{ij} to the marginal cost W/A_{ij}, which is also equal to the inverse of the price elasticity of demand according to equation (8). This is known as the inverse elasticity pricing rule in oligopolistic competition (or Lerner rule). Under the nested CES utility structure, this elasticity, and thus the markup, can be expressed simply by the elasticities of substitution, θ and η:

$$\mu_{ij}=\left[1-\frac{1}{\theta}s_{ij}-\frac{1}{\eta}\left(1-s_{ij}\right)\right]^{-1}, \tag{9}$$

where $s_{ij}:=p_{ij}y_{ij}/\left(\sum_{i'}p_{i'j}y_{i'j}\right)$ is firm i's sales share in market j. Equation (9) suggests that the markups contain the information on the elasticity of substitution within and between markets weighted by sales shares. For example, a monopolist's markup only depends on the between-market elasticity because it has no competitors in its market. In contrast, a small business has to face fierce competition within its market, which determines its markup.

Finally, market clearing closes the economy. Lemma 2 summarizes the subgame equilibrium.

Lemma 2 (Subgame Equilibrium) *Given TFP A_{ij}, the equilibrium markup is determined by equation (9), which can be further solved from:*

$$s_{ij}=\frac{\left(\mu_{ij}/A_{ij}\right)^{1-\eta}}{\sum_{i'}\left(\mu_{ij}/A_{ij}\right)^{1-\eta}}.$$

The equilibrium wage W and output Y are pinned down by:

$$\frac{W}{P}=\left[\left(\int_0^J\frac{1}{J}\left[\frac{1}{I_j}\sum_i\left(\frac{\mu_{ij}}{A_{ij}}\right)^{1-\eta}\right]^{\frac{1-\theta}{1-\eta}}dj\right)^{\frac{1}{1-\theta}}\right]^{-1} \quad \text{and} \quad Y=\left[\int_0^J\sum_i\frac{1}{A_{ij}}\frac{1}{J}\frac{1}{I_j}\left(\frac{p_{ij}}{p_j}\right)^{-\eta}\left(\frac{p_j}{P}\right)^{-\theta}dj\right]^{-1}\overline{\varphi}W^{\varphi},$$

where $p_{ij}=\mu_{ij}W/A_{ij}$. Finally, the equilibrium outputs, employment and gross profits are:

$$y_{ij}=\frac{1}{J}\frac{1}{I_j}\left(\frac{p_{ij}}{p_j}\right)^{-\eta}\left(\frac{p_j}{P}\right)^{-\theta}Y, \quad l_{ij}=\frac{y_{ij}}{A_{ij}}, \quad \text{and} \quad \widetilde{\pi}_{ij}=(\mu_{ij}-1)Wl_{ij}. \tag{10}$$

Proof. See Appendix B.2 for derivation and more intuition. ■

Stage 1. Matching Managers to Firms. Anticipating the gross profits in stage 2, firms compete for managers in a frictionless matching market. We define a stable match in Definition 1.

Definition 1 (Stablility) *A match is stable if and only if, for any two firms ij and $i'j'$, the total gross profits $\widetilde{\pi}_{ij} + \widetilde{\pi}_{i'j'}$ cannot be improved by swapping managers.*

If this condition is not satisfied for two firms, then both firms can be made better off by matching and redistributing the surplus. Furthermore, the complementarity between manager ability and firm type assumed in the technology (4) indicates that the matching output, $\widetilde{\pi}_{ij}$, is supermodular. In a classical matching model, supermodularity is sufficient for positive assortative matching (PAM) (see for example, Becker, 1973; Chade et al., 2017), but in the presence of the externality from strategic interaction, here this is no longer the case — the profitability of a firm also depends on the TFP of its competitors. Consequently, we cannot explicitly find the stable match and we will use a computational algorithm to find the matching.[14]

Given the stable matching Γ, we solve the equilibrium salary schedule, $\omega(x)$. The firms' stage 1 optimization problem (6) yields the FOC:

$$\frac{\partial \widetilde{\pi}_{ij}}{\partial A_{ij}} \frac{\partial A_{ij}}{\partial x_{ij}} - \frac{d}{dx}\omega(x_{ij}) = 0. \tag{11}$$

The marginal revenue of hiring a higher ability manager equals the marginal cost. Before we solve this differential equation (11), it is instructive to point out that along the equilibrium allocation, the marginal contribution to gross profits (equation (10), $\widetilde{\pi}_{ij} = (\mu_{ij} - 1)Wl_{ij}$) of TFP can be decomposed as follows:

$$\frac{\partial \widetilde{\pi}_{ij}}{\partial A_{ij}} = \underbrace{\frac{\partial \mu_{ij}}{\partial A_{ij}} W l_{ij}}_{\text{Markup channel}} + \underbrace{(\mu_{ij} - 1) W \frac{\partial l_{ij}}{\partial A_{ij}}}_{\text{Firm Size channel}}. \tag{12}$$

The marginal contribution of TFP to gross profits consists of the Market Power channel which increases the markups given output, and the Firm Size channel which generally increases output given markups. Note that in this general equilibrium model μ_{ij} and l_{ij} are jointly determined, and this decomposition captures the first-order effect of productivity on gross profits. If the marginal contribution to gross profits can be decomposed, then Manager Pay can similarly be decomposed in Proposition 1.

[14] The stable match is not necessarily efficient either, as firms fail to internalize this externality when making their matching decisions. In addition, in the presence of externalities, the stable matching may be mixed and there may be multiple stable equilibria. For further theoretical results, see as Chade and Eeckhout (2020).

Proposition 1 (Manager Pay) *Given stable matching Γ, the executive salary schedule $\omega(x)$ satisfies:*

$$\omega(x_{ij}) = \omega_0 + \int_{\underline{x}}^{x_{ij}} \left[\underbrace{\frac{\partial \mu_{i'j'}}{\partial A_{i'j'}} W l_{i'j'}}_{\text{Markup channel}} + \underbrace{\left(\mu_{i'j'} - 1\right) W \frac{\partial l_{i'j'}}{\partial A_{i'j'}}}_{\text{Firm size channel}} \right] \times \underbrace{\left[\alpha A_{j'} \left(\frac{A_{i'j'}}{A_{j'} x_{i'j'}} \right)^{1-\gamma} \right]}_{\partial A_{i'j'} / \partial x_{i'j'}} dF\left(x_{i'j'}\right),$$

where ω_0 is the reservation utility that determines the wage for the lowest-type manager.[15]

Proposition 1 provides insights into the properties of executive compensation in this model. First, ω is increasing in x, since $\partial \widetilde{\pi}_{ij} / \partial A_{ij} > 0$. Second, when α increases, Manager Pay (net of the reservation utility) increases proportionally. On the other hand, when managers are more complementary to firms (i.e., when γ decreases), the salary schedule can become either steeper or flatter, depending on the distribution of the types of firms and managers. Finally, Proposition 1 suggests that Manager Pay can be decomposed into two separate channels: the market power channel and the firm size channel, which comes directly from the gross profits equation (12). The first channel shows that high-ability managers are valuable because they allow firms to exert greater market power and hence earn higher gross profit. The second effect is consistent with the conventional wisdom about firm size, that a firm can adjust its production decision to make more profit when it is more productive due to the manager ability.

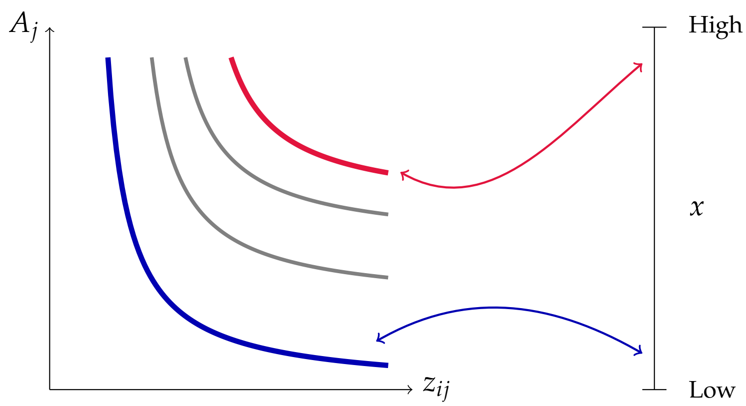


Figure 3: Matching of Managers to firm-market pairs (z_{ij}, A_j) with iso-wage curves

We can also learn about the stable matching from Proposition 1. The match surplus is generally increasing in z_{ij} and A_j, though not always due to the externalities from competition in the market. The same firm type z_{ij} will make lower (higher) profits if all competitors z_{-ij} are high (low) types. In the absence of those externalities, the matching pattern of managers x to pairs (z_{ij}, A_j) is illustrated in

[15] We can also write $\widetilde{\pi}_{ij} = (1 - 1/\mu_{ij}) r_{ij}$ where r_{ij} stands for revenue, and decompose Manager Pay into the channel of market power and revenue. Appendix D documents this decomposition. Our main results are robust, but this way will underestimate the effect of market power because the influence of markups on Manager Pay through revenue is attributed to the firm size (revenue) channel.

Figure 3. High type managers match with high z_{ij} firms in high A_j markets. But there is a trade-off as managers get the same wage for pairs with (low z_{ij}, high A_j) and (high z_{ij}, low A_j). This results in indifference maps that correspond to iso-wage curves for the manager. Given the match surplus (gross profits) is complementary in x and (z_{ij}, A_j), those indifference curves are ordered in the equilibrium matching from high x to low x as illustrated in the Figure. When there are externalities, these indifference maps are 'noisy' in the sense that they depend on the realization of productivities in a given market. In our quantitative analysis in Section 4.6, we plot the kernel of those indifference maps derived in the presence of externalities and confirm that high ability managers are more likely to match with high-type firms in both z_{ij} and A_j.

3.3 Determinants of Manager Pay

To understand the determinants of Manager Pay, we first investigate the market power channel, that is, how managers influence the firms' gross profits through markups. Using the implicit function theorem on the FOC (8), we can derive the markup elasticity of TFP:

$$\varepsilon_{ij}^{\mu} := \frac{\partial \mu_{ij}}{\partial A_{ij}} \frac{A_{ij}}{\mu_{ij}} = \underbrace{\left[\frac{(\eta-1)\left(1-\phi_{ij}\right)}{1+(\eta-1)\left(\frac{1}{\theta}-\frac{1}{\eta}\right)\mu_{ij}s_{ij}} \right]}_{\frac{\partial s_{ij}}{\partial A_{ij}} \frac{A_{ij}}{s_{ij}},\ \downarrow \text{ in } A_{ij}} \times \underbrace{\left[\left(\frac{1}{\theta}-\frac{1}{\eta}\right)\mu_{ij}s_{ij} \right]}_{\frac{d\mu_{ij}}{ds_{ij}} \frac{s_{ij}}{\mu_{ij}},\ \uparrow \text{ in } A_{ij}} \in [0,1), \tag{13}$$

where

$$\phi_{ij} := \left[\frac{s_{ij}}{1+(\eta-1)\left(\frac{1}{\theta}-\frac{1}{\eta}\right)\mu_{ij}s_{ij}} \right] \Big/ \left[\sum_{i'} \frac{s_{i'j}}{1+(\eta-1)\left(\frac{1}{\theta}-\frac{1}{\eta}\right)\mu_{i'j}s_{i'j}} \right]$$

is a weight that measures the relative importance of the firm i in the market j. The way we write this elasticity indicates that the impact of higher TFP can be decoupled into two components: (1) higher TFP leads to a higher share of sales; and (2) a higher share leads to a higher markup. Note that the first part is decreasing in A_{ij} because it is harder to make a giant firm bigger because of the CES demand structure. On the other hand, the second term is increasing in A_{ij} due to the convexity of the markup expression (9). Thus, although higher TFP always contributes to a higher markup, the size of the markup elasticity depends on the trade-off between these two opposing effects.

Similarly, we can write the firm size channel as:

$$\varepsilon_{ij}^{l} := \frac{\partial l_{ij}}{\partial A_{ij}} \frac{A_{ij}}{l_{ij}} = \phi_{ij} \underbrace{\left[\theta - 1 \right]}_{\text{Monopoly}} + \left(1-\phi_{ij}\right) \underbrace{\left[\frac{\eta}{1+\left(\frac{1}{\theta}-\frac{1}{\eta}\right)(\eta-1)\,\mu_{ij}s_{ij}} - 1 \right]}_{\text{Strategic interaction, } \downarrow \text{ in } A_{ij}}, \tag{14}$$

which can be viewed as the ϕ_{ij}-weighted sum of the monopolist's elasticity, $\theta - 1$, and a term measuring strategic interaction. The first part is positive, which means that a monopolist will hire more labor when its TFP increases. In this case, only θ enters the elasticity because there is no competition within the market. The second term comes from the strategic interaction, which is decreasing in A_{ij}. For a small firm, better technology motivates it to grow so it can have a bigger share and exert a higher markup. However, strategic interaction makes a large firm less willing to produce because it is too expensive to raise shares due to the CES demand structure. The net effect of TFP on firm size depends on the trade-off between the monopolistic and the strategic interaction parts.

Proposition 2 (Elasticities of TFP) *The markup and firm size elasticities of TFP are given by equation* (13) *and* (14)*, respectively. They have following properties:*

1. *The markup elasticity first increases with sales share, then decreases, with*

$$\lim_{s_{ij}\to 0} \varepsilon_{ij}^{\mu} = \lim_{s_{ij}\to 1} \varepsilon_{ij}^{\mu} = 0;$$

2. *The firm size elasticity first decreases with sales share, then increases, with*

$$\lim_{s_{ij}\to 0} \varepsilon_{ij}^{l} = \eta - 1 > 0 \quad \text{and} \quad \lim_{s_{ij}\to 1} \varepsilon_{ij}^{l} = \theta - 1 > 0.$$

In addition, ε_{ij}^{l} can be negative when s_{ij} is moderately large.

Proof. See Appendix B.3 for the proof as well as an example under duopoly. ■

We summarize the important properties of these elasticities in Proposition 2. Depending on the relative firm size within a market s_{ij}, a firm's markup and employment will react differently to a TFP increase. Intuitively, for a small firm, the increase in gross profits is mainly due to the increase in employment, while for a large (but not monopolist) firm, the markup becomes the dominating channel that contributes to gross profits. Therefore, Proposition 2 suggests a heterogeneity of the markup and firm size effects among managers who match with different sizes of firms, which we will further elaborate in the empirical part.

4 Quantitative Exercise

We quantify the model *year by year* using Simulated Method of Moments in this part. Section 4.1 documents the strategy we implement to solve the matching problem. We further map our theory to the data by generalizing the production function in Section 4.2. In Section 4.3, we parametrize the model. The targeted moments are presented in Section 4.4, based on which we estimate the parameters in Section 4.5. Finally, we investigate some key properties of the matching equilibrium in Section 4.6.

4.1 Matching algorithm

In the presence of externalities, finding the stable matching equilibrium defined in Definition 1 is a problem that is known to require non-polynomial time. To verify stability, we have to check the condition for all pairs of firms in the economy. This verification grows exponentially with the number of firms in the economy. As such, for the large setting that we consider, there is no hope to find the exact solution for the stable matching.

In order to solve for the equilibrium matching, we therefore use an algorithm that yields an approximate stable matching, exploiting the fact that the strategic interaction only occurs between a small number of I_j firms in each market.[16] Our algorithm uses a proxy for positive sorting between manager types and firm conditional profitability rather than firm type. Because of externalities, the firm type now is no longer a sufficient statistic of the ranking of firms. However, the marginal product of the firm does give us a ranking, since matching occurs based on which firm makes the largest contribution to gross profits. The reason why the algorithm is approximate is that we need to know the allocation in order to calculate the marginal product. To that end, assuming all firms are matched with the same manager. Specifically, we follow these steps to obtain the approximate matching allocation:

(a) Compute the marginal contribution of the manager ability on gross profits for each firm, assuming all firms are matched with the average manager $\overline{x}$: $d\widetilde{\pi}_{ij}/dx_{ij}|_{\overline{x}}$.

(b) Construct the PAM allocation between the manager types x and firm's conditional profitability, $d\widetilde{\pi}_{ij}/dx_{ij}|_{\overline{x}}$. That is, a high-type manager matches the firm with high $d\widetilde{\pi}_{ij}/dx_{ij}|_{\overline{x}}$.

In Appendix C.1 we verify the efficiency for a smaller sample with 200 markets where we can calculate the equilibrium allocation using brute force and show that our approximate stable matching obtained with our algorithm comes very close to the exact stable matching. We further show that this finding is robust over different J, which ensures that we can generalize this verification to the large economy we consider here.

[16] A similar problem arises when modeling entry – as modeled in Berry (1992) – in large economies with imperfect competition. The decision for firms to enter depends on the entry decision of all other firms, which implies we need to verify the entry decision for all possible sequences of firms entering. See De Loecker, Eeckhout, and Mongey (2021) for an algorithm that yields an approximate entry equilibrium.

4.2 Generalized production function

In order to reconcile our technology with the data, where we observe intermediate inputs and capital, we follow De Loecker et al. (2021) and extend our production function into a more general form:

$$y_{ij} = A_{ij} \left(l_{ij} + m_{ij}\right)^{\zeta} k_{ij}^{1-\zeta}. \tag{15}$$

We assume that the material m_{ij} is perfectly substitutable with labor, which allows us to estimate the production function without knowing the prices of the materials. The capital k_{ij} in a standard Cobb-Douglas way. Furthermore, for tractability, we set the supply of capital and materials exogenously. Capital supply is assumed to be inelastic at the price R. Because materials are perfectly substitutable with labor, we do not explicitly specify its supply, but instead assume that it can be automatically adjusted so that the material share, $m_{ij}/(l_{ij} + m_{ij})$, is equal to an estimated parameter ψ at equilibrium.

Lemma 3 *The production function* (15) *can be equivalently expressed by a labor-only production function:*

$$y_{ij} = \widehat{A}_{ij} l_{ij} \quad , \quad \textit{where} \quad \widehat{A}_{ij} := \frac{1}{\psi} \left[\frac{W/\zeta}{R/(1-\zeta)}\right]^{1-\zeta} A_{ij},$$

which incurs a constant marginal cost:

$$mc_{ij} = \frac{1}{\psi}\frac{1}{\zeta}\frac{W}{\widehat{A}_{ij}}.$$

Proof. See Appendix B.4. ■

As each single firm cannot influence aggregate wage W, it will take the input-adjusted TFP, $\widehat{A}_{ij}$, as given. The marginal cost expression (3) is intuitive: the term $W/\widehat{A}_{ij}$ is the marginal cost of labor, while $1/\psi$ and $1/\zeta$ adjust for the cost share of materials and capital, respectively. Lemma 3 demonstrates that there is a one-to-one mapping between this general production function (15) and the labor-only production function that our theory is built on. Therefore, this general model shares the same insights and can be solved in the same way as the simplified model in Section 3.

4.3 Parametrization

Recall the TFP function (4):

$$A_{ij} = A_j \left[\alpha x_{ij}^{\gamma} + (1-\alpha) z_{ij}^{\gamma}\right]^{\frac{1}{\gamma}}.$$

We assume that $F(x_{ij})$, $G(z_{ij})$, and $H(A_j)$ are independent and lognormally distributed. This rules out any negative realizations and has been shown to be consistent with the productivity distribution in the data.[17] Furthermore, as we will endogenously estimate $\{\alpha, \gamma\}$, we are unable to distinguish between $F(x_{ij})$ and $G(z_{ij})$. Being aware that the distribution of manager ability should be relatively stable over time, we normalize its distribution throughout the quantitative exercise to $\log x_{ij} \sim \mathcal{N}(-0.5, 1)$ such that the mean of x_{ij} is 1. Moreover, we assume that the mean of z_{ij} is also normalized to 1. Its standard deviation σ_z will determine the lognormal distribution of z_{ij}. The market component A_j therefore captures the TFP level of firms, whose distribution is determined by its mean and standard deviation, m_A and σ_A.

Table 1: Endogenous, estimated parameters (time-varying)

	Parameter	Meaning
I. Match	α	The importance of manager relative to firm type
	γ	The elasticity of substitutes between manager and firm type
II. Market	m_I	Market structure $I_j \sim \mathcal{N}\left(m_I, \sigma_I^2\right)$, $I_j \in \mathbb{N}_+ \cap [1, 10]$
	σ_I	
III. Firm	σ_z	Standard deviation of firm type z_{ij}
	m_A	Mean of market-level productivity A_j
	σ_A	Standard deviation of market-level productivity A_j
IV. Aggregates	$\overline{\varphi}$	Aggregate labor supply level
	ψ	Factor share: labor in labor + material, or material supply
	ω_0	Reservation utility of managers

To mimic the continuum of markets in the simulation, we set the number of markets equal to $J = 10,000$.[18] Furthermore, we assume that the number of firms in each market, I_j, is random to capture the heterogeneity across markets that we see in the data: I_j is an integer drawn exogenously from a truncated normal distribution $\mathcal{N}\left(m_I, \sigma_I^2\right)$ within the range $[1, 10]$.[19]

To summarize, Table 1 lists the endogenous parameters that we estimate. They are organized in four categories: I. Match; II. Market; III. Firm; IV. Aggregates. In addition, we take some exogenous parameters from the literature or calculate them directly from the data. Those are listed in Table 2. On the goods demand side, we take the elasticities of substitution, η and θ, from De Loecker et al. (2021) who quantify a model with a similar demand side, and we also use their user cost of capital R. We

[17] For example, using LBD data, Deb et al. (2020a) back out the firm-level productivity distribution which is close to log-normal.

[18] Since we have neutralized the love of variety effect, a change in the number of markets does not make a systematic difference in our model. Our model is converging to the continuous case when $J \to +\infty$.

[19] Specifically, we first draw a number from the normal distribution within the range $(0, 10]$, then round it to the nearest integer greater than or equal to that number. The assumption that the distribution of I_j is truncated normal is not crucial to our analysis. We have also done the analysis with the log normal distribution and the beta distribution, both of which give us robust results. Finally, the choice of the upper bound of the truncation comes from De Loecker et al. (2021), whose estimates for the number of potential entrants in each market is less than ten over this period. Our estimates in Section 4.5 show that the upper bound is slack and therefore not crucial.

Table 2: Exogenous parameters

Parameter	Meaning	Value	Source
η	Within-sector elasticity of demand	5.75	De Loecker et al. (2021)
θ	Between-sector elasticity of demand	1.20	De Loecker et al. (2021)
R	User cost of capital	1.16	De Loecker et al. (2021)
φ	Labor supply elasticity	0.25	Chetty et al. (2011)
ζ	Factor share: labor + material in variable cost	0.88	Compustat data

obtain the elasticity of labor supply, φ, from the meta study Chetty, Guren, Manoli, and Weber (2011), and we adjust the intercept $\overline{\varphi}$ to match the level of employment of the model with the data. Given the Cobb-Douglas specification (15), the elasticity ζ is equal to the input share at equilibrium and is quite stable across years, so we compute it directly from the Compustat data.

4.4 Targeted Moments

To capture the evolution of executive compensation and markups, we estimate the set of parameters listed in Table 1 that best matches the key moments of the data. We estimate the model annually: because the model is static, the estimates in different years are completely independent. In this Section, we limit ourselves to listing the targeted moments with a brief description. Table 3 lists the 10 moments that we target. The targeted moments, like the parameters, can be categorized into the same four groups, those corresponding to the matching, to the market, to the firm, and to the aggregates. While all parameters affect all moments in this general equilibrium model, in the table we also list the corresponding key parameter that affects each of the moments most directly. Next, we motivate our choice of the targeted moments. We also refer further to Appendix C.2, where we report the comparative statics predictions of how the parameters affect the selected model moments.

I. Match. We motivate our choice of moments on the matching side by showing how executive compensations are determined by $\{\alpha, \gamma\}$. Notice that manager ability x_{ij} influences gross profits exclusively through TFP A_{ij}. The expression below, which comes from the CES technology function (4), further gives us an intuitive way to understand the payoff share of managers:

$$\frac{\partial A_{ij}}{\partial x_{ij}}\frac{x_{ij}}{A_{ij}} + \frac{\partial A_{ij}}{\partial z_{ij}}\frac{z_{ij}}{A_{ij}} = 1 \quad , \quad \text{where} \quad \frac{\partial A_{ij}}{\partial x_{ij}}\frac{x_{ij}}{A_{ij}} = \alpha\left(\frac{x_{ij}}{A_{ij}}\right)^{\gamma} \quad \text{and} \quad \frac{\partial A_{ij}}{\partial z_{ij}}\frac{z_{ij}}{A_{ij}} = (1-\alpha)\left(\frac{z_{ij}}{A_{ij}}\right)^{\gamma}.$$

To see the intuition more clearly, assume for now that there is no reservation utility nor market power. Then in a Cobb-Douglas world (i.e., $\gamma = 0$), the manager share will be constant and equal to α, which is commonly assumed in many matching literature (for example, Becker, 1973). The bigger α is, the more

Table 3: Targeted Moments

		Moment	Key Parameter(s)
I. Match	Average salary share	$\mathbb{E}(\log \chi_{ij}) := \mathbb{E}(\log \frac{\omega_{ij}}{r_{ij}})$	α
	Slope salary share-sales	$\mathbb{K} := \frac{\text{Cov}(\log \chi_{ij}, \log r_{ij})}{\mathbb{V}(\log r_{ij})}$	γ
II. Market	Average markup	$\mathbb{E}(\mu_{ij})$	m_I
	Variance markup (between)	$\mathbb{V}(\log \mu_j)$	σ_I
III. Firm	Variance markup (within)	$\mathbb{V}(\log \mu_{ij} \mid j)$	σ_z
	Average worker's wage	$\mathbb{E}(W)$	m_A
	Variance sales	$\mathbb{V}(\log r_{ij})$	σ_A
IV. Aggregates	Average employment	$\mathbb{E}(l_{ij})$	$\overline{\varphi}$
	Average manager salary	$\mathbb{E}_x(\omega(x))$	ψ
	Manager salary, bot. 1%	$\omega(x \mid p1)$	ω_0

Notes: We base all our moments on the data discussed in Section 2. The markups are estimated using the production approach. Unlike the model, in the data there is not a single wage W for the production workers, both within and between firms, so $\mathbb{E}(W)$ denotes the average wage across all production workers.

managers get. We therefore use the average log share of manager salary out of total sales, which we define as:

$$\chi_{ij} := \frac{\omega_{ij}}{r_{ij}} \quad \text{and} \quad r_{ij} := p_{ij} y_{ij}.$$

While α pins down the average salary share of the manager, the salary share is not a constant in the data, as is shown in the panel A of Figure 4. This implies the case when γ is non-zero. We therefore use the slope of the linear prediction of $\log \chi_{ij}$ on $\log r_{ij}$ to inform us about the elasticity of substitution, γ. Panel B and C of Figure 4 reiterates the logic of our choice of parameters by plotting the relationship between $\log \chi_{ij}$ and $\log r_{ij}$ when each of the parameters $\{\alpha, \gamma\}$ change.

II. Market. Equation (9) indicates a systematic relationship between the average markups and the number of firms in each market. In a representative economy where firms are identical, Figure 5a shows that markups will increase monotonically as I_j decreases, which helps us identify the average number of firms m_I.[20] Furthermore, because the number of firms differs in different markets, this monotonicity also makes the distribution of markups *across* markets informative on σ_I. Figure 5b illustrates that, when I_j gets less dispersed, market-level markups μ_j also become more concentrated. Therefore, we will exploit the between-market variance of markups to identify σ_I.

[20]Some readers may think of using the information on the number of firms from the dataset instead of estimating it. However, the market definition in the data is kind of ambiguous. For example, a coffee house in New York does not compete with the one in California even if they have the same industry code.

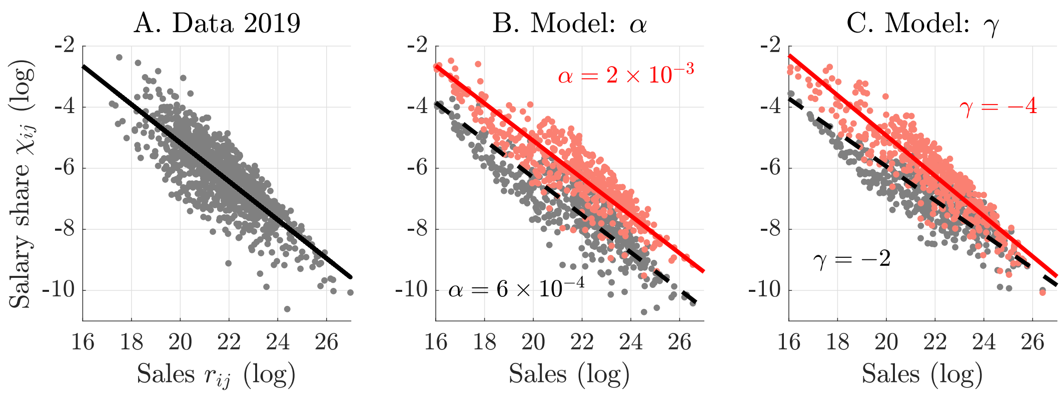
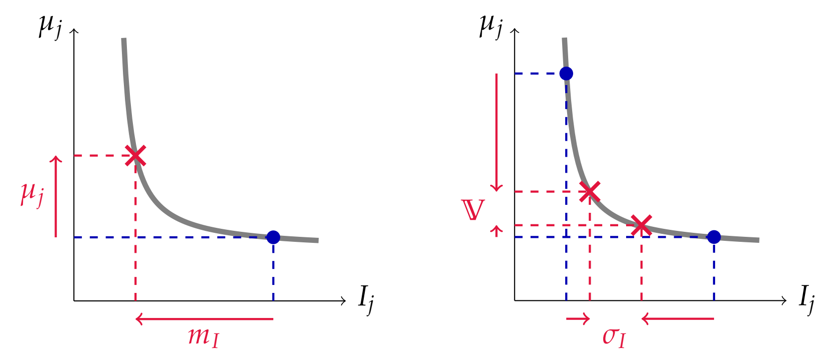


Figure 4: Identification of parameters in category "I. Match"

Notes: We plot log sales ($\log r_{ij}$) on the x-axis and log salary shares ($\log \chi_{ij}$) on the y-axis. Panel A shows the negative correlation in the data with 1144 observations in 2019. In Panel B and C, points with different colors represent for firms in different economy. As there are a larger number of CEOs in our model each year, we randomly select 500 representatives of them in each economy to plot. The baseline parameter is the estimates in 2019.



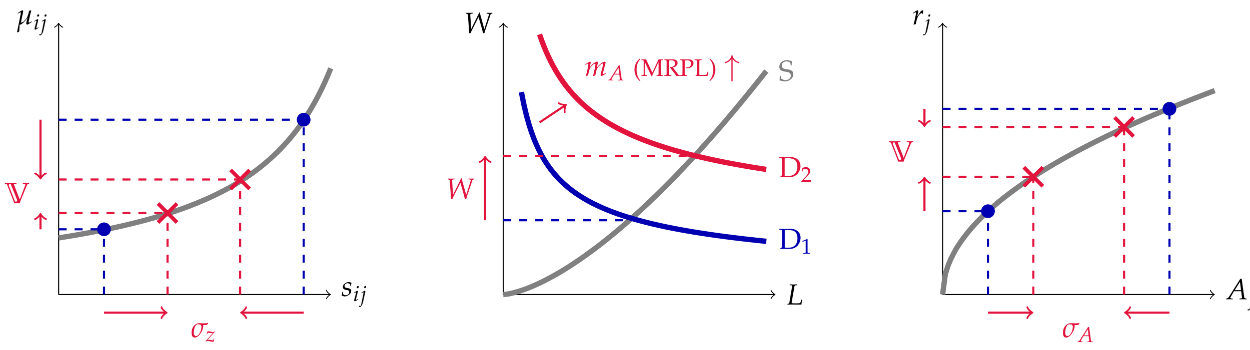
(a) Change in m_I (b) Change in σ_I

Figure 5: Identification of parameters in category "II. Market"

Notes: This figure shows the determinant of markups in a representative economy where firms have the same TFP. From Equation (9), we have: $\mu_{ij} = \left[1 - \frac{1}{\eta} - \left(\frac{1}{\theta} - \frac{1}{\eta}\right)\frac{1}{I_j}\right]^{-1}$ that is declining in I_j. The two panels demonstrate how the markup will respond when m_I and σ_I decline (from blue dots to red crosses), respectively.

III. Firm. The variance of markups *within* each market μ_{ij} is in turn determined by the variance in firm type σ_z.[21] As Figure 6a shows, a smaller σ_z will reduce the difference in s_{ij}, which eventually reduces the within-market variance of markups according to Equation (9). On the other hand, the panel B shows that the level of A_j influences the marginal revenue product of labor (MRPL), which shifts the labor demand function and eventually determines worker's wage. Finally, as the revenue is monotonically increasing over productivity, less dispersion in A_j leads to smaller variance in revenue, which becomes a good target for us to identify σ_A. This idea is shown in Figure 6c.

[21] Recall that Lemma 2 shows that the within-market distribution of markups is uniquely determined by the TFP.



(a) Change in σ_z (b) Change in m_A (c) Change in σ_A

Figure 6: Identification of parameters in category "III. Firm"

IV. Aggregates. Finally, we want to match the level of the variables in our model economy to the data. Specifically, we will use three aggregate parameters, $\{\overline{\varphi}, \psi, \omega_0\}$, to match the firm-level average employment, and average executive compensation. In the model, $\overline{\varphi}$ is the intercept of the labor supply (in log) that can match the employment level, and ψ adjusts the level of the manager's compensation. Given any set of parameters in the first three categories, $\{\overline{\varphi}, \psi\}$ can be uniquely pinned down by the model.[22] We directly take the reservation utility ω_0 as the first percentile of Manager Pay in each year from data.

4.5 Estimation results

We estimate the ten endogenous parameters jointly. Figure 7 shows that the model moments fit the data quite well. The corresponding parameters are displayed in Figure 8.

I. Match. We first report the parameters that correspond to the match, $\{\alpha, \gamma\}$, in the first column of Figure 8. Estimates of α, which measure the relative importance of managers, are minuscule all the time. This observation is consistent with Gabaix and Landier (2008), who show that managers make only a small difference on firms. However, our interpretations differ. In their setting, the small impact managers make stems from the fact that the dispersion in manager talent is very low. Instead, we show that the impact of managers is small due to the way the manager ability enters the production function, i.e., through the parameter α. Moreover, we find that α is generally increasing over time, suggesting that managers play an increasingly important role.

The estimated elasticity of substitution γ is negative, which confirms the complementarity between firms and managers that is commonly assumed in the literature. Furthermore, γ was relatively stable,

[22] See Appendix C.3 for more details.

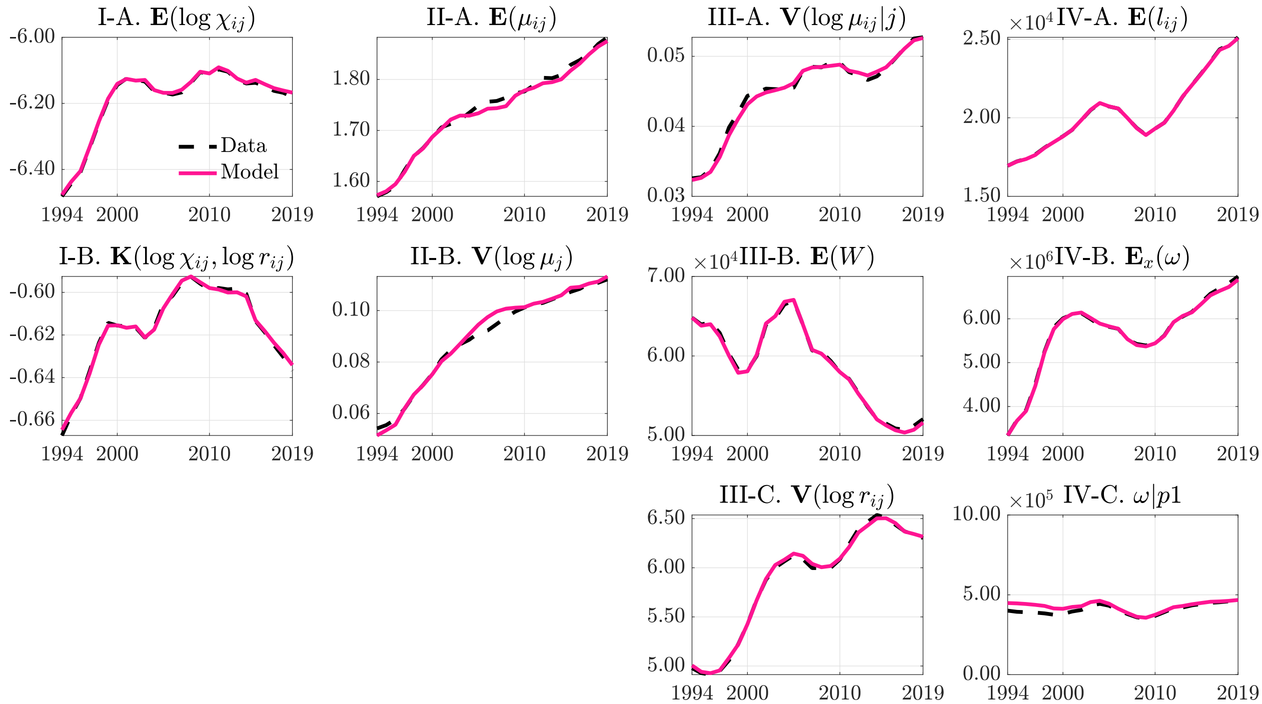


Figure 7: Targeted moments: I. Match, II. Market, III. Firm, and IV. Aggregates

Notes: Data moments are computed annually. Moments in categories "II. Market" and "III. Firm" are generated from Compustat sample, while the ones in category "I. Match" and "IV. Aggregates" are from ExecuComp sample due to data limitation. The latter sample is a sub-sample of the former one. We apply a five-year centered moving average in plotting both data and model moments.

and then sharply declined from -2.22 in 2014 to -3.55 in 2019. This trend corresponds to the increasingly negative correlation between salary share and sales that is shown in Panel I-B of Figure 7 after 2014. Therefore, managers have recently become more complementary to firms.

II. Market. The second column in Figure 8 reports the estimated parameters $\{m_I, \sigma_I\}$ in the category of market from 1994 to 2019. Consistent with the rise of market power, we see an increasingly concentrated market structure over time from two perspectives. First, the average number of firms in each market steadily declines from 4.40 to 3.15, suggesting that there is less competition overall. Second, the dispersion in the number of competitors σ_I is also decreasing, from 1.56 to 1.16. As a result, most markets will have a concentrated market structure and there are fewer markets that tend towards being competitive. This finding confirms the results in the literature that document the increase in concentration (Gutiérrez and Philippon, 2017; Grullon et al., 2016; De Loecker et al., 2021).

III. Firm. The results of our estimation also suggest an increasing dispersion in firm type. Panel III-A of Figure 8 shows that its standard deviation σ_z increases from 0.51 to 0.77. This change mainly contributes to the increase in the variance of the log markups within and between markets. The same

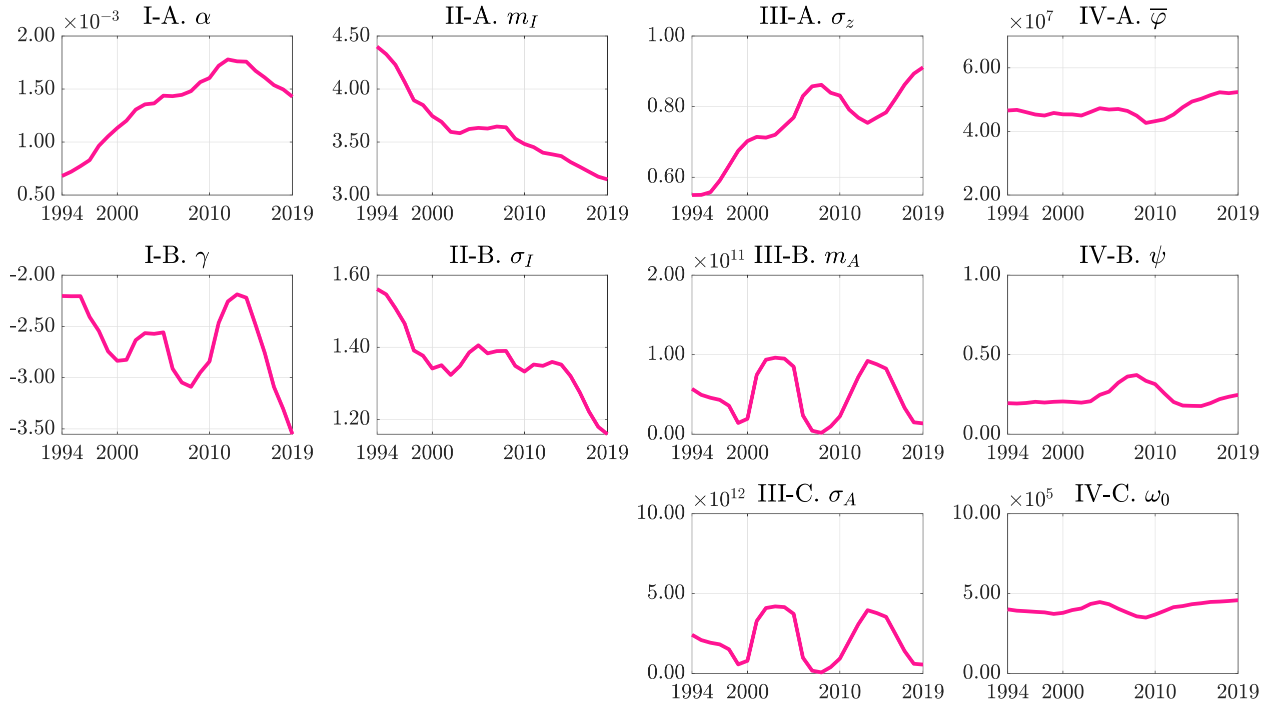


Figure 8: Parameters: I. Match, II. Market, III. Firm, and IV. Aggregates

Notes: All parameters are plotted in five-year centered moving average.

trend is documented in other literature as well (see for example, De Loecker et al., 2021; Deb et al., 2020a). One implication of this quantitative result is the rise of superstar firms, which is consistent with the findings of Autor, Dorn, Katz, Patterson, and Van Reenen (2020). Moreover, we also find that the average production worker wage is slightly decreasing in this sample, from \$65.8 thousand to \$59.3 thousand, which is consistent with the wage stagnation of production workers in the economy. The overall decline in m_A matches this trend. We also document a huge difference across markets σ_A, which comes from the huge variance in sales and is within our expectation. Aggregating across widely different sectors implies there are huge productivity differences, say between labor-intensive sectors such as retail and sectors such as biotech.

IV. Aggregates. In order for our model to match the levels in the data, we scale the economy by aggregated parameters $\{\overline{\varphi}, \psi, \omega_0\}$. Column IV in Figure 7 shows that the average number of production workers grows from 16.9 thousand to 25.1 thousand over time, which is much larger than the average firm size in the entire economy. This of course stems from the selection on large firms in the pool of publicly traded firms. The average executive compensation doubles from \$3.34 million to \$6.96 million, while the lowest manager pay is almost flat. The same trends show up in the aggregates in Figure 8. Note that we actually treat ψ as a residual term that matches the Manager Pay from the model to the data. This term is quite stable and is within a reasonable range except for during the Great Recession, which indicates that our model predicts the evolution of Manager Pay over time quite well.

4.6 Matching

In this section, we analyze the properties of the equilibrium match in our estimated economy. Understanding these results is essential for interpreting executive compensation. All results are robust in different years, so we will take the year 2019 as the baseline in presenting the crosssectional results.

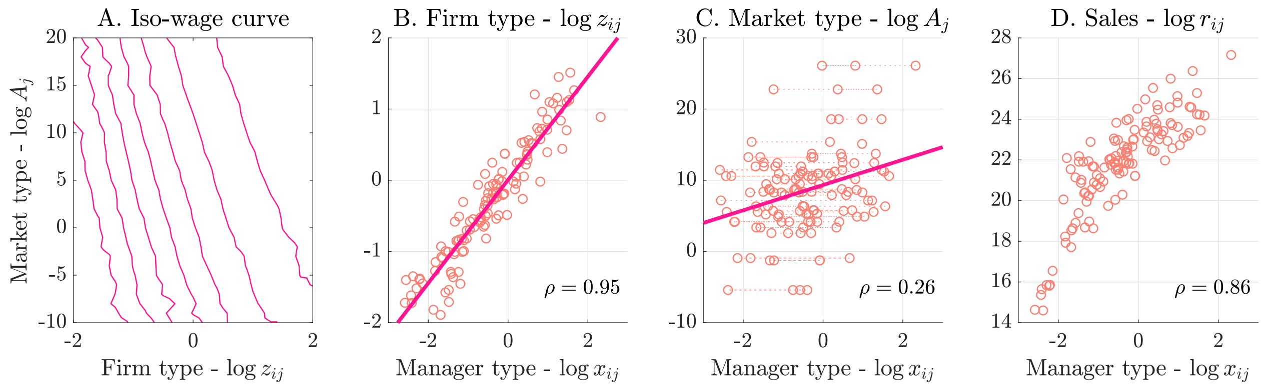


Figure 9: Matching: managers and firms in 2019

Notes: Panel A plots managers' approximate isowage curve at equilibrium by taking grids over $(\log(z_{ij}), \log(A_j))$ and computing its local average manager pay. Panel B to D plot the relationship between manager type and firm type, market type, and sales, respectively. As there are a larger number of CEOs in our model each year, we randomly select 40 representative markets to plot in those panels. The solid line is the linear approximation from OLS. We also report the Spearman rank correlation coefficient in each of them.

Figure 9 shows how managers are matched with firms. Panel A reports the manager's iso-wage curves, which are consistent with the theoretical prediction in Figure 3. Basically, higher-type managers can earn more by working for firms with higher type z_{ij} and A_j. Panel B to D support these insights by showing the correlation between managers' type on the one hand, and firm type z_{ij}, market productivity A_j, and sales r_{ij}. Because there are multiple dimensions and because there are externalities, we do not expect to find perfect positive sorting. Still, we expect to find a strong positive correlation. On all three dimensions, better managers tend to match with more productive firms, they are in more productive markets, and they match with higher sales firms. Moreover, consistent with the data, we observe that manager ability is more closely correlated to firm type than the market productivity, which suggests that managers are mainly hired for competition within markets. The last panel of course follows from the fact that more productive firms higher more workers, *and* they tend to exert more market power setting higher prices and hence generating larger revenue.

In addition, we can also check the relationship between the type of CEOs and the elasticity of TFP on markup ε^{μ}_{ij} and on employment ε^{l}_{ij}, which has been discussed in Proposition 2. Figure 10 shows that the

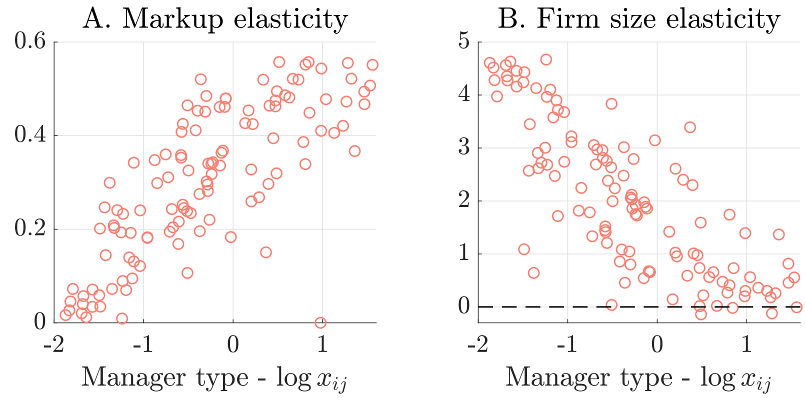


Figure 10: Matching: managers and elasticities in 2019

Notes: These elasticities are computed under the equilibrium assignment. Again, we randomly select 40 representative markets in the whole economy to plot in those panels.

markup elasticity generally increases with manager type, which means that a high-type manager will contribute more to the corresponding firm's profit through the markup. In contrast, the employment elasticity is decreasing in manager type and may even be negative for some high-ability managers. Top managers in top firms hire less labor, which is consistent with the lower labor shares in superstar firms.[23] These different elasticities drive the heterogeneity in salaries between manager types, which is a topic that we will further elaborate on in Section 5.3.

5 Main Results

With the estimates of the technology in hand, we can now analyze the different determinants of Manager Pay, which are summarized in Figure 11. Our main focus is on the contribution to Manager Pay from two channels: market power and firm size.[24] First, in Section 5.1 we detail this decomposition based on Proposition 1. Second, we further analyze in Section 5.2 the contribution of different categories of parameters to Manager Pay through each of these two channels: 1. $\{\alpha, \gamma\}$ for the match; 2. $\{m_I, \sigma_I\}$ for market structure; 3. $\{\sigma_z, \mu_A, \sigma_A\}$ for firms; and 4. $\{\overline{\varphi}, \psi\}$ for inputs supply. In Section 5.3, we analyze inequality in salaries among managers and how this heterogeneity is determined by each of these two channels, which corresponds to Proposition 2. Finally, we investigate a counterfactual economy without market power in Section 5.4.

[23]For example, see Autor, Dorn, Katz, Patterson, and Van Reenen (2020) and De Loecker et al. (2020).

[24]Throughout this section, we will tease out the reservation utility as it is negligible and flat over time, as is shown in Panel IV-C of Figure 8.

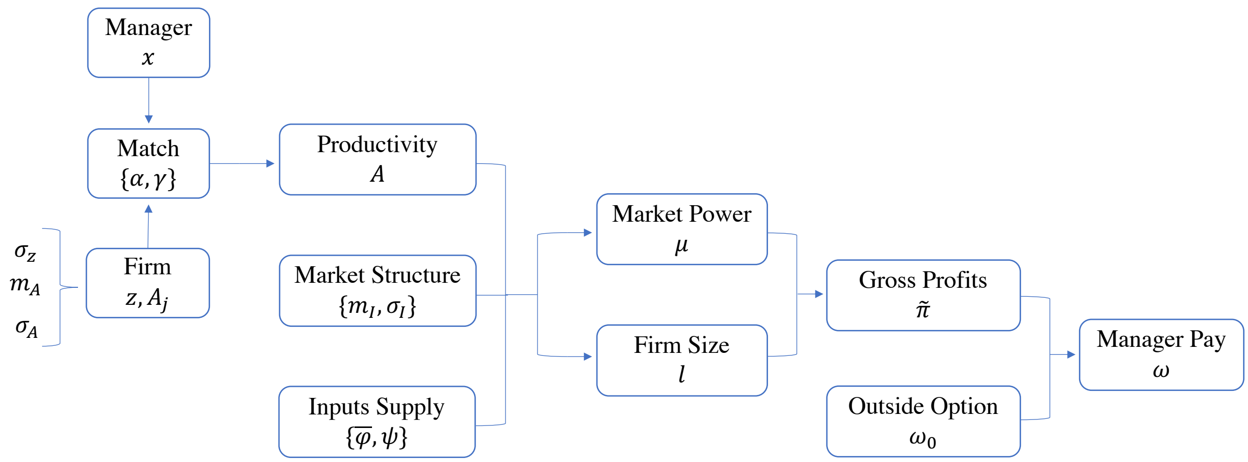


Figure 11: Determinants of Manager Salaries

5.1 The rise of Manager Pay: market power vs. firm size

In Figure 12, we plot the contribution to Manager Pay of the market power and firm size channels. Panel A shows that both market power and firm size effects play important roles in determining executive salaries. Over the period, the average Manager Pay (net of reservation utility) increases from \$2.94 million to \$6.43 million, where the market power effect increases from \$1.12 million to \$3.14 million and the firm size effect increases from \$1.82 million to \$3.30 million. Panel B further shows that market power determines 45.8% of total Manager Pay on average. Moreover, its importance has been steadily increasing over time, from 38.0% in 1994 to 48.8% in 2019. Correspondingly, the importance of the firm size channel is declining.

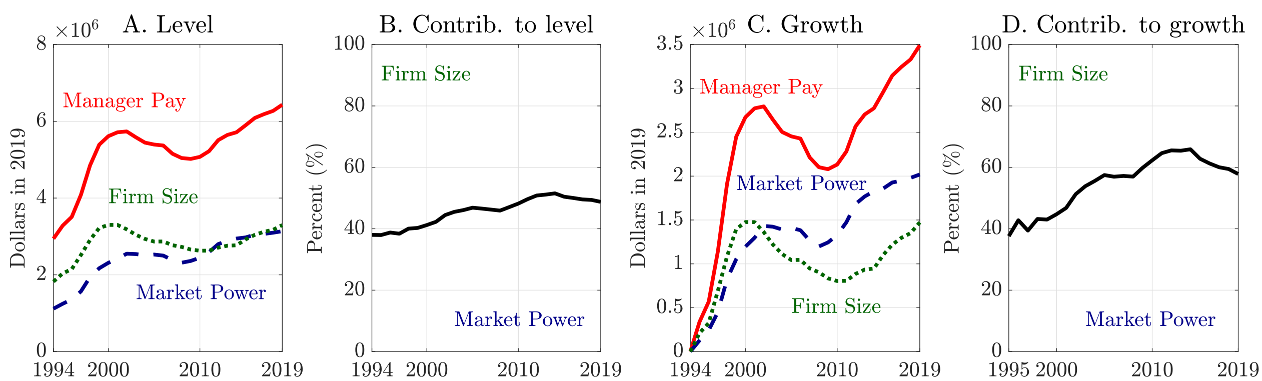


Figure 12: Manager Pay decomposition into Market Power and Firm Size, by year

Notes: Panel C and D plot the cumulative change from 1994. Panel D starts from 1995 because we take 1994 as the baseline year for the time change. All results plotted are five-year moving averages.

In addition, we can also decompose the change of Manager Pay over time and attribute it to each channel. Panel C shows the cumulative change in average Manager Pay and its components relative to the baseline year 1994. During this period, the Manager Pay increases by \$3.49 million, of which \$2.02 million is due to the increase in market power and \$1.47 million due to the firm size effect. Panel D in Figure 12 further shows that 57.8% of the cumulative increase in executive compensation over this period is through the increase in market power, while the remaining 42.2% is through the change in firm size.

5.2 Factor decomposition

Empowered by our structural model, we can also analyze the contribution of each primitive parameter to Manager Pay through the channels of market power and firm size. To do this, we keep all parameters fixed at their 1994 values, and then feed in one or more estimated, year-specific parameters, plotting the cumulative changes in the effects of market power and firm size on Manager Pay. Note that this decomposition is not perfect as we are only checking the stand-alone effects of changing each set of parameters without considering the indirect effect from their interaction with changes in other primitives. Despite this shortcoming, we can still see the direct effect of each parameter.

Market Power channel. We first check the impact of the primitive parameters on Manager Pay through the market power channel. In the panel A of Figure 13, we decompose the gross change in the market power component (i.e., the blue, dashed line from Figure 12.A) into three objects: market structure $\{m_I, \sigma_I\}$, productivity A_{ij}, and the inputs supply $\{\overline{\varphi}, \psi\}$. Over the entire time period, the changes in technology is the dominating factor that raises Manager Pay through the market power channel, which contributes \$1.33 million and account for 65.9% of the total growth. The changes in market structure and inputs alone have tiny effects on this market power component.

We then further decompose the TFP change into the match category $\{\alpha, \gamma\}$ and the firm type category $\{\sigma_z, m_A, \sigma_A\}$. Panel B shows that the evolution in match component is the dominating factor that contributes to the TFP change. Specifically, according to the panel C, the increasing importance of managers α plays an important role that contributes to the growth of market power effect by \$1.14 million, while the increasing complementarity becomes more important only most recently and contributes by \$0.34 million. Finally, Panel D demonstrates that overall firm type has little influence on the market power channel, but it does have a significant impact during the Great Recession.

Firm Size channel. We then do the same decomposition on the firm size effect. In Panel A of Figure 14, the baseline is the gross change in the firm size channel, i.e., the green, dotted line in Figure 12.A. It's decomposition suggests that the change in TFP again is the dominating factor that accounts for 70.1%

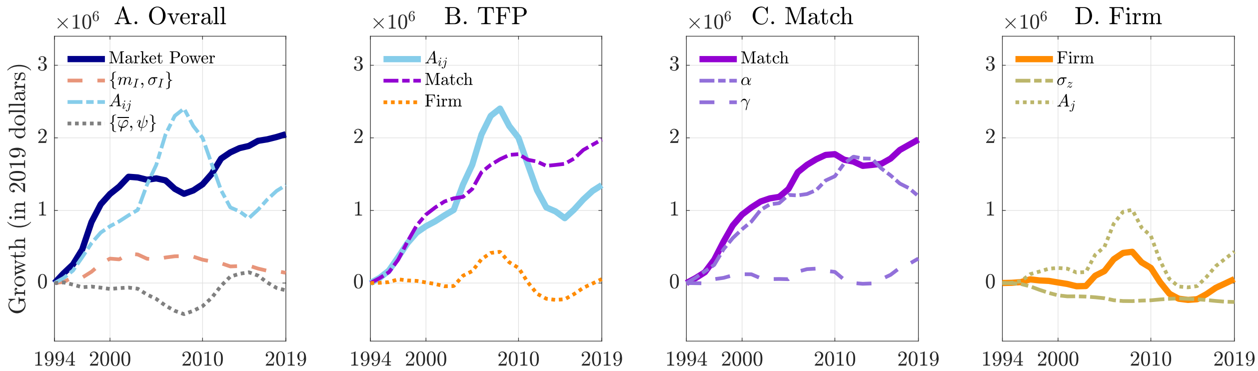


Figure 13: Factor decomposition: market power channel

Notes: We set 1994 estimates as our baseline parameters. In each case, we only change a certain set of parameters, solve the economy, and compute the market power component in the executive compensation. We choose the level of market power component at 1994 as the reference point and plot the cumulative change from this point in each counterfactual economy. Because the changes in μ_A and σ_A are highly correlated with each other, we bundle these two together in panel D. All the results are plotted in five-year centered moving average.

($1.03 million) of the increase in firm size channel. The shifts in market structure and inputs supply have almost no influence on the firm size effect.

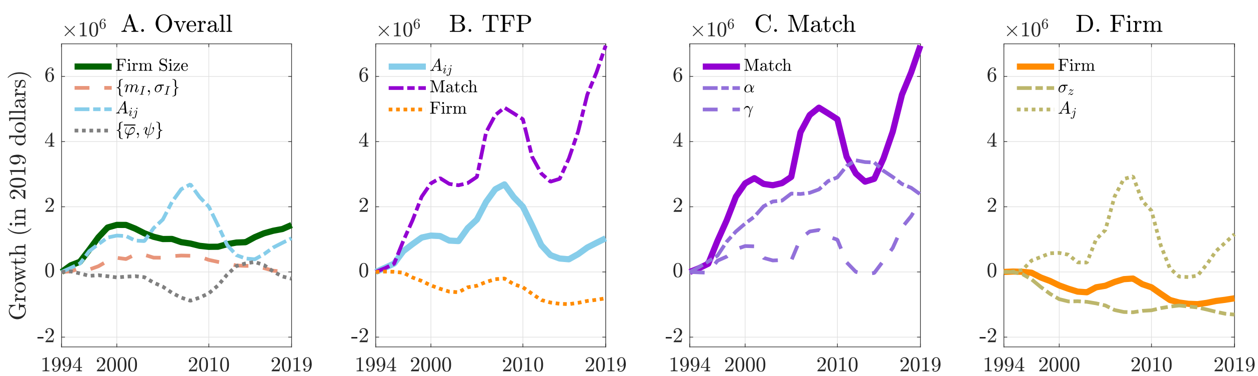


Figure 14: Factor decomposition: firm size channel

Moreover, from the subsequent panels, we learn that among TFP change, parameters from the match category has a huge and positive effect. The increase in α makes managers more important, which directly drives up the Manager Pay by $2.22 million through the firm size channel. On the other hand, the complementarity γ determines the convexity of the managers' wage schedule, whose recent change accounts for $2.29 million of increase in the firm size effect. However, the huge effect from $\{\alpha, \gamma\}$ will be mostly offset by the negative influence from the firm side that is mainly due to the increasing dispersion in firm type, σ_z. The change in γ and market productivity A_j mainly lead to the hump in the TFP effect during the Great Recession.

5.3 Heterogeneity and inequality among managers

We now analyze inequality in salaries among managers and how this heterogeneity is determined by each of these two channels. Panel A and B of Figure 15 plot the evolution of Manager Pay at different percentiles over time, both in the data and as predicted by the model. In the data, we see significant inequality among managers, which is also increasing over time. The pay of the lower-ranked managers is almost flat from 1994 to 2019, while the compensation for high-paid managers increases substantially, including p50, p75 and p90. Panel C and D further present the distribution of Manager Pay in both data and model. Even though we do not target it, our model captures the characteristic of the changes in distribution of Manager Pay remarkably well. In this section, we detail how the channels of market power and firm size contribute to the evolution of the distribution.

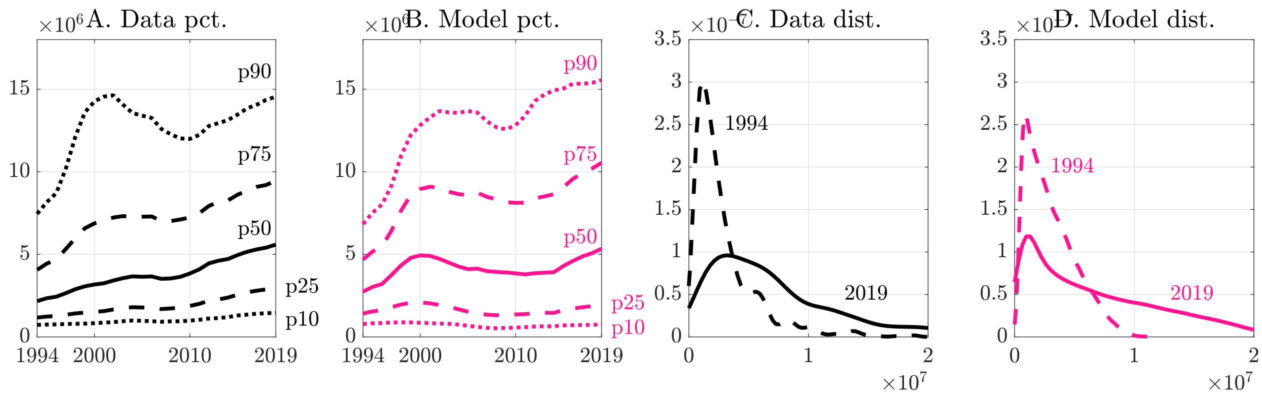


Figure 15: Evolution of Manager Pay for managers in different percentiles

Notes: All the percentiles in Panel A and B are plotted in five-year centered moving average. Panel C and D show the kernel distribution of Manager Pay in the data and the model.

In the theory, Proposition 2 indicates that for small, low TFP firms, the firm size channel dominates the market power channel, while the importance of the market power channel should generally increase in firms' revenues. To understand the mechanism, we first analyze heterogeneity in the cross-section. In the first two panels of Figure 16, we plot the salary (net of reservation utility) of each percentile of managers, as well as the corresponding decomposition of the effects of market power and firm size in 2019. Panel A shows that the effect of market power channel is more convex than the firm size channel. Furthermore, Panel B demonstrates that for the lowest type of managers, almost all of their salary comes from the firm size effect. The market power channel, by contrast, becomes increasingly important when the manager is more talented due to the overall positive sorting. For the top managers, 80.3% of their salaries is due to market power.[25] This discrepancy contributes to the huge inequality in

[25] Observe also a peculiar feature of the largest firms in our model. There is a sharp decrease in the firm size effect among the very top managers. This is because the best managers are matched with superstar, but not monopolistic, firms whose employment elasticity of TFP (equation (14)) is negative. This insight is also confirmed by Figure 10 that the employment

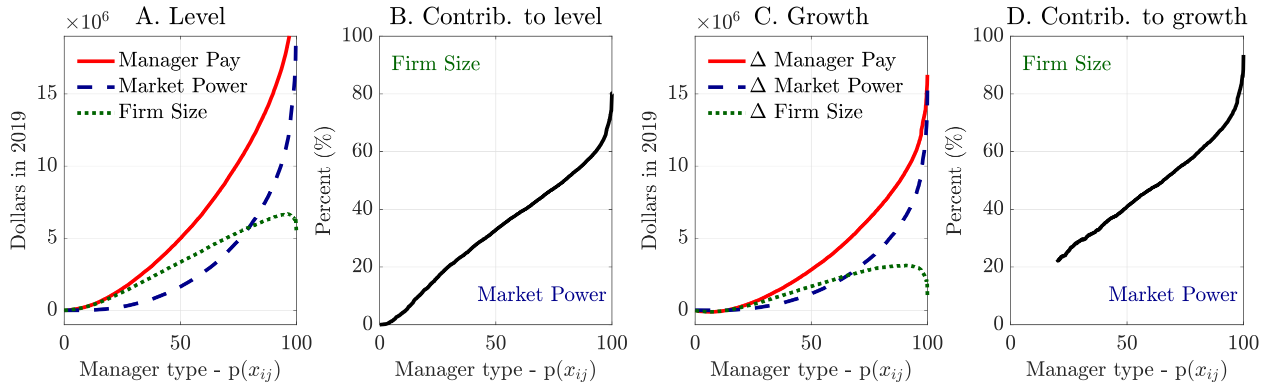


Figure 16: Distribution of Manager Pay and its decomposition

Notes: Panel A and B depict the distribution of Manager Pay and its decomposition in the year 2019. Panel C and D plot the growth of Manager Pay from 1994 to 2019 and decompose it into the two channels. The Manager Pay for the bottom CEOs drops from 1994 to 2019, which means our contribution calculation in panel D makes no sense. Therefore, we only calculate and plot the contribution of market power and firm size in panel D for the percentile of CEOs who get paid more.

Manager Pay.

We now zoom in on the change in Manager Pay over time. From Section 5.1, we learn that Manager Pay is increasing faster through the market power channel than the firm size channel. Combining with the fact that the impact of the market power channel is larger for the high-ability managers, this result suggests that the larger inequality would be generated among managers across their types. For the same percentile of managers, Panel C and D in Figure 16 plots the difference in salaries from 1994 to 2019, as well as the differences attributable to the channels of market power and firm size. Clearly, driven by the larger increase in the effect of market power, the high-ability managers benefit much more than the low-ranked ones.[26] Panel D further confirms that not just the level, but also the change in Manager Pay is mainly driven by the market power channel for the top managers and by the firm size channel for those ranked at the bottom.

5.4 Counterfactuals

In this section, we discuss the role of market power by illustrating counterfactual examples. We will first investigate the welfare effect of technology and market power, then further focus on the Manager Pay that is induced by those counterfactual exercises.

elasticity is negative for some high-ability managers.

[26] Once again, the sharp decrease in the effect of firm size for top managers stems from the presence of superstar firms. It suggests that there are more superstars in 2019 than there were in 1994. This observation aligns with the increasing variance in the types of firm σ_z.

TFP and Market Power. Welfare is determined by many factors, among which we are especially interested in the roles of technology and market power in this paper.[27] Panel A in Figure 17 reports the evolution of the aggregated productivity and welfare over time. We see a slight increase in technology overall, which peaks before the Great Recession. This trend is mainly driven by the wage stagnation in our sample (Figure 7). However, the welfare is generally declining over the same period, as is shown by the pink, solid line. We observe a discrepancy between the increasing technology and declining social welfare, which is mainly attributed to the rise of market power by De Loecker et al. (2021) and Deb et al. (2020b).

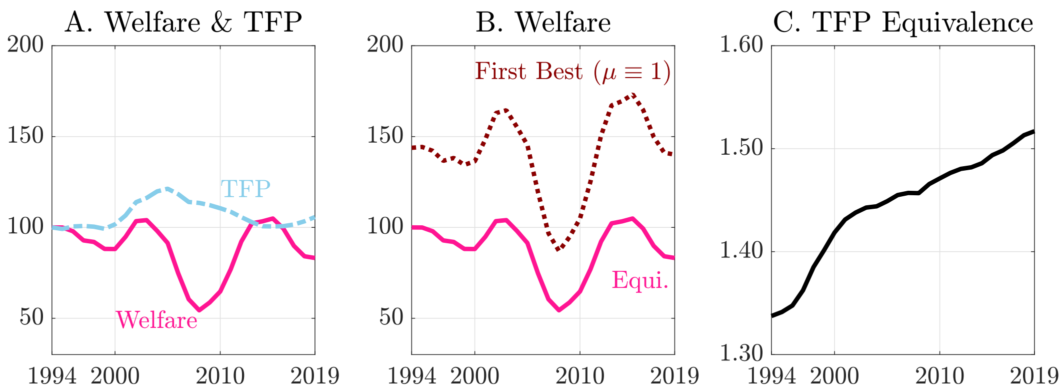


Figure 17: Counterfactual analysis: welfare

Notes: Panel A plots the time series of the aggregate TFP and welfare in our model. Based on De Loecker et al. (2021), the TFP is defined in CES aggregates: $A = [(\int_0^J A_j^{\theta-1} dj)/J]^{1/(\theta-1)}$ and $A_j = (\sum_i A_{ij}^{\eta-1}/I_j)^{1/(\eta-1)}$, while welfare is the net utility of households defined in Equation (2). We normalize their value in year 1994 to 100 for both variables. Panel B presents the social welfare in the First Best economy without output market power. Panel C reports the TFP equivalence of our model, which is defined as how much the technology A_{ij} has to increase to compensate for the welfare loss due to market power.

We further show that market power indeed leads to a significant welfare loss. In a counterfactual economy where firms are forced to price at their marginal costs, the social welfare (the brown, dotted line in Panel B) can on average increase by 58.4%.[28] Moreover, this welfare loss due to market power is constantly increasing over the sample period. In Figure 17.C, we plot the TFP equivalence λ of this welfare loss, that is, firms have to increase their productivity to λA_{ij} in order to realize the same welfare as the first best case. It turns out that the welfare effect of market power can be compensated by a 33.8% increase of TFP in 1994, while this number has increased to 51.7% by year 2019. This evolution aligns with the rise of markup in the real economy.

Manager Pay. We assume households are representative in our model, so Manager Pay plays no role in determining welfare. However, we are still curious about how managers will be paid in those coun-

[27] We further refer readers to De Loecker et al. (2021) for a complete discussion.

[28] The assignment of managers is still determined by the algorithm described in Section 4.1, given that the markups of all firms are $1 + \varepsilon$. The ε here makes sure that managers are not indifferent among all jobs.

terfactual economies. In Figure 18, we plot the evolution of Manager pay as well as the pay schedule (2019) in the baseline economy, the first-best economy, and the economy with a 30% increase in TFP.

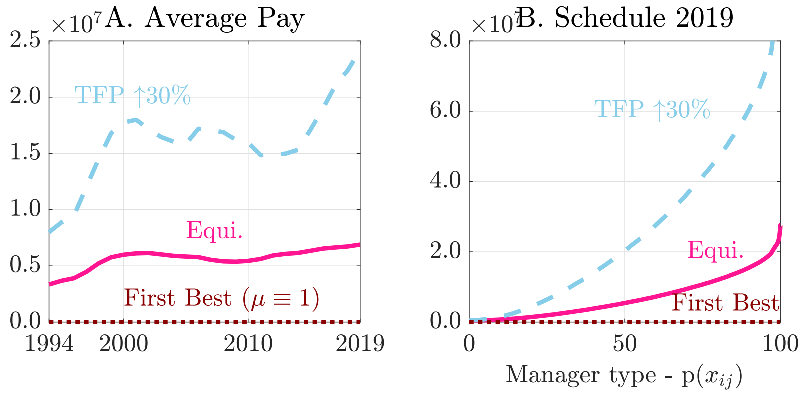


Figure 18: Counterfactual analysis: Manager Pay

Interestingly, when there is no market power (the first-best case), all managers will only earn the reservation utility, which is tiny compared to what they earn in the real world. The intuition is that firms will always earn zero profits no matter how productive they are, which makes a high-ability manager "useless". Notice that this conclusion also depends on the assumption that there is no incentive problem for managers. We also find that the expansion in firm type alone will lead to an increase in Manager Pay (the blue, dashed lines), even though managers' ability is fixed. This finding confirms Gabaix and Landier (2008)'s insights that shifts in firm type account for a part of increase in Manager Pay over the past few decades.

6 Conclusion

Market power in the goods market distorts the efficient allocation of resources. In this paper, we have shown that market power also distorts Manager Pay, as managers are paid in part for market power. Without market power, superstar managers would earn less. Currently, managers are paid to create profits, but more profits for the firm do not necessarily create more value in the economy. Better managers grow the firm which increases value, but they also increase market power, which is inefficient.

The main insight this paper offers is to decompose the contribution of market power to Manager Pay as distinct from firm size. We estimate the model using Compustat data on executive compensation which allows us to quantify the contribution of market power. On average, 45.8% of pay is due to market power, growing from 38.0% in 1994 to 48.8% in 2019. Market power accounts for 57.8% of growth over this period. Most striking is the fact that there is a lot of heterogeneity among managers. For the top managers, 80.3% of their pay is due to market power. The growth of their pay due to market power is even larger. The best managers are lured by large, high markup firms where they create high profits for the shareholders, but disproportionately little additional value to the economy. The rise in the top 1 percent income is not only of concern on the grounds of equity, it is also of concern for efficiency.

The mechanism that we identify and that is behind the rewards these managers receive crucially hinges on the competitive pressures within a market. In the presence of Cournot competition, the most productive firms extract higher rents than the less productive firms. Because of the complementarity between manager ability and firm productivity, the most productive firms can widen the gap even more by hiring a highly skilled manager. This increases their markups even further. The lower productive firms have low markups and hence have little to gain from hiring a superstar manager. Because there is competition for managers, all top firms in their own market who benefit from having a top manager will bid up the top wages. They are paid for increasing the gap between their direct competitors. This resembles the view held by Warren Buffett (2007) and summarized by the quote:

> *I don't want a business that's easy for competitors. I want a business with a moat around it. [...] Our managers of the businesses we run, I've got one message for them, which is to widen the moat.*

Of course, this mechanism is not restricted to CEOs. The ability of the holders of all managerial positions in the firm that affect the productivity of the workers they supervise helps increase the gap between their own firm's productivity and that of the competitors. The impact is highest the higher up in the management hierarchy, but since one in five workers supervises some workers, this has implications for the distribution of earnings. And because the rise in inequality resides mainly in the top percentiles of the income distribution, and managers tend to have top earnings, our mechanism can help explain the rise in income inequality.

Finally, the central mechanism that links market power to compensation is not restricted to managers. A superstar coder who improves an algorithm that is be used by a dominant tech firm for example, will command a superstar salary as her code will help her firm outperform competitors. And in the sports leagues, there is strategic interaction that derives from the zero-sum nature of sports competitions. The team that attracts the top players is more likely to win games, and this will make them bid up the compensation for the top players.

Appendix

Appendix A Data

Appendix A.1 Description

Compustat. We obtain firm-level financial variables of U.S. publicly listed companies active at any point during the period 1950-2019. We access the Compustat North America Fundamentals Annual and download the annual accounts for all companies through WRDS on October 28, 2021. We exclude firms that do not report an industry code, employees, cost-of-goods (COGS), SG&A, capital, or sales. All financial variables are deflated with the appropriate deflators. We do the following truncation to the data set: (1) we drop all firms that report negative sales, COGS, or SG&A; (2) we eliminate firms whose sales are lower than COGS; (3) we eliminate firms with estimated markups in the top and bottom 1%, where the percentiles are computed for each year separately.

ExecuComp. Our data for Manager Pay comes from ExecuComp during the period of 1992 to 2019. All financial variables are deflated with the appropriate deflators. We drop firms that have zero TDC1 or TDC2. We also annually eliminate firms with TDC1 and TDC2 in the top and bottom 1%. We are using TDC1 as our Manager Pay throughout the paper, but the results are robust over different definitions. This data can be mapped into Compustat data set by gvkey and year.

Appendix A.2 Regression

Given the positive correlation between firm level markups and executive compensation, we further analyze this relation including covariates about the firm characteristics (number of employees, sales, and variable and fixed costs) as well as year, firm and industry fixed effects. Table A.1 reports this exercise.

We treat column (1) as our baseline regression, with all covariates and where we only control the year fixed effects. We find that the average treatment effect is 0.133, highly significant and close to the raw correlation. A one percent increase in the firm level markup increases Manager Pay by 0.133 percent. However, even after controlling for some objects at the firm level, different firms are still hardly comparable. Therefore, in column (2) we additionally control for firm-level fixed effects and exploit the variation in the same firms over time. Now the coefficient more than doubles to 0.309. Next we control for a fixed effects at the industry level, capturing the idea that firms in the same market are comparable. Column (3) and (4) perform this exercise by controlling the regression at the industry and the industry

Table A.1: Regression: the executive salary elasticity of markup

	log Manager Pay				
	(1)	(2)	(3)	(4)	(5)
log markup	0.123 (0.0146)	0.309 (0.0306)	0.180 (0.0179)	0.184 (0.0191)	0.257 (0.0342)
Controls					
Employees	0.00133 (0.000253)	0.00118 (0.000233)	0.00172 (0.000263)	0.00154 (0.000269)	0.00113 (0.000266)
Sales	6.79e-08 (8.27e-09)	1.65e-08 (4.61e-09)	6.06e-08 (7.94e-09)	6.02e-08 (8.20e-09)	8.47e-09 (3.82e-09)
COGS	-6.49e-08 (8.67e-09)	-1.44e-08 (5.12e-09)	-5.94e-08 (8.41e-09)	-5.88e-08 (8.75e-09)	-6.74e-09 (4.43e-09)
SG&A	-5.85e-08 (1.50e-08)	-2.92e-08 (7.53e-09)	-4.84e-08 (1.48e-08)	-4.43e-08 (1.49e-08)	-1.93e-08 (6.41e-09)
Fixed Effects					
Year	Y	Y	Y	–	–
Firm		Y			Y
Industry		–	Y	–	–
Industry $\times$ year				Y	Y
R-squared	0.155	0.669	0.228	0.282	0.721
Observations	33263	33263	33263	31982	31850

Notes: The robust standard errors under heteroscedasticity are documented in the parenthesis. In the fixed effects rows, "Y" stands for "yes" and "–" means this fixed effect has already been covered by some other fixed effects. Industry is defined at 4-digit NAICS code level. The number of observations in column (4) and (5) drops because there are firms that are alone in an industry by a year, which does not provide any variation.

by year level, respectively. In both cases, the elasticity of Manager Pay with respect to markups is around 0.180 and highly significant. Finally, we control all fixed effects in column (5), and the results are significant and robust.

Appendix A.3 Supplementary figures

Selection in ExecuComp data set. We observe substantial differences with the samples in 1992 and 1993. Specifically, the panel A of Figure A.1 shows that the average sales of sampling firms is more than $9 million in 1992, which is abnormally greater than the level in other years. The same problem also exists in 1993. Furthermore, the panel B shows that there is a systematic difference of sample selection in 1992 and 1993. The sampled firms in these two years are overall larger than firms in subsequent years. For this reason, we eliminate the year 1992 and 1993 from our analysis.

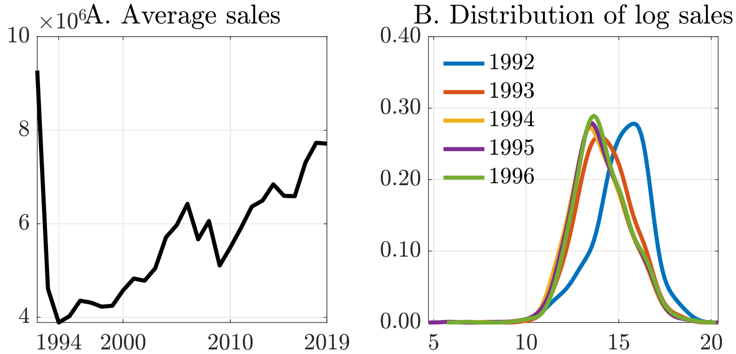


Figure A.1: Sample selection in 1992 and 1993

Lognormal distribution of manager share in data. Figure A.2 reports the kernel distribution of $\log \chi_{ij}$ in the data. It demonstrates that χ_{ij} follows a lognormal distribution. Based on this property, we are constructing moments with $\log \chi_{ij}$ instead of χ_{ij}.

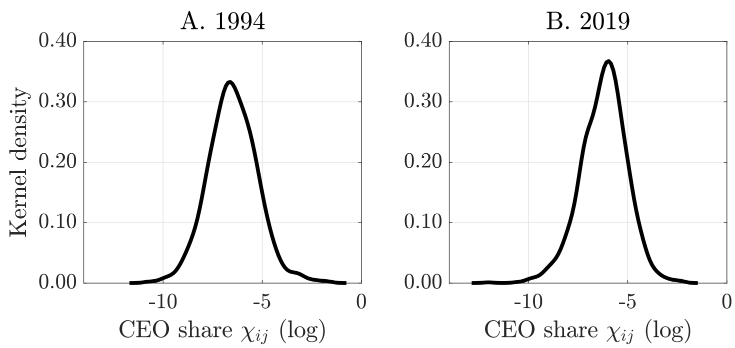


Figure A.2: Normality of log Manager share $\log \chi_{ij}$

Appendix B Model proof

Appendix B.1 Lemma 1: household solution

Recall the household problem:

$$\max_{\{c_{ij}\},L} U(C,L) \quad , \quad \text{s.t.} \quad \int_0^J \left(\sum_{i=1}^{I_j} p_{ij} c_{ij} \right) dj \leq WL + \Omega + \Pi.$$

Because there is a continuum of identical households, any single household cannot influence the aggregate manager pay, Ω, and profits, Π. They will take those aggregates as given in optimizing their utility. We start our analysis by deriving the aggregate labor supply function.

Labor supply. Given any wage W and price index P, the household chooses labor supply L to maximize utility:

$$\max_{L} U = \frac{WL + \Omega + \Pi}{P} - \overline{\varphi}^{-\frac{1}{\varphi}} \frac{L^{1+\frac{1}{\varphi}}}{1+\frac{1}{\varphi}},$$

which incurs first order condition:

$$\frac{W}{P} = \overline{\varphi}^{-\frac{1}{\varphi}} L^{\frac{1}{\varphi}} \quad \Leftrightarrow \quad L = \overline{\varphi} \left(\frac{W}{P}\right)^{\varphi}. \tag{B.1}$$

Inverse demand function. We then derive the inverse demand function by solving households' cost-minimization problem. Within each market j and given utility $\bar{c}_j$, the household will choose the consumption bundle to minimize the expenditure:

$$\min_{\{c_{ij}\}} E = \sum_i p_{ij} c_{ij} \quad \text{s.t.} \quad c_j(c_{ij}) = \bar{c}_j.$$

The FOC gives:

$$I_j^{-\frac{1}{\eta}} c_{ij}^{\frac{\eta-1}{\eta}} c_j^{\frac{1}{\eta}} = \lambda_j^{-1} p_{ij} c_{ij} \quad \Rightarrow \quad c_j = \lambda_j^{-1} \sum_i p_{ij} c_{ij},$$

where λ_j is the shadow price for goods at market j. Hence, we further define λ_j as the price index for this market. The FOCs lead to:

$$c_{ij} = I_j^{-\frac{1}{\eta}} \left(\frac{p_{ij}}{p_j}\right)^{-\eta} \bar{c}_j \quad \text{and} \quad p_j = \left[\sum_i \frac{1}{I_j} p_{ij}^{1-\eta}\right]^{\frac{1}{1-\eta}}. \tag{B.2}$$

Similarly, we can solve the expenditure minimizing problem at the economy level, which incurs:

$$c_j = J^{-\frac{1}{\theta}} \left(\frac{p_j}{P}\right)^{-\theta} \overline{C} \quad \text{and} \quad P = \left[\int_0^J \frac{1}{J} p_j^{1-\theta} dj\right]^{\frac{1}{1-\theta}}. \tag{B.3}$$

Combining equation (B.2) and (B.3), we get the demand system from the household side:

$$y_{ij} = \frac{1}{J} \frac{1}{I_j} \left(\frac{p_{ij}}{p_j}\right)^{-\eta} \left(\frac{p_j}{P}\right)^{-\theta} Y. \tag{B.4}$$

Appendix B.2 Lemma 2: sub-game equilibrium

In this section, we derive the output market equilibrium in second stage given any matching allocation x_{ij} from the period one. To begin with, recall the firm-level FOC:

$$p_{ij}A_{ij} = \mu_{ij}W \quad \text{where} \quad \mu_{ij} := \left[1 + \frac{dp_{ij}}{dy_{ij}}\frac{y_{ij}}{p_{ij}}\right]^{-1} = \left[1 - \frac{1}{\theta}s_{ij} - \frac{1}{\eta}\left(1 - s_{ij}\right)\right]^{-1}, \tag{B.5}$$

where the second equality comes from the elasticity of demand function (B.4). The CES structure incurs following property:

$$s_{ij} = \frac{p_{ij}^{1-\eta}}{\sum_{i'} p_{i'j}^{1-\eta}}. \tag{B.6}$$

Combining equation (B.5) and (B.6), we can solve for markups μ_{ij} (or equivalently, sales shares s_{ij}) directly from TFP A_{ij} by:

$$s_{ij} = \frac{\left(\mu_{ij}/A_{ij}\right)^{1-\eta}}{\sum_{i'}\left(\mu_{i'j}/A_{i'j}\right)^{1-\eta}}.$$

Therefore, we will take μ_{ij} and s_{ij} as the primitives for the subsequent analysis.

Output market clearing. As we take the price index as the numeraire, the goods clearing condition simply requires the prices implied by markups are consistent with this normalization, i.e.,

$$\left[\int_0^J \frac{1}{J}\left(\frac{1}{I_j}\sum_i p_{ij}^{1-\eta}\right)^{\frac{1-\theta}{1-\eta}} dj\right]^{\frac{1}{1-\theta}} = P \quad , \quad \text{where} \quad p_{ij} = \mu_{ij}\frac{W}{A_{ij}}.$$

This condition gives us the equilibrium wage:

$$\frac{W}{P} = \left[\left(\int_0^1 \frac{1}{J}\left[\frac{1}{I_j}\sum_i \left(\frac{\mu_{ij}}{A_{ij}}\right)^{1-\eta}\right]^{\frac{1-\theta}{1-\eta}} dj\right)^{\frac{1}{1-\theta}}\right]^{-1}. \tag{B.7}$$

The equilibrium wage is the marginal revenue product of labor *without* markups. To see this more clearly, imagine a homogenous economy where $A_{ij} \equiv A$ and $\mu_{ij} \equiv \mu$. The equation (B.7) becomes $W = AP/\mu$, where the term AP is marginal revenue of labor, while the markup μ puts a wedge that becomes the gross profit of the firms. Furthermore, the term $1/I_j$ neutralizes the effect of love of variety — it prevents the change in I_j from directly influencing equilibrium wage. As a result, all changes in W are due to the evolution of markups, TFP, and supply of inputs.

Labor market clearing. Finally, labor market clearing pins down the aggregate labor supply L, using the household's labor supply decision (B.1) in conjunction with the equilibrium wage:

$$\overline{\varphi} W^{\varphi} = \int_0^1 \left[\sum_i \frac{1}{A_{ij}} \underbrace{\frac{1}{J}\frac{1}{I_j}\left(\frac{p_{ij}}{p_j}\right)^{-\eta}\left(\frac{p_j}{P}\right)^{-\theta} Y}_{\text{Output } y_{ij}} \right] dj. \tag{B.8}$$

The LHS is the labor supply function and the RHS is the aggregate labor demand function. This condition eventually pins down the output level Y. After pinning down aggregates W and Y, other equilibrium objects can be further derived from the inverse demand function and production function.

Appendix B.3 Proposition 2: markup and employment elasticities of TFP

In this section, we first present the proof for the two elasticities of TFP shown in the paper. We then give an illustration using an example of a duopoly market.

The method is implicit function theorem. By taking derivatives of both sides of the FOC (B.5) *w.r.t.* A_{ij} and A_{kj} ($k \neq i$), we get:

$$\frac{\partial \mu_{ij}}{\partial A_{ij}}\frac{A_{ij}}{\mu_{ij}} = \frac{\left(\frac{1}{\theta}-\frac{1}{\eta}\right)(\eta-1)\,\mu_{ij}s_{ij}\left[\left(\sum_{i'} s_{i'j}\frac{\partial \mu_{i'j}}{\partial A_{ij}}\frac{A_{ij}}{\mu_{i'j}}\right)+\left(1-s_{ij}\right)\right]}{1+\left(\frac{1}{\theta}-\frac{1}{\eta}\right)(\eta-1)\,\mu_{ij}s_{ij}}$$
$$\frac{\partial \mu_{kj}}{\partial A_{ij}}\frac{A_{ij}}{\mu_{kj}} = \frac{\left(\frac{1}{\theta}-\frac{1}{\eta}\right)(\eta-1)\,\mu_{kj}s_{kj}\left[\sum_{i'} s_{i'j}\frac{A_{ij}}{\mu_{i'j}}\frac{\partial \mu_{i'j}}{\partial A_{ij}}-s_{ij}\right]}{1+\left(\frac{1}{\theta}-\frac{1}{\eta}\right)(\eta-1)\,\mu_{kj}s_{kj}}.$$

Sum them up with the sales weight, we get:

$$\sum_{i'} s_{i'j}\frac{\partial \mu_{i'j}}{\partial A_{ij}}\frac{A_{ij}}{\mu_{i'j}} = s_{ij}-\phi_{ij} \quad \text{where} \quad \phi_{ij} := \frac{\frac{s_{ij}}{1+\left(\frac{1}{\theta}-\frac{1}{\eta}\right)(\eta-1)\mu_{ij}s_{ij}}}{\sum_{i'}\frac{s_{i'j}}{1+\left(\frac{1}{\theta}-\frac{1}{\eta}\right)(\eta-1)\mu_{i'j}s_{i'j}}}.$$

This equation in turn gives us the markup elasticity of TFP:

$$\frac{\partial \mu_{ij}}{\partial A_{ij}}\frac{A_{ij}}{\mu_{ij}} = \frac{\left(\frac{1}{\theta}-\frac{1}{\eta}\right)(\eta-1)\,\mu_{ij}s_{ij}}{1+\left(\frac{1}{\theta}-\frac{1}{\eta}\right)(\eta-1)\,\mu_{ij}s_{ij}}\left(1-\phi_{ij}\right) \tag{B.9}$$

$$\frac{\partial \mu_{kj}}{\partial A_{ij}}\frac{A_{ij}}{\mu_{kj}} = -\frac{\left(\frac{1}{\theta}-\frac{1}{\eta}\right)(\eta-1)\,\mu_{kj}s_{kj}}{1+\left(\frac{1}{\theta}-\frac{1}{\eta}\right)(\eta-1)\,\mu_{kj}s_{kj}}\phi_{ij}. \tag{B.10}$$

Furthermore, by using the inverse demand function and production function from the sub-game equilibrium, we can write the equilibrium employment l_{ij} as:

$$l_{ij} = \frac{1}{A_{ij}} \left(\frac{\mu_{ij}}{A_{ij}} \right)^{-\eta} \left[\frac{1}{I_j} \sum_{i' \in j} \left(\frac{\mu_{i'j}}{A_{i'j}} \right)^{1-\eta} \right]^{\frac{\eta-\theta}{1-\eta}} \left(\frac{Y}{I_j J} \right) \left(\frac{W}{P} \right)^{-\frac{1}{\theta}},$$

from which we get:

$$\frac{\partial l_{ij}}{\partial A_{ij}} \frac{A_{ij}}{l_{ij}} = \left[\frac{\eta}{1 + \left(\frac{1}{\theta} - \frac{1}{\eta} \right) (\eta - 1) \mu_{ij} s_{ij}} - 1 \right] \left(1 - \phi_{ij}\right) + (\theta - 1) \phi_{ij}. \tag{B.11}$$

A duopoly example. In a duopoly economy, we have analytical form for all the equilibrium objects, which makes it an ideal example for us to check the property of aforementioned elasticities. In Figure B.1, we plot the markup and employment elasticities of TFP against the sales share s_{ij}. Their behaviors follow the theoretical interpretation we made in the paper, that the markup elasticity first increases then declines over the firm size, while the employment one is decreasing over s_{ij} until the firm converges to the monopolist.

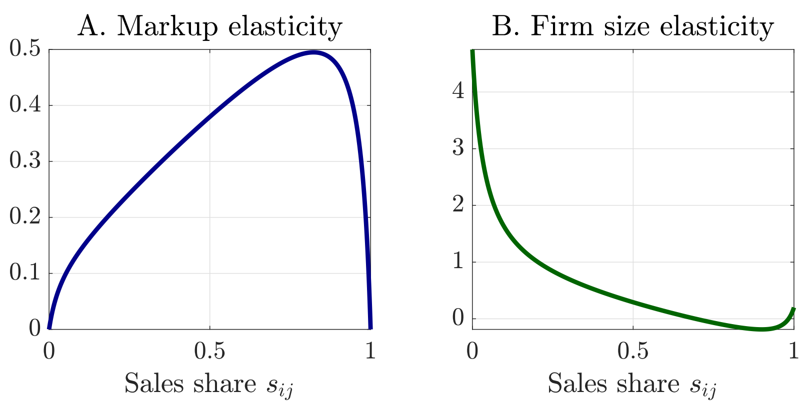


Figure B.1: Markup and employment elasticity of TFP

Notes: We plot the example of a duopoly market here. By construction, sales shares of the two firms are s_{ij} and $1 - s_{ij}$, respectively. Every object has a closed-form expression. The elasticity of substitutes are set as: $\theta = 1.2$ and $\eta = 5.75$.

Appendix B.4 Lemma 3: production transformation

We prove Lemma 3 by solving the cost minimization problem of firms. The Lagrangian problem can be written as:

$$\mathcal{L}(l_{ij}, m_{ij}, k_{ij}; \overline{y}_{ij}) = W l_{ij} + P^m m_{ij} + R k_{ij} - \lambda_{ij} \left[A_{ij} \left(l_{ij} + m_{ij} \right)^{\zeta} k_{ij}^{1-\zeta} - \overline{y}_{ij} \right],$$

with FOCs:

$$\frac{\partial \mathcal{L}}{\partial l_{ij}} = W - \frac{\lambda_{ij}\zeta}{l_{ij}+m_{ij}}\left[A_{ij}\left(l_{ij}+m_{ij}\right)^{\zeta}k_{ij}^{1-\zeta}\right] = 0,$$
$$\frac{\partial \mathcal{L}}{\partial m_{ij}} = P^{m} - \frac{\lambda_{ij}\zeta}{l_{ij}+m_{ij}}\left[A_{ij}\left(l_{ij}+m_{ij}\right)^{\zeta}k_{ij}^{1-\zeta}\right] = 0,$$
$$\frac{\partial \mathcal{L}}{\partial k_{ij}} = R - \frac{\lambda_{ij}(1-\zeta)}{k_{ij}}\left[A_{ij}\left(l_{ij}+m_{ij}\right)^{\zeta}k_{ij}^{1-\zeta}\right] = 0,$$

where P^m is the price for materials. This set of FOCs give us the optimal inputs choices:

$$m_{ij} = \frac{1-\psi}{\psi}l_{ij} \quad \text{and} \quad k_{ij} = \frac{1}{\psi}\frac{W/\zeta}{R/(1-\zeta)}l_{ij}, \tag{B.12}$$

where $\psi := l_{ij}/(l_{ij}+m_{ij})$ is an exogenous parameter for all firms. Note also that since labor and materials are perfectly substitutable, at equilibrium we must have $P^m = W$.

Appendix C Quantification

Appendix C.1 Verifying the efficiency of the approximate algorithm

To check the efficiency of this approximation algorithm, we compare the exact stable matching to the approximate stable matching obtained with our approximate algorithm. We do this for an economy with $J = 200$ markets where we can still calculate the equilibrium stable matching exactly. Figure C.1 confirms first that, due to the externalities, the PAM allocation between the types of firms and the manager type x (the diagonal line in the left panel) is no longer stable. More importantly, it shows that there is remarkable overlap between the allocations of the exact and the approximate stable matching. For our purpose, this naturally implies that the estimated salary schedule (in the right panel) under the approximate stable matching is virtually identical that under the exact stable matching. Moreover, the total revenue change (in absolute value) between the exact and approximate matching is 0.001% of the total revenue from the exact matching, and the total pay change (in absolute value) is 1.17% of the total Manager Pay, both of which are negligible.

To address the concern that the robustness we have observed in Figure C.1 may be due to the fact that J is small, we further repeat this exercise over different values of J. The result is reported in Figure C.2. We see that as J increases, the differences in revenue and manager pay between approximate and exact matching are robustly small, which suggests that our approximation does a good job regardless of the number of markets (firms). Furthermore, we can make a conclusion that the approximate stable matching is close to the exact one for a large economy that we are considering in the quantitative

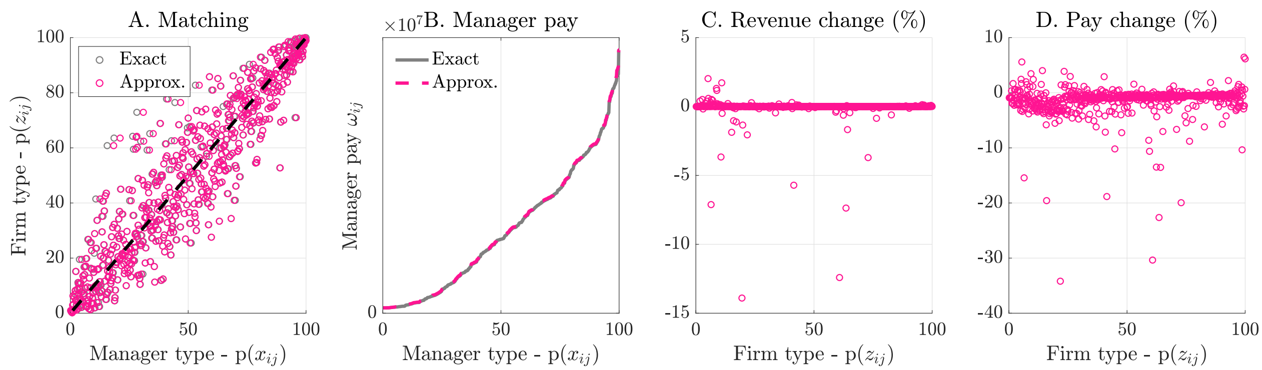


Figure C.1: Comparison: Exact and Approximate Stable Matching

Notes: We set $J = 200$ in this exercise. The set of parameter is taken from the estimates in 2019, which is presented in Section 4.5. The PAM is derived in above algorithm. To find the stable matching, we iterate over all pairs of firms and shift managers if they can get better off, until all of them satisfy the condition in Definition 1. Panel C and D report the revenue difference for each firm as a share of the exact revenue, and the pay difference for each firm as a share of the exact pay.

Figure C.2: Robustness of Approximate Stable Matching over J

Notes: These figures report the gross revenue (manager pay) difference as a share of the exact gross revenue (pay) in absolute value for different number of markets J.

exercises.

Appendix C.2 Comparative static

Category I. Match

IMPORTANCE OF MANAGERS - α. Figure C.3 reports the comparative static results for $\{\alpha, \gamma\}$. The importance of the manager is measured by the share of the manager α. As is shown by Proposition 1, an increase in α will proportionally raise the marginal contribution of managers for all firms. This leads to the two conclusions regarding moments: first, the average salary share of managers will increase; and second, the slope of salary share on sales will be constant.

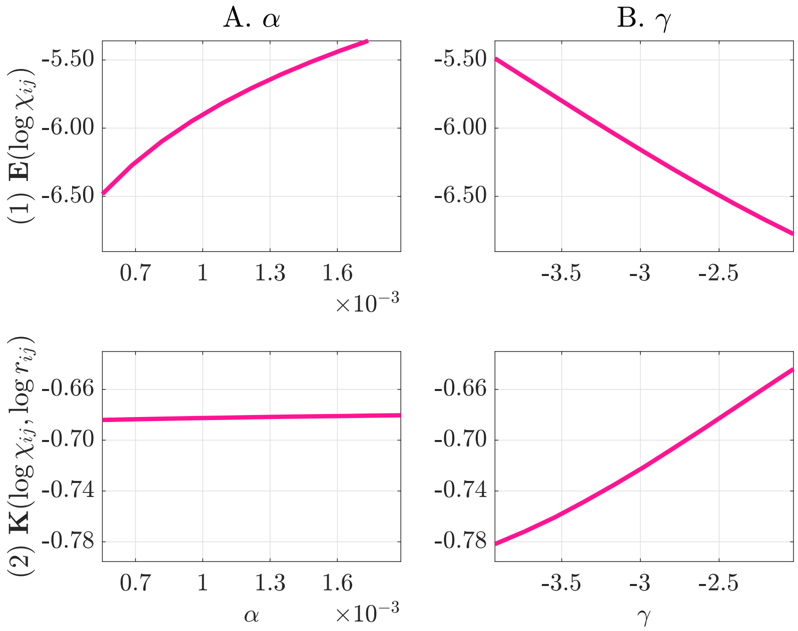


Figure C.3: Comparative static: I. Match

Notes: In this exercise, we move parameters and check how the model moments response. In each column, we move only one parameter while fixing all others. The baseline parameters are the estimates in 1994, which is presented in Section 4.5. The range of each parameter is chosen as the range of corresponding estimates from 1994 to 2019. To reduce the noise due to reservation utility, we fix its relative level $\omega_0/\mathbb{E}(\omega)$ rather than the absolute level ω_0.

COMPLEMENTARITY - γ. When γ increases, manager ability and firm type become less complementary. The first implication is that managers will get paid less because they become less productive. This shows up in a declining average salary share in Panel 1.B. Furthermore, as we have discussed in Section 4.4, the slope of salary share on sales becomes flatter, which aligns with the results in Column two of Figure C.3.

Category II. Market

MEAN OF MARKET STRUCTURE DISTRIBUTION - m_I. We first look at the effect of m_I, the average number of firms in each market, which is shown in the first column of Figure C.4. As the average number of firms increases, the economy becomes more competitive, so the markup level goes down. On the other hand, when there are more competitive, low-markup markets, the between-market variance of markups also decreases.

STANDARD DEVIATION OF MARKET STRUCTURE DISTRIBUTION - σ_I. An increase in σ_I makes the distribution of I_j more dispersed, so it mainly impacts the heterogeneity across markets. As expected, Column two in Figure C.4 shows that a larger σ_I leads to a larger between-market variance of markups. The effect on the markup level is negligible.

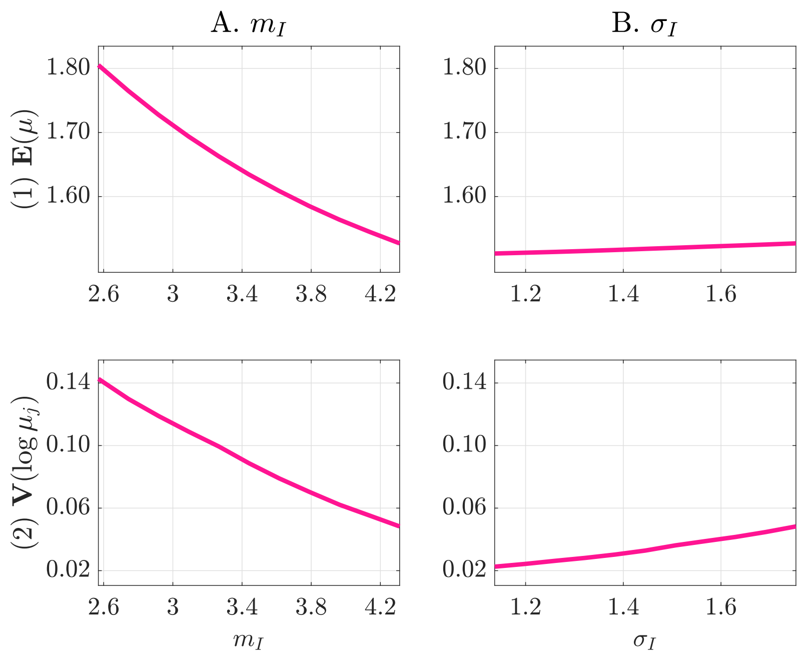


Figure C.4: Comparative static: II. Market

Category III. Firm

STANDARD DEVIATION OF FIRM TYPE - σ_z. Figure C.5 presents the comparative static over firm-level parameters. The change in standard deviation of the z_{ij} influences mainly the variance of firm types. Larger heterogeneity among firms will direct make the markup distribution more dispersed within each market. Moreover, as we fix the mean of z_{ij} to 1, changes in its standard deviation will not heavily influence the level of technology, and thus the worker's wage. Finally, this increase will also naturally show up in the increasing variance of the revenue distribution.

MEAN OF MARKET PRODUCTIVITY - μ_A. Column B shows that the level of z_j only shifts the unskilled wage level. Clearly, higher TFP induces greater marginal revenue product of labor, which leads to larger labor demand and hence drives the equilibrium wage up. It does not influence the within-market variance of markups because markups only depend on the relative productivity of firms in the same market. It also has negligible impact on the variance of revenue.

STANDARD DEVIATION OF MARKET PRODUCTIVITY - σ_A. The last parameter is the standard deviation of the market-level productivity shock, A_j. Since the markups are determined *within* each market according to Lemma 2, this market-level shock will not influence the markup distribution at all. Therefore, its only effect is on the firm size distribution. By making firms more different across markets, a larger σ_A will drive the variance of firm size up. This intuition is confirmed by the column three in Fig-

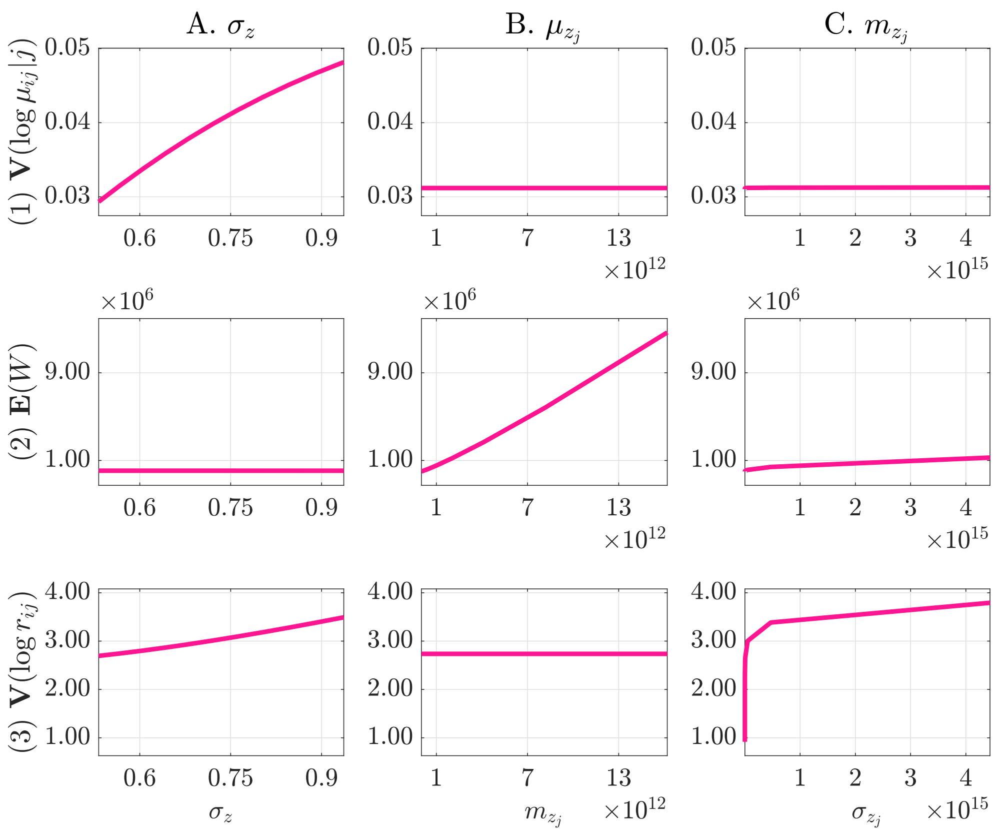


Figure C.5: Comparative static: III. Firm [NOTATION]

ure C.5. Finally, σ_A has a slightly positive impact on W because an increase in the standard deviation of a lognormal distribution will also contribute to a larger expectation. A higher TFP level hence leads to higher wages, as is shown in Panel 2.C.

Appendix C.3 Rescaling

We simply take the reservation utility ω_0 from data. This section documents the way we use the parameters $\{\overline{\varphi}, \psi\}$ to match the average employee and the average manager pay from model to the data. Note that the constant return to scale allows us to rescale the model without influencing any other moments we targeted in the first three categories.

First, the parameter $\overline{\varphi}$ can be simply derived from the labor supply function:

$$L = \overline{\varphi} \left(\frac{W}{P} \right)^{\varphi} \quad \Leftrightarrow \quad \overline{\varphi} = \frac{L}{(W/P)^{\varphi}}. \tag{C.1}$$

Then, because we match the exact wage and average employment, the revenue expression:

$$r_{ij} = \frac{\mu_{ij} W l_{ij}}{\zeta \psi}$$

indicates that revenue (and thus manager pay) are proportional to $1/\psi$, based on which we can easily find the right ψ to match the level of Manager Pay.

Appendix D Main results: using revenue for firm size

In this section, we report our decomposition exercise where we interpret revenue r_{ij} as firm size. We will first present the decomposition equation and detail why this way of decomposition will underestimate the effect of market power. Finally, we show the corresponding quantitative results.

Decomposition equation. We can write the equilibrium gross profit $\widetilde{\pi}_{ij}$ as:

$$\widetilde{\pi}_{ij} = \left(1 - \frac{1}{\mu_{ij}}\right) r_{ij}.$$

Therefore, we get another way to decompose the marginal contribution of manager, i.e.,

$$\begin{aligned} \frac{\partial \widetilde{\pi}_{ij}}{\partial x_{ij}} &= \left[\frac{\partial}{\partial A_{ij}}\left(1 - \frac{1}{\mu_{ij}}\right) r_{ij} + \left(1 - \frac{1}{\mu_{ij}}\right)\frac{\partial r_{ij}}{\partial A_{ij}}\right]\frac{\partial A_{ij}}{\partial x_{ij}} \\ &= \left[\frac{1}{\mu_{ij}}\left(\frac{\partial \mu_{ij}}{\partial A_{ij}} W l_{ij}\right) + \left(1 - \frac{1}{\mu_{ij}}\right)\frac{\partial r_{ij}}{\partial A_{ij}}\right]\frac{\partial A_{ij}}{\partial x_{ij}} \end{aligned} \tag{D.1}$$

which further gives us the way to decompose Manager Pay:

$$\omega(x_{ij}) = \omega_0 + \int_{\underline{x}}^{x_{ij}} \left[\underbrace{\frac{1}{\mu_{ij}}\left(\frac{\partial \mu_{i'j'}}{\partial A_{i'j'}} W l_{i'j'}\right)}_{\text{Markup channel}} + \underbrace{\left(1 - \frac{1}{\mu_{i'j'}}\right)\frac{\partial r_{i'j'}}{\partial A_{i'j'}}}_{\text{Firm size channel}}\right] \times \underbrace{\left[\alpha A_{j'}\left(\frac{A_{i'j'}}{A_{j'} x_{i'j'}}\right)^{1-\gamma}\right]}_{\partial A_{i'j'}/\partial x_{i'j'}} dF\left(x_{i'j'}\right). \tag{D.2}$$

Notice that, compared to Proposition 1, the market power channel in Equation (D.2) is being rescaled by a factor $1/\mu_{ij}$. This difference comes from the fact that markups directly enter the expression for revenue, that is, $r_{ij} = \mu_{ij} W l_{ij}$. Therefore, decomposition (D.2) ignores the contribution of market power on Manager Pay through revenue, and thus underestimates the effect of market power.

Quantitation. Nevertheless, we find that even when we are underestimating the market power effect, we still quantify a significant influence from it and see a robust increase of this effect over time. Figure

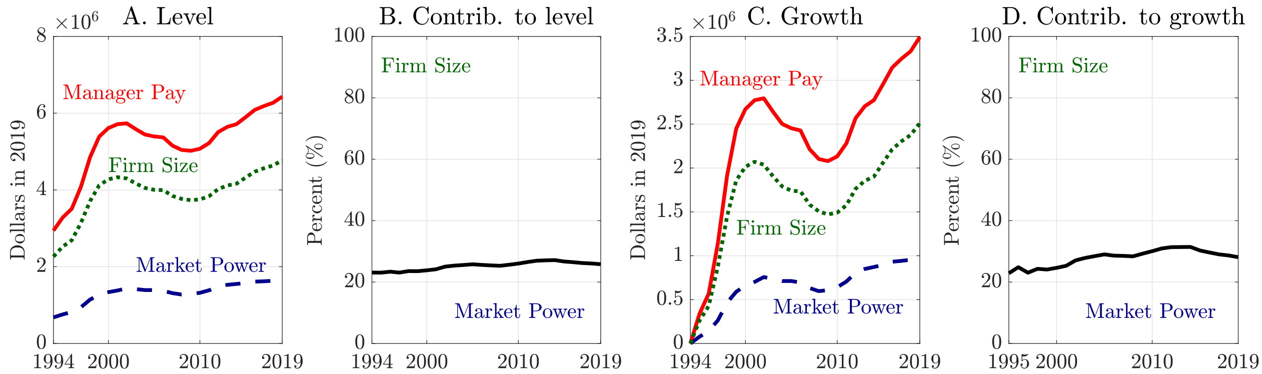


Figure D.1: Manager Pay decomposition into Market Power and Firm Size (Revenue), by year

D.1 shows the decomposition of Manager Pay level. As we expect, the market power channel is less important in this case, which accounts for \$0.68 million in 1994 and \$1.66 million in 2019. Over time, the market power component still plays a slightly more important role, whose share increases from 23.1% to 25.8%. Furthermore, Panel C and D show that market power contributes to the growth in Manager Pay by \$0.98 million (28.1% of the total growth). Our main results still hold in this specification, although this method actually underestimates the effect of market power.

We also revisit the results regarding distribution. Figure D.2 demonstrates that the heterogeneity in market power and firm size channels still hold true in this decomposition. Basically, market power contributes to the compensation of high-ability managers (30.9%) more than those low-ability ones, and so does its contribution to growth (31.1% for the top manager).

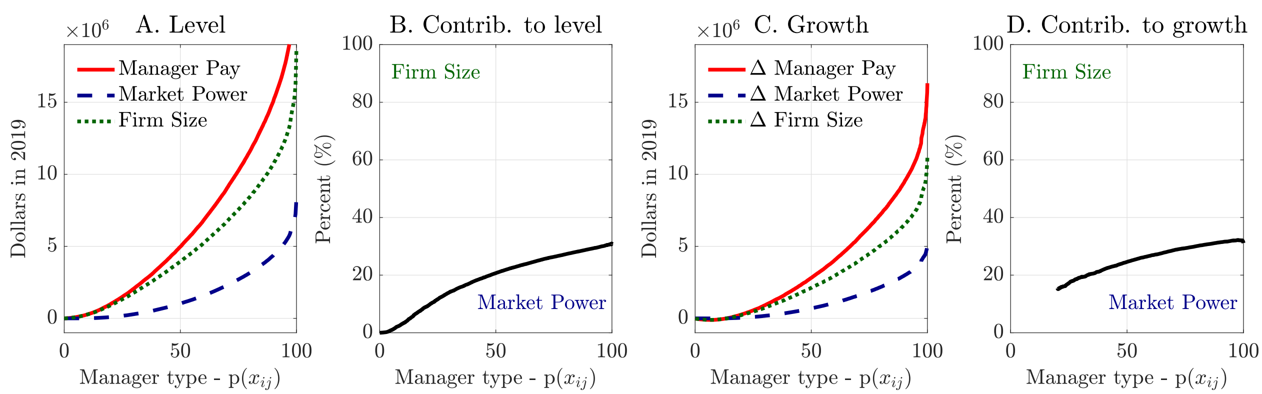


Figure D.2: Distribution of Manager Pay and its decomposition: revenue as firm size

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