Are Managers Paid for Market Power?*

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February 7, 2022

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: 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 between 1994 and 2019, we quantitatively analyze how market power affects Manager Pay and how it changes over time. We attribute on average 54.5% of Manager Pay to market power, the remainder is due to firm size. Over time, 61.2% 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, 95.8% of their pay in 2019 is due to market power, and so is nearly all of the growth since 1994. For the lower-ranked managers, pay is determined mainly by firm size. 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.

*We are grateful for comments and feedback from numerous colleagues and seminar audiences. De Loecker acknowledges support from the ERC, Consolidator grant 816638, and Eeckhout from the ERC, Advanced grant 882499, from AEI (Severo Ochoa, Barcelona School of Economics CEX2019-000915-S), and from PGC2018-096370-B-I00.

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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.

Warren Buffett, 2007

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. As 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). 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.[4] Whether firms grow large due to technological change or via mergers and acquisitions, it is predominantly large superstar firms that exert market power. The fact that market power and firm size correlate poses a challenge to tease out the role of each in determining the pay of managers. 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

[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 high markup firms. See Autor, Dorn, Katz, Patterson, and Van Reenen (2020) and De Loecker et al. (2020).

from the premise that productivity 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 can 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 54.5% of Manager Pay to market power, the remainder is due to firm size. Over time, 61.2% 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, 95.8% 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. Top managers are hired disproportionately by firms with market power, and they get rewarded for it.

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. 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. Of course, the match value of a matched pair is determined by the profits the pair generates in their market. And profits depend on market power and 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.

Using Compustat data, we annually estimate the primitive parameters of the model to match moments of the data that are relevant for the mechanism in the model. Markups and sales are key to determine the firm productivity distribution as well as the market structure. The moments on Manager

Pay pin down the complementarity in the production technology as well as the distribution of manager ability. And aggregate moments on average firm size, average wages, and average Manager salaries ensure that the levels in the economy are accurately pinned down. From the estimated parameters, we learn that the market structure leads to fewer competitors in the economy, while the variance of firm productivities increases. Both contribute to an increase in market power. Also the variance of manager abilities increases, but the productivity effect is partly offset by a decline in the degree of complementarity. Finally, we find that aggregate productivity increases.

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 which Edmans and Gabaix (2016) and Edmans, Gabaix, and Jenter (2017) for comprehensive survey of the literature, and for evidence in 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 have high markups 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 and firm size and market power. 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. 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. (2020) document the effect of market power on the skill premium and the wage level of all workers. And Kaplan and Zoch (2020) analyzes 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, 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)).[8,9]

[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.

[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).

[9]Also, to be consistent with our structural analysis, we control for Manager Pay in the production function estimation.

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.

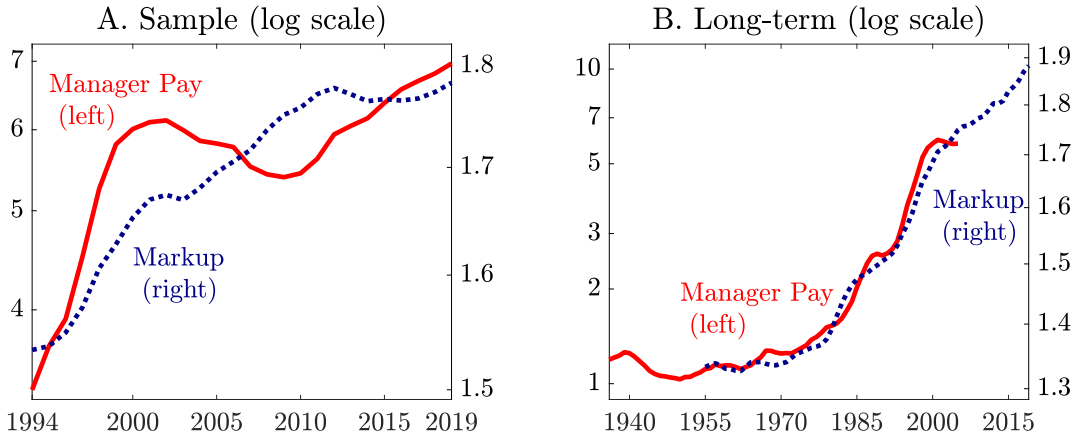


Figure 1: The evolution of Manager Pay and markups

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.

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 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.

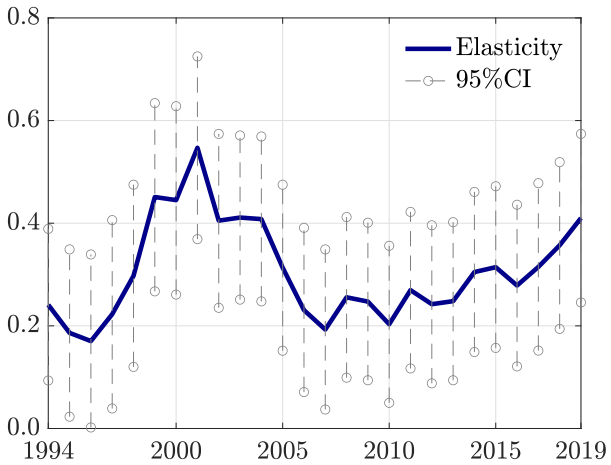


Figure 2: The elasticity of markups on Manager Pay over time

Notes: This figure reports the coefficients β_t in regression specification (1). The 95% confidence interval (CI) is constructed with robust standard errors under heteroscedasticity.

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 $F(x)$.[10] 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.[11] 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 to substitute goods within a market (say Pepsi vs. Coke) than across markets (soft drinks vs. cars). The CES aggregates are defined as:

$$C = \left[\int_0^J J^{-\frac{1}{\theta}} c_j^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} \quad \text{and} \quad c_j = \left[\sum_{i=1}^{I_j} I_j^{-\frac{1}{\eta}} c_{ij}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \tag{2}$$

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, Eeckhout, and Mongey (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.[12] 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

[10] 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.

[11] The measure J is endogenous, which can adjust such that $M = J \times \mathbb{E}(I_j)$.

[12] 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.

labor L:

$$U(C, L) = C - \overline{\varphi}^{-\frac{1}{\varphi}} \frac{L^{1+\frac{1}{\varphi}}}{1+\frac{1}{\varphi}}, \tag{3}$$

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:

$$\max_{\{c_{ij}\}, L} U(C, L) \quad , \quad \text{s.t.} \quad \int_0^J \left(\sum_{i=1}^{I_j} p_{ij} c_{ij} \right) dj \leq WL + \Omega + \Pi. \tag{4}$$

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 market-level productivity z_j that commonly affects all firms in the same market and which captures technology differences across markets, with $z_j \sim H(z_j)$. When a firm matches with a manager of type x, the firm-specific Total Factor Productivity (TFP) A_{ij} is defined as:

$$A_{ij} = z_j \left[\alpha x_{ij}^{\gamma} + (1-\alpha) z_{ij}^{\gamma} \right]^{\frac{1}{\gamma}}. \tag{5}$$

Both the manager ability x and the firm type z determine the TFP of the firm. The share α measures the importance of the manager relative to the firm type. The expression (5) 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 CEOs and firms are complementary. This CES functional form allows for a flexible specification of the TFP technology. For example, when $\gamma = 0$, the expression (5) 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} by a firm of type z_{ij} with a manager of ability x, the technology that deter-

mines the quantity of output y_{ij} as a function of inputs of production labor is linear:

$$y_{ij} = A_{ij} l_{ij}. \tag{6}$$

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: $\{x, z_{ij}, z_j\}$. 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:

$$\max_{x_{ij}} \pi_{ij} = \widetilde{\pi}_{ij}(A_{ij}|A_{-ij}) - \omega\left(x_{ij}\right), \tag{7}$$

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 (7), that the profit of the firm ij depends not only on its own TFP A_{ij} but also on the types of its competitors, A_{-ij}.[13] 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 z_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 their rivals in the same market.[14] Given the production technology (6), the firms make production decisions to maximize gross profits:

$$\max_{l_{ij}} \widetilde{\pi}_{ij} = p_{ij} y_{ij} - W l_{ij}, \tag{8}$$

subject to the production technology (6) and (5). 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 (7) of the matching game, taking as given the stage two subgame, which includes prices p_{ij}, the wage W, and

[13] 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.

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

allocations l_{ij} that solve (8) 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 (4) yields:*

(a) Goods demand function:

$$y_{ij} = \frac{1}{J}\frac{1}{I_j}\left(\frac{p_{ij}}{p_j}\right)^{-\eta}\left(\frac{p_j}{P}\right)^{-\theta} Y, \tag{9}$$

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:

$$L = \overline{\varphi} W^{\varphi}. \tag{10}$$

Proof. See Appendix B.1. ■

We now turn to the firm's optimal production decision. The profit maximization problem (8) yields the first order condition:

$$p_{ij}(y_{ij})\left[1 + \frac{dp_{ij}}{dy_{ij}}\frac{y_{ij}}{p_{ij}}\right]\frac{dy_{ij}}{dl_{ij}} = W \quad \Leftrightarrow \quad p_{ij}\underbrace{\left(1+\varepsilon_{ij}^{P}\right)}_{\mu_{ij}^{-1}} A_{ij} = W. \tag{11}$$

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 (11). 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:

$$\mu_{ij} = \left[1 - \frac{1}{\theta}s_{ij} - \frac{1}{\eta}\left(1 - s_{ij}\right)\right]^{-1}, \tag{12}$$

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 (12) 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 (12), 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:

$$y_{ij} = \frac{1}{J}\frac{1}{I_j}\left(\frac{p_{ij}}{p_j}\right)^{-\eta}\left(\frac{p_j}{P}\right)^{-\theta} Y, \quad l_{ij} = \frac{y_{ij}}{A_{ij}}, \quad \text{and} \quad \widetilde{\pi}_{ij} = (\mu_{ij} - 1)Wl_{ij}. \tag{13}$$

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 as follows:

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 changing 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 (5) 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.[15]

After determining the stable matching Γ, we solve the equilibrium salary schedule, $\omega(x)$. The firms' stage 1 optimization problem (7) yields the FOC:

$$\frac{\partial \widetilde{\pi}_{ij}}{\partial A_{ij}} \frac{\partial A_{ij}}{\partial x_{ij}} - \frac{d}{dx}\omega(x_{ij}) = 0. \tag{14}$$

The marginal revenue of hiring a higher ability manager equals the marginal cost. Solving this differential equation (14) gives us the equilibrium manager pay.

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

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

where ω_0 is the reservation utility that determines the wage for the lowest-type CEO.

The proposition 1 gives us 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 reservation utility) will increase 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 (13). First, 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.

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

[15] 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).

theorem on the FOC (11), we can derive the markup elasticity of TFP:

$$\varepsilon_{ij}^{\mu} := \frac{\partial \mu_{ij}}{\partial A_{ij}} \frac{A_{ij}}{\mu_{ij}} = \underbrace{\left[\frac{(\eta-1)\left(1-\phi_{ij}\right)}{1+(\eta-1)\left(\frac{1}{\theta}-\frac{1}{\eta}\right)\mu_{ij}s_{ij}}\right]}_{\frac{\partial s_{ij}}{\partial A_{ij}}\frac{A_{ij}}{s_{ij}},\ \downarrow \text{ in } A_{ij}} \times \underbrace{\left[\left(\frac{1}{\theta}-\frac{1}{\eta}\right)\mu_{ij}s_{ij}\right]}_{\frac{d\mu_{ij}}{ds_{ij}}\frac{s_{ij}}{\mu_{ij}},\ \uparrow \text{ in } A_{ij}} \in [0,1)\,, \tag{15}$$

where

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

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 (12). 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:

$$\varepsilon_{ij}^{l} := \frac{\partial l_{ij}}{\partial A_{ij}} \frac{A_{ij}}{l_{ij}} = \phi_{ij} \underbrace{\left[\theta-1\right]}_{\text{Monopoly}} + \left(1-\phi_{ij}\right) \underbrace{\left[\frac{\eta}{1+\left(\frac{1}{\theta}-\frac{1}{\eta}\right)(\eta-1)\,\mu_{ij}s_{ij}}-1\right]}_{\text{Strategic interaction, } \downarrow \text{ in } A_{ij}}, \tag{16}$$

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 employment elasticities of TFP are given by equation* (15) *and* (16)*, 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 employment elasticity first decreases with sales share, then increases, with*

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

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

Proof. See Appendix B.3 for derivation and a duopoly example. ■

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 using Simulated Method of Moments in this part. We first map our theory to the data by generalizing the production function in Section 4.1. In Section 4.2, we parametrize the model. Section 4.3 documents the strategy we implement to solve the matching problem. 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 General 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:

$$y_{ij} = A_{ij} \left(l_{ij} + m_{ij}\right)^{\zeta} k_{ij}^{1-\zeta}. \tag{17}$$

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* (17) *can be equivalently expressed by a labor-only production function:*

$$y_{ij} = \widehat{A}_{ij} l_{ij} \quad , \quad \text{where} \quad \widehat{A}_{ij} := \frac{1}{\psi}\left[\frac{W/\zeta}{R/(1-\zeta)}\right]^{\zeta} A_{ij}, \tag{18}$$

which incurs a constant marginal cost:

$$mc_{ij} = \frac{1}{\psi}\frac{1}{\zeta}\frac{W}{\widehat{A}_{ij}}. \tag{19}$$

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 (19) 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 (17) 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.

4.2 Parametrization

We assume that $F(x_{ij})$, $G(z_{ij})$, and $H(z_j)$ are lognormally distributed. This rules out any negative realizations and has been shown to be consistent with the productivity distribution in the data.[16] Without loss of generosity, we normalize the mean of all the types to one and capture the TFP level by an economy-wide constant $\overline{A}$. Therefore, we can rewrite the TFP function (5) as:

$$A_{ij} = \overline{A} z_j \left[\alpha x_{ij}^{\gamma} + (1-\alpha) z_{ij}^{\gamma}\right]^{\frac{1}{\gamma}}, \tag{20}$$

where

$$\log x_{ij} \sim \mathcal{N}\left(-\frac{\sigma_x^2}{2}, \sigma_x^2\right) \quad , \quad \log z_{ij} \sim \mathcal{N}\left(-\frac{\sigma_z^2}{2}, \sigma_z^2\right) \quad , \quad \log z_j \sim \mathcal{N}\left(-\frac{\sigma_{z_j}^2}{2}, \sigma_{z_j}^2\right). \tag{21}$$

All types are assumed to be drawn independently.

To mimic the continuum of markets in the simulation, we set the number of firms equal to $50,000$ so

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

that J is large enough.[17] Furthermore, we assume that the number of firms in each market, I_j, is random to capture the heterogeneity across market 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 $[1, 10]$.[18]

Table 1: Endogenous, estimated parameters

	Parameter	Meaning
I. Firm	σ_z	Firm type $\log z_{ij} \sim \mathcal{N}\left(-\sigma_z^2/2, \sigma_z^2\right)$
	σ_{z_j}	Market type $\log z_j \sim \mathcal{N}\left(-\sigma_{z_j}^2/2, \sigma_{z_j}^2\right)$
	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	
II. Manager	σ_x	Manager type $\log x_{ij} \sim \mathcal{N}\left(-\sigma_x^2/2, \sigma_x^2\right)$
	γ	The elasticity of substitutes between manager and firm type
	α	The importance of manager relative to firm type
	ω_0	Manager's reservation utility
III. Aggregates	$\overline{A}$	Aggregate TFP level
	$\overline{\varphi}$	Aggregate labor supply level
	ψ	Factor share: labor in labor + material, or material supply

To summarize, Table 1 lists the endogenous parameters that we estimate. They are organized in three categories: I. Firm; II. Manager; III. 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 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. Finally, given the Cobb-Douglas specification (17), the elasticity ζ is equal to the input share at equilibrium, so we compute it directly from the Compustat data.

4.3 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

[17] 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 $J \to +\infty$.

[18] 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, Eeckhout, and Mongey (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

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.[19] 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 manager $\overline{x} = 1$: $d\widetilde{\pi}_{ij}/dx_{ij}|_{\overline{x}=1}$.

(b) Construct the PAM allocation between the manager types x and firm's conditional profitability, $d\widetilde{\pi}_{ij}/dx_{ij}|_{\overline{x}=1}$. That is, a high-type manager matches the firm with high $d\widetilde{\pi}_{ij}/dx_{ij}|_{\overline{x}=1}$.

In Appendix C.1 we verify the efficiency for a smaller sample with 100 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.

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

[19] 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.

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 three groups, those corresponding to the firm, to the manager, 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. Next, we motivate our choice of the targeted moments. We also refer further to Appendix C.2 and Appendix C.3, where we report the comparative statics predictions how the parameters affect the selected model moments.

Table 3: Targeted Moments

		Moment	Key Parameter(s)
I. Firm	Average markup	$\mathbb{E}(\mu_{ij})$	m_I
	Variance markup (between)	$\mathbb{V}(\log \mu_j)$	σ_I
	Variance markup (within)	$\mathbb{V}(\log \mu_{ij}\|j)$	σ_z
	Variance Sales	$\mathbb{V}(\log r_{ij})$	σ_{z_j}
II. Manager	Average salary share	$\mathbb{E}(\log \chi_{ij}) := \mathbb{E}(\log \frac{\omega_{ij}}{r_{ij}})$	α
	Correlation Salary-Sales	$\mathbb{C}(\log \chi_{ij}, \log r_{ij})$	γ
	Variance Salary Share	$\mathbb{V}(\log \chi_{ij})$	σ_x
	Salary share bottom 10%	$\mathbb{E}(\log \chi_{ij}\|p10)$	ω_0
III. Aggregates	Average worker's wage	$\mathbb{E}(W)$	$\overline{A}$
	Average employment	$\mathbb{E}(l_{ij})$	$\overline{\varphi}$
	Average manager salary	$\mathbb{E}_x(\omega(x))$	ψ

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.

I. Firm. There is a systematic relationship between the average markups and the number of firms in each market. This implies markups increase monotonically as the average number of firms in the market m_I decreases. But number of firms in each market also affects the distribution of markups. Because the number of firms differs in different markets, the variance in the number of firms *across* markets σ_I therefore monotonically determines the variance of markups *across* markets μ_j. The variance of markups *within* each market μ_{ij} is in turn determined by the variance in firm type σ_z.[20] Finally, the difference in TFP levels *between* markets measured by σ_{z_j} creates heterogeneity in the sales distribution. Targeting this moment allows us match the firm size distribution in the data, which is one of the key elements that ultimately determine executive compensation.

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

II. Manager. We motivate our choice of moments on the manager side by executive compensation and how they are determined by the key manager parameters. Under the CES technology function (5), we can write the elasticity of gross profits with respect to TFP:

$$\frac{\partial \widetilde{\pi}_{ij}}{\partial A_{ij}} \frac{A_{ij}}{\widetilde{\pi}_{ij}} = \left(\frac{\partial \widetilde{\pi}_{ij}}{\partial A_{ij}} \frac{A_{ij}}{\widetilde{\pi}_{ij}} \right) \times \overbrace{\left[\underbrace{\alpha \left(\frac{x_{ij}}{A_{ij}} \right)^{\gamma}}_{\frac{\partial A_{ij}}{\partial x_{ij}} \frac{x_{ij}}{A_{ij}}} + \underbrace{(1-\alpha) \left(\frac{z_{ij}}{A_{ij}} \right)^{\gamma}}_{\frac{\partial A_{ij}}{\partial z_{ij}} \frac{z_{ij}}{A_{ij}}} \right]}^{1}, \tag{22}$$

which gives us an intuitive way to see the payoff share of managers. 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 (see for example Becker, 1973). The bigger α is, the more managers get. We therefore use the average log share of manager salary out of total sales which we define as:

$$\chi_{ij} := \frac{\omega_{ij}}{r_{ij}} \quad \text{and} \quad r_{ij} := p_{ij} y_{ij}.^{21} \tag{23}$$

While α pins down the average salary share of the manager, the salary share is not constant. In fact, in our model, this is the case when γ is non-zero. We use the correlation between manager salary shares and sales to inform us about the elasticity of substitution, γ.[22] The variance of the manager salary share χ_{ij} is directly affected by the standard deviation of the manager ability type, σ_x. Finally, the reservation utility ω_0 shifts the salaries of all managers by a constant. By construction, however, this constant influences the χ_{ij} more for small firms than for large ones. We use the average $\log \chi_{ij}$ of firms within the bottom 10% to identify ω_0.[23] Figure 3 shows the logic of our choice of parameters by plotting the relationship between $\log \chi_{ij}$ and $\log r_{ij}$ when each of the parameters $\{\alpha, \gamma, \sigma_x, \omega_0\}$ change.

III. 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, $\{\overline{A}, \overline{\varphi}, \psi\}$, to match the worker-level average wage, firm-level average employment, and average executive compensation: in the model, aggregate TFP $\overline{A}$ is of the order of magnitude of the wage, $\overline{\varphi}$ is the intercept of the labor supply (in log), and ψ adjusts the level of the manager's compensation. Thanks to our constant return to scale setup, any change in these three parameters will *not* influence the distribution of the model, which includes the eight moments

[21] Since χ_{ij} follows a lognormal distribution in the data (see Figure A.2), we will always use $\log \chi_{ij}$ to construct targeted moments.

[22] As we will see below, this correlation coefficient is significantly negative in the data, which suggests that the CES technology with strong complements is more plausible than the Cobb-Douglas specification.

[23] The results are robust when we choose a different percentiles such as the bottom 5% or 25%.

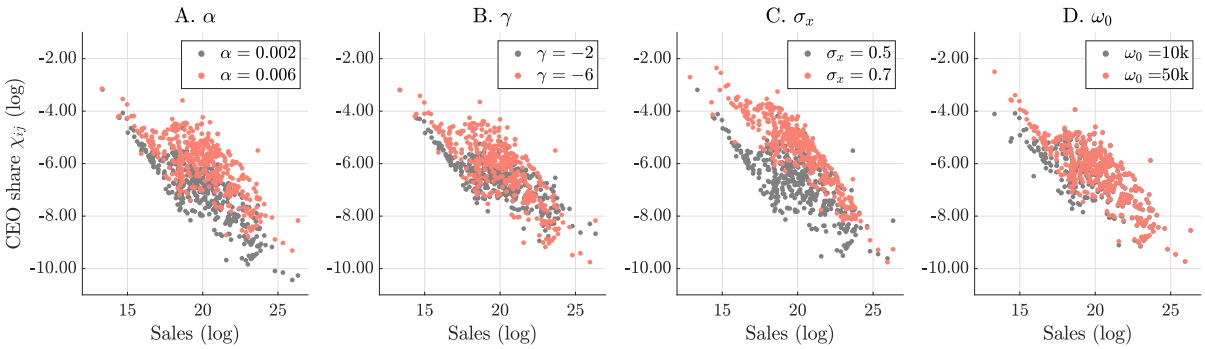


Figure 3: The identification of manager parameters

Notes: We plot log sales ($\log r_{ij}$) on the x-axis and log CEO shares ($\log \chi_{ij}$) on the y-axis. To make the scatter plot clear, the number of markets J is set to 100. Points with different colors represent for firms in different economy. The baseline parameter is the estimates in 1994.

mentioned before. Therefore, this rescaling process to match the aggregates can be carried out *after* the estimation of the parameters the correspond to the firm and to the manager. For more details, see Appendix C.4.

4.5 Estimation results

We present the quantitative results of our estimation. Figure 4 shows the performance of the estimates for I. Firm and II. Manager. The model moments fit the data quite well. The corresponding estimated parameters are displayed in Figure 5 and 6. Figure 7 and 8 present the estimation of model aggregates.

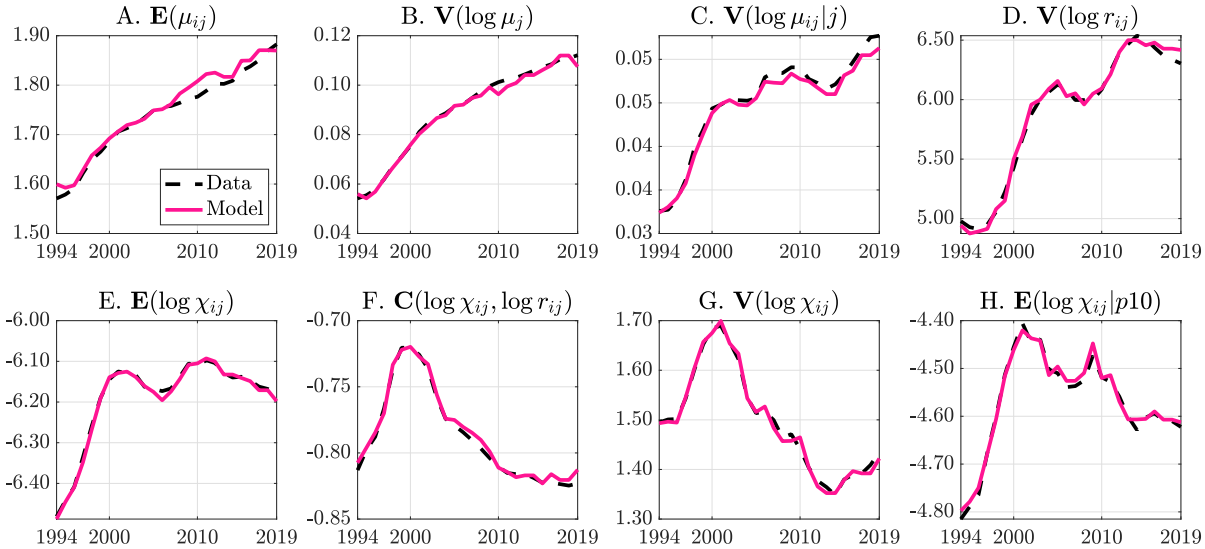


Figure 4: Targeted moments: I. Firm; and II. Manager

Notes: Data moments are computed annually and we apply a five-year centered moving average. Moments A to D are generated from Compustat sample, while moments E to H are from ExecuComp sample. The latter one is a sub-sample of the former one. We target these smoothed moments in the estimation of the model.

I. Firm Figure 5 reports the estimated parameters for the firm $\{m_I, \sigma_I, \sigma_z, \sigma_{z_j}\}$ 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 is steadily declining, suggesting that there is less competition overall. Second, the dispersion in the number of competitors σ_I is also decreasing. 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, Larkin, and Michaely, 2016; De Loecker, Eeckhout, and Mongey, 2021).

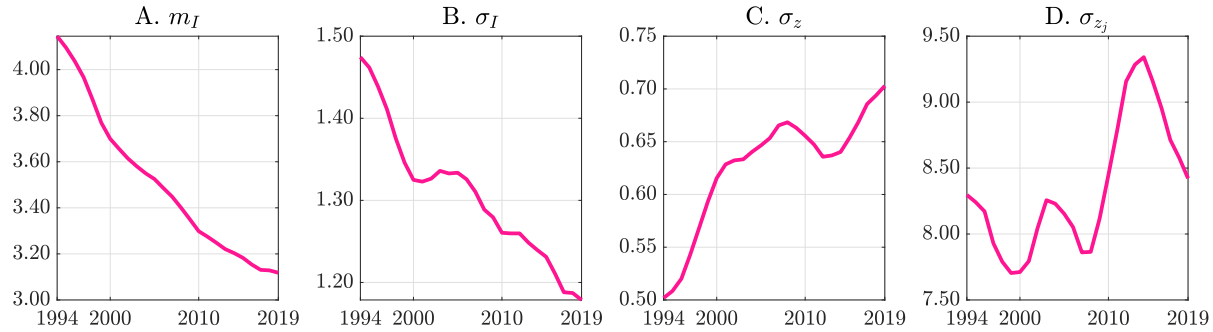


Figure 5: Parameters: I. Firm

Notes: The parameters plotted are five-year moving averages. Panel A and B report the mean and standard deviation of I_j *after* truncation and rounding.

The results of our estimation also suggest an increasing dispersion in firm type, with its standard deviation σ_z increasing from 0.49 to 0.71. This change mainly contributes to the increase in the variance of the log markups within and between markets, as well as the variance of log sales.[24] 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).

Finally, we also document an increasing heterogeneity in technology between different markets. This evolution further contributes to the increase in the variance of log sales. The high value of σ_{z_j} indicates that there is a tremendous difference across markets, which is in line with out expectations. Aggregating across widely different sectors implies there are huge productivity differences, say between labor-intensive sectors such as retail and sectors such as biotech. The variance across sectors appears to be increasing somewhat, especially after the Great Recession.

II. Manager. Next we report the parameters that correspond to the manager, $\{\alpha, \sigma_x, \gamma, \omega_0\}$. When interpreting these estimation results, note that the firm parameters also influence the moments that involve

[24] De Loecker et al. (2021), using a model with entry estimated on the same Compustat data, and Deb et al. (2020), using US Census data, document the same trend using different methodologies

the manager salary share. For example, an increase in the variance of the firm type influences the distribution of the manager's salary χ_{ij}.[25]

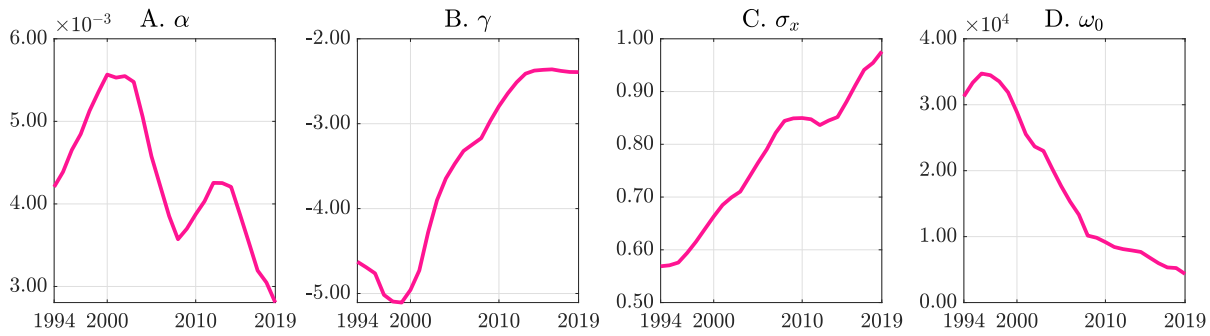


Figure 6: Parameters: II. Manager

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

Estimates of α are minuscule all the time, which means managers only marginally influence firms. This result is consistent with Gabaix and Landier (2008), who show that CEOs make only a small difference on firms. However, our interpretations differ. In their setting, the small impact CEOs 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 peaks in 2000 but then drops, which aligns with Bertrand (2009) that the bull market of the 1990s generated a larger demand for top-quality managers. The general trend is that managers are losing importance over time.

As with the variance in firm type, we also document a growing dispersion in manager ability. The standard deviation, σ_x, increases from 0.56 to 0.97 from 1994 to 2019. Furthermore, our quantitative results show that the dispersion in manager is substantially smaller than the total dispersion in firm type $\sigma_z + \sigma_{z_j}$ as in Gabaix and Landier (2008). This comparison is important because the relative size between types of managers and firms determines the role of γ. The estimated elasticity of substitution γ is becoming less negative, meaning that the types x and z become less complementary over time.

Finally, we estimate a small and decreasing reservation utility ω_0, falling from \$30.6 thousand to \$5.13 thousand. Given the reservation utility is so low relative to the executive salaries, the reservation utility has no impact on model salary, and ω_0 is therefore effectively close to zero.

III. Aggregates. In order for our model to match the average employee, the average unskilled wage, and the average executive compensation in the data, we scale the economy by aggregates $\{\overline{\varphi}, \overline{A}, \psi\}$. Figure 7 reports the aggregated data we are using. Over time, the average number of production workers

[25] In Appendix C.5, we consider a counterfactual world where only the parameters on the firm side change.

grows from 16.9 thousand to 25.1 thousand, 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. 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. Finally, the average executive compensation doubles from \$3.34 million to \$6.96 million.

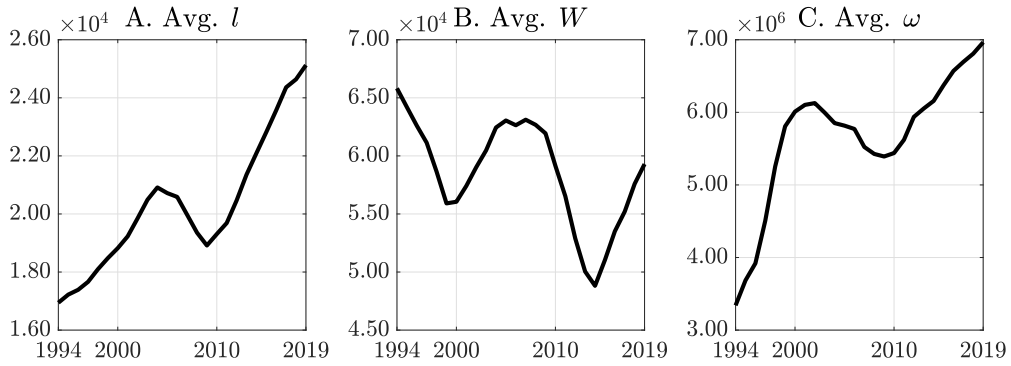


Figure 7: Data and model: aggregates

Notes: We compute the aggregates from ExecuComp sample to make our model results comparable to the CEO data. The first panel plots the average number of employees at firm level. Panel B plots the worker-level average wages. Panel C plots the CEO level average compensation. All of them are plotted in five-year moving average.

Figure 8 reports our estimates for the parameters $\{\overline{\varphi}, \overline{A}, \psi\}$. The labor supply parameter, $\overline{\varphi}$, is determined by the employment L and wage W and generally increases over time. The TFP level $\overline{A}$, which matches the wage level, is generally increasing, confirming TFP growth even if wages of production workers are falling. Finally, the supply of material, ψ, is adjusted to match the level of Manager Pay. These set of aggregate parameters exactly match the levels of the model's moments to the data.

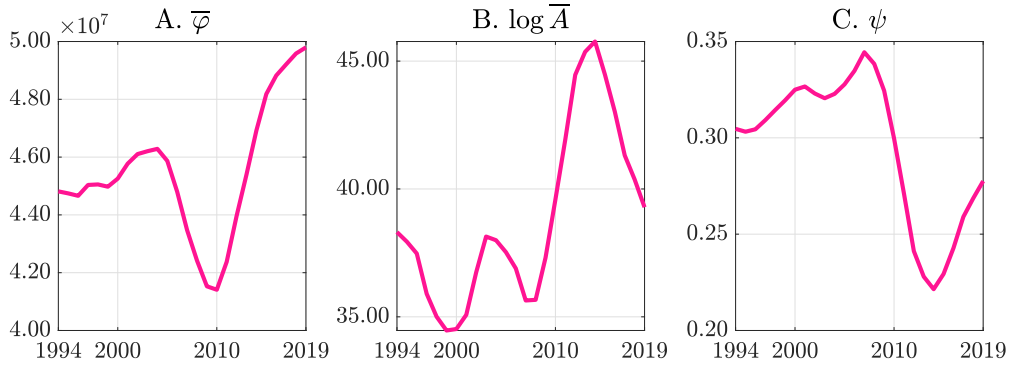


Figure 8: Parameters: aggregates

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

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 later. Because the results are robust in different years, we will take the year 2019 as an example throughout this part.

Figure 9 shows the correlation between managers' types x_{ij} on the one hand, and firm type z_{ij},, market productivity z_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.[26] The latter 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 more sales

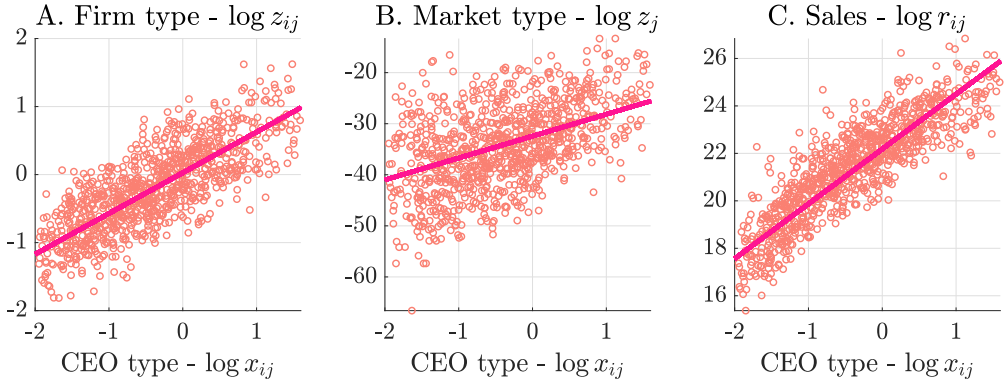


Figure 9: Matching: managers and firms (2019)

Notes: As there are a larger number of CEOs in our model each year, we randomly select 1,000 representative of them to plot in this figure. The solid line is the linear prediction from OLS.

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}, that is, equation (15) and (16). Figure 10 shows that the markup elasticity generally increases with manager type, which means that a high-type manager will contribute more to the corresponding firm's markup. In contrast, the employment elasticity is decreasing in manager type and may even be negative for top CEOs. Top managers in top firms hire less labor, which is consistent with the lower labor shares in superstar firms (see Autor, Dorn, Katz, Patterson, and Van Reenen (2020), De Loecker et al. (2020). These different elasticities drive the heterogeneity in salaries between manager types, a topic we further elaborate on in Section 5.3.

[26]The spearman rank correlation coefficient for each of these dimensions are 0.80, 0.52, and 0.88, respectively.

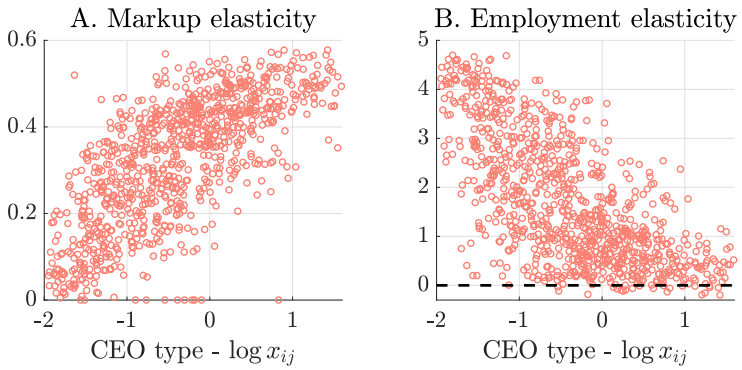


Figure 10: Matching: managers and elasticities (2019)

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. First, in Section 5.1 we detail this decomposition derived in Proposition 1. Second, we further analyze in Section 5.2 the contribution of different primitive parameters to Manager Pay through each of these two channels: 1. $\{\gamma, \alpha, \sigma_x\}$ for managers; 2. $\{\sigma_z, \sigma_{z_j}, \overline{A}\}$ for firms; 3. $\{m_I, \sigma_I\}$ for market structure; 4. $\{\overline{\varphi}, \psi\}$ for inputs supply. Finally, 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.

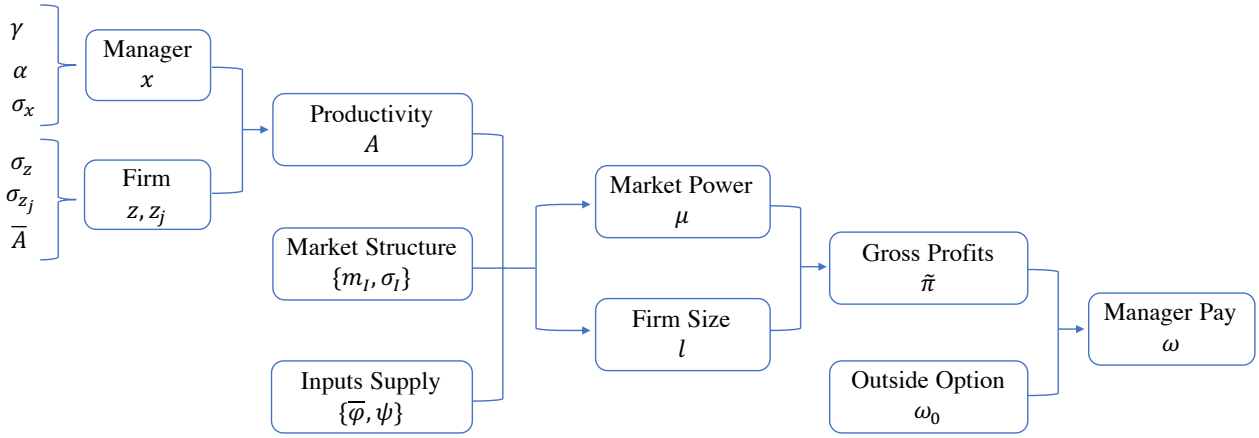


Figure 11: Determinants of Manager Salaries

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

In Figure 12, we plot the contribution to Manager Pay of each of the channel components. Panel A shows that both market power and firm size effects play important roles in determining executive salaries. On

average, 54.5% of Manager Pay is through the market power channel, while 45.1% is due to firm size. The reservation utility accounts for the remaining 0.4%, which is negligible in this exercise. As Panel B further shows, this share of roughly 55-45 constant, with the market power component rising slightly from 48.7% in 1994 to 54.5% in 2019.

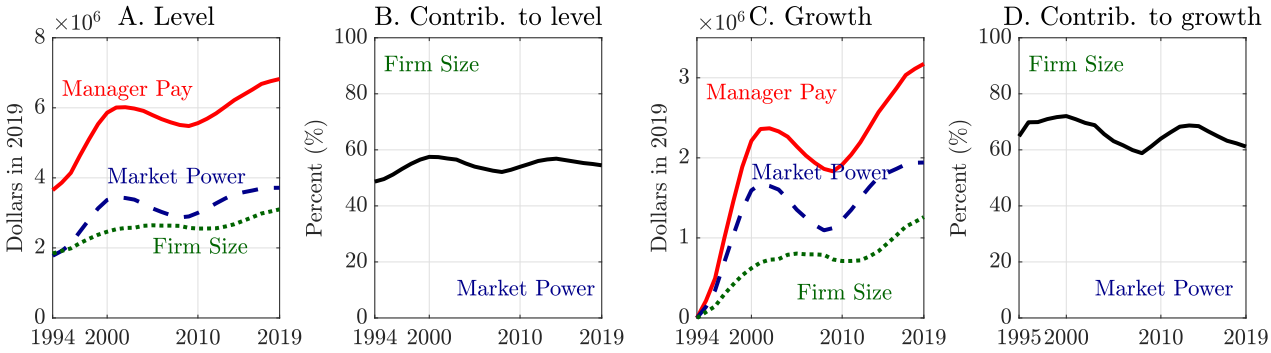


Figure 12: Manager Pay decomposition into Market Power and Firm Size, by year

Notes: The reservation utility also changes across time, but its contribution is negligible. Therefore, we ignore it in this decomposition exercise. 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.

With the average Manager Pay increasing by 87.0%, we can decompose the change 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 \$3.17 million, of which \$1.94 million comes from the increase in market power and \$1.26 million from the firm size effect. Panel D in Figure 12 further shows that 61.2% of the cumulative increase in executive compensation over this period is through the increase in market power.

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 percentage 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 panel A of Figure 13, the baseline is the gross change in the market power component, i.e., the blue, dashed line from Figure 12.A, which we decompose into three objects: market

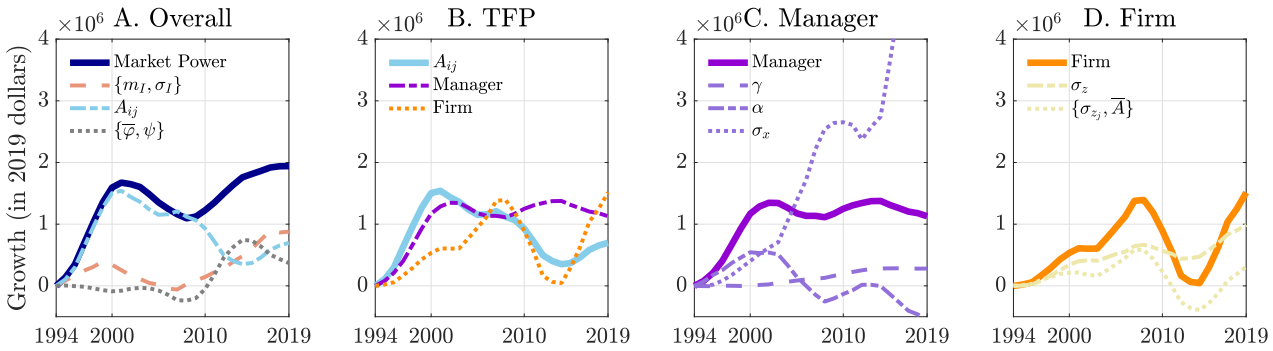


Figure 13: Factor decomposition: market power channel

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 σ_{z_j} and $\overline{A}$ are huge and will neutralize the effects of each other, we bundle these two together in panel D. All lines are plotted in five-year moving average.

structure $\{m_I, \sigma_I\}$, TFP $\{\gamma, \alpha, \sigma_x, \sigma_z, \sigma_{z_j}, \overline{A}\}$, and the inputs supply $\{\overline{\varphi}, \psi\}$. Over the entire time period, these three sets of parameters increase the effect of market power by \$0.88 million, \$0.70 million, and \$0.37 million, which account for 45.3%, 36.1%, and 19.1% of the total growth, respectively. The change in the market structure has the greatest influence because it directly affects the markup of each firm. Moreover, this exercise suggests that prior to 2008, almost all of the increase in the market power channel is due to technological change. After the Great Recession, the contribution of technological progress appears to have slowed down this effect on the market power channel, though it picked up again after around 2014.

We then further decompose the TFP change into the manager component $\{\gamma, \alpha, \sigma_x\}$ and the firm component $\{\sigma_z, \sigma_{z_j}, \overline{A}\}$. Panel B shows that changes from both components have similar impacts on Manager Pay. Specifically, according to panel C, the increase in the variance of manager types, σ_x, is the most important factor driving the market power effect up by \$6.67 million, which is 343% of the total growth. However, this exorbitant effect is neutralized by the opposing effect from γ. On the other hand, the increase of σ_z contributes 51.1% of the market power channel, which is the main force of the change from the firm side.

Firm Size channel. We then do the same decomposition for the firm size effect. In Panel A in Figure 14, the baseline is the gross change in the firm size channel, the green, dotted line in Figure 12.A. It's decomposition suggests that the changes in market structure, TFP, and inputs supply have similar impacts on the firm size effect. In general, they will lead to an increase in this channel by \$0.56 million, \$0.52 million, and \$0.38 million, which account for 44.6%, 41.6% and 30.3% of the total change, respectively. Again, we find that until 2008, the main source of change comes from the technological change. The shift

in inputs supply has the same effect as in the market power channel because it influences the economy only through the aggregates.

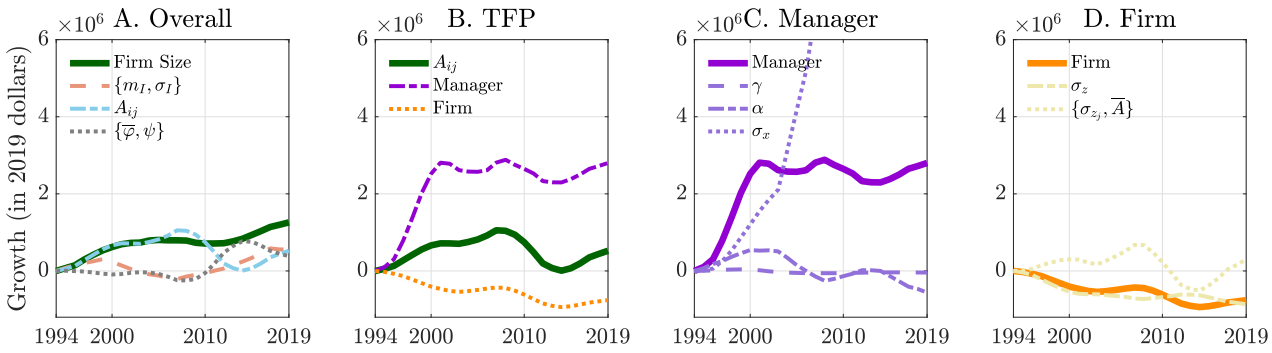


Figure 14: Factor decomposition: firm size channel

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 firm size component in the executive compensation. We choose the level at 1994 as the reference point and plot the cumulative change from this point in each counterfactual economy. Because the changes in σ_{z_j} and $\overline{A}$ are huge and will neutralize the effects of each other, we bundle these two together in panel D. All lines are plotted in five-year moving average.

Moreover, from the subsequent panels, we learn that among TFP change, only the increase in σ_x has a positive effects on this firm size channel. Changes in all other parameters have a marginal or even negative influence on Manager Pay through the firm size channel.

5.3 Heterogeneity among managers

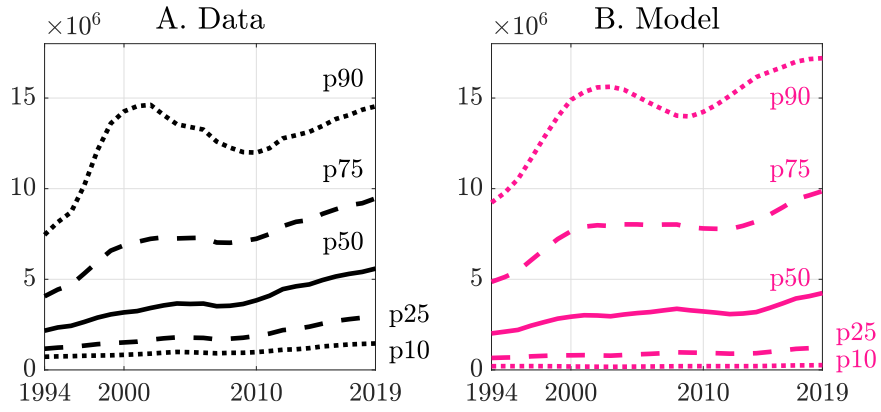


Figure 15: Evolution of Manager Pay for CEOs in different percentiles

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

We now analyze inequality in salaries among managers and how this heterogeneity is determined by each of these two channels. Figure 15 plots 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 a significant difference in the evolution of Manager Pay in different parts of the distribution. 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. Our model captures the characteristic of the changing distribution of Manager Pay remarkably well, in particular for the top half of the distribution which is where most of the change occurs. In this section, we detail how the channels of market power and firm size contribute to the evolution of the distribution.

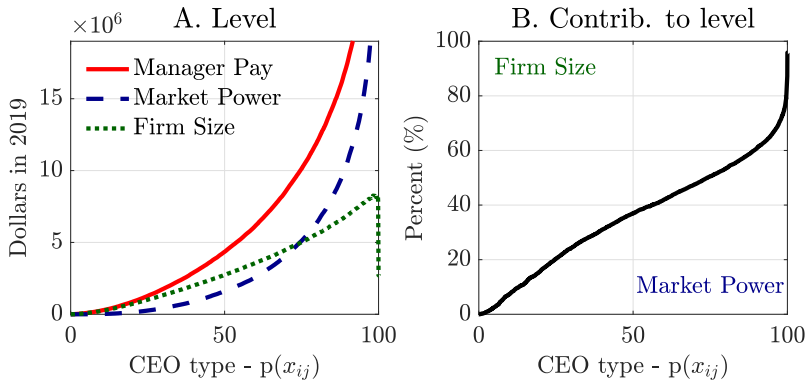


Figure 16: Distribution of Manager Pay and its components in 2019

In the theory, Proposition 2 indicates that for small, low TFP firms, the firm size channel dominates the market power channel, while for larger firms the market power channel dominates. To understand the mechanism, we first analyze heterogeneity in the cross-section. In Figure 16, we plot the salary of each percentile of managers, as well as the corresponding decomposition of the effects of market power and firm size in 2019.[27] The graph shows that the effect of market power channel is more convex than the firm size channel. For the lowest type of managers, almost all of their salary (net of reservation utility) comes from the firm size effect. The market power channel, by contrast, becomes increasingly important when the CEO is more talented. For the top managers, 95.8% of their salaries is due to market power.[28]

We now zoom in on the change in Manager Pay over time. The impact of the market power channel is larger for the top managers, which leads to larger inequality. For the same percentile of managers, Figure 17 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 top managers benefit much more than the low-ranked.[29] Panel B confirms that not just the level, but also the change in Manager Pay is mainly driven by the market power channel for the top

[27] We take the latest year as an example; all the results are robust in other years.

[28] Observe also a peculiar feature of monopolistic 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 (16)) is negative. This insight is also confirmed by Figure 10.

[29] 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, market σ_{z_j}, and CEO σ_x.

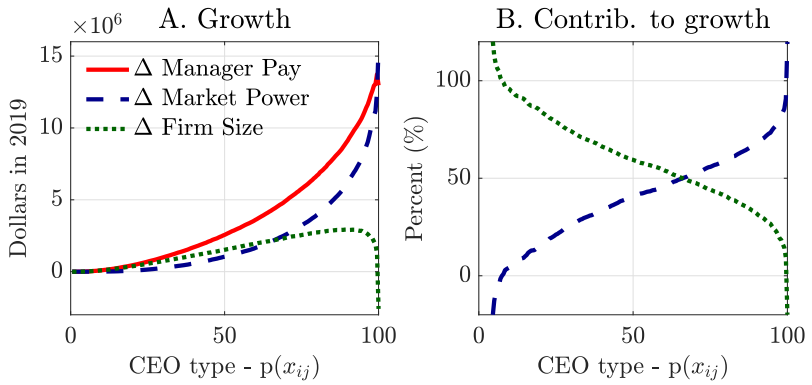


Figure 17: Distribution of differences in Manager Pay and its components from 1994 to 2019

Notes: The Manager Pay for the bottom 3% of CEOs drops from 1994 to 2019, which means our contribution calculation makes no sense there. So we only calculate and plot the contribution of market power and firm size in panel B for the percentile of CEOs who get paid more. Moreover, for simplicity, we adjust for the reservation utility change in this graph, which can have a big influence for CEOs in the left tail.

managers and by the firm size channel for those ranked at the bottom.

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 and that would be more efficient. 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, more than half of pay is due to market power, and 61.2% of growth between 1994 and 2019. Most striking is the fact that there is a lot of heterogeneity among managers. For the top managers, 95.8% 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.

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 by year level, respectively. In both cases, the elasticity of Manager Pay with respect to

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

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

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.

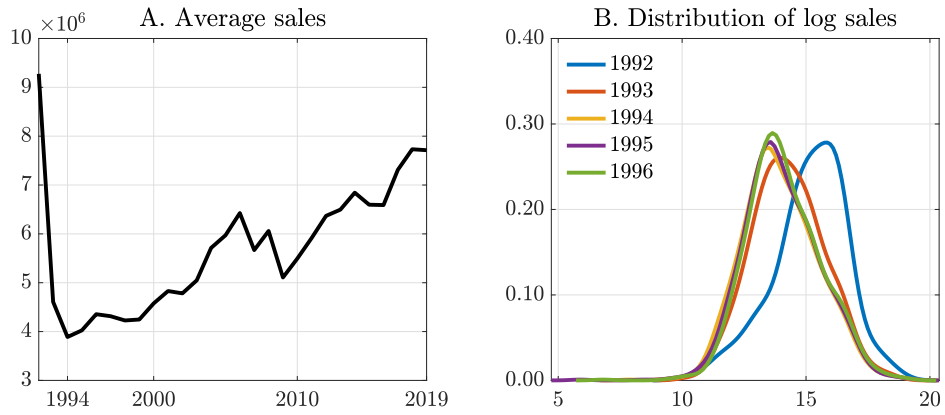


Figure A.1: Sample selection in 1992 and 1993

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}.

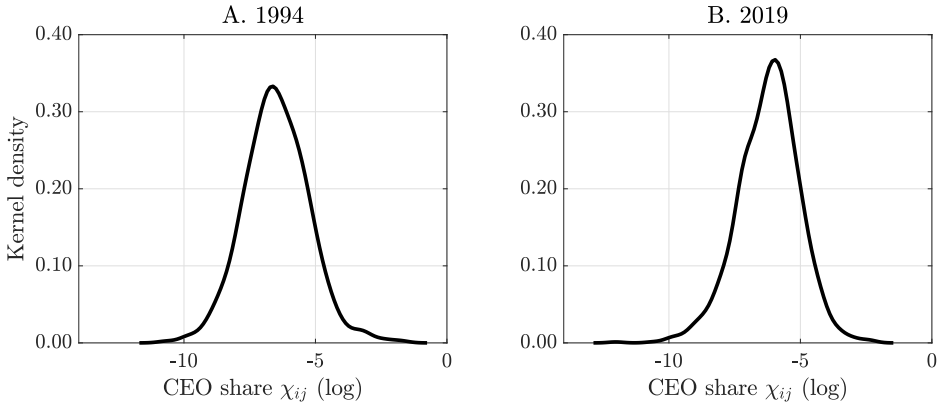


Figure A.2: Normality of log CEO share $\log \chi_{ij}$

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:

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

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:

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

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 term 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:

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

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.

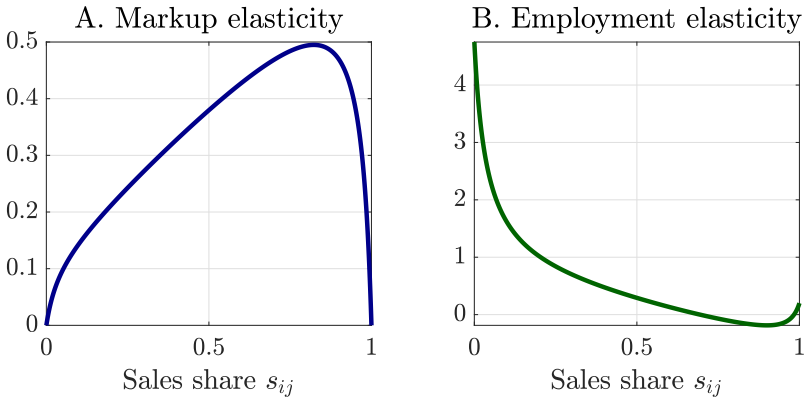


Figure B.1: Markup and employment elasticity of TFP

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:

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

with FOCs:

$$\frac{\partial \mathcal{L}}{\partial l_{ij}} = W - \frac{\lambda_{ij}\zeta}{l_{ij}+m_{ij}}\left[A_{ij}\left(l_{ij}+m_{ij}\right)^{\zeta} k_{ij}^{1-\zeta}\right] = 0, \tag{B.12}$$

$$\frac{\partial \mathcal{L}}{\partial m_{ij}} = P^m - \frac{\lambda_{ij}\zeta}{l_{ij}+m_{ij}}\left[A_{ij}\left(l_{ij}+m_{ij}\right)^{\zeta} k_{ij}^{1-\zeta}\right] = 0, \tag{B.13}$$

$$\frac{\partial \mathcal{L}}{\partial k_{ij}} = R - \frac{\lambda_{ij}(1-\zeta)}{k_{ij}}\left[A_{ij}\left(l_{ij}+m_{ij}\right)^{\zeta} k_{ij}^{1-\zeta}\right] = 0, \tag{B.14}$$

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

$$m_{ij} = \frac{1-\psi}{\psi} l_{ij} \quad \text{and} \quad k_{ij} = \frac{1}{\psi}\frac{W/\zeta}{R/(1-\zeta)} l_{ij}, \tag{B.15}$$

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 100 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 (absolute value) between the exact and approximate matching is 0.05% of the total revenue from the exact matching, and the total pay change (absolute value) is 1.54% of the total Manager Pay, both of which are tiny.

Appendix C.2 Comparative static at firm side

Mean of market structure distribution - m_I. We first look at the effect of m_I, the average number of firms in each market. 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. There is almost no effect of m_I on the

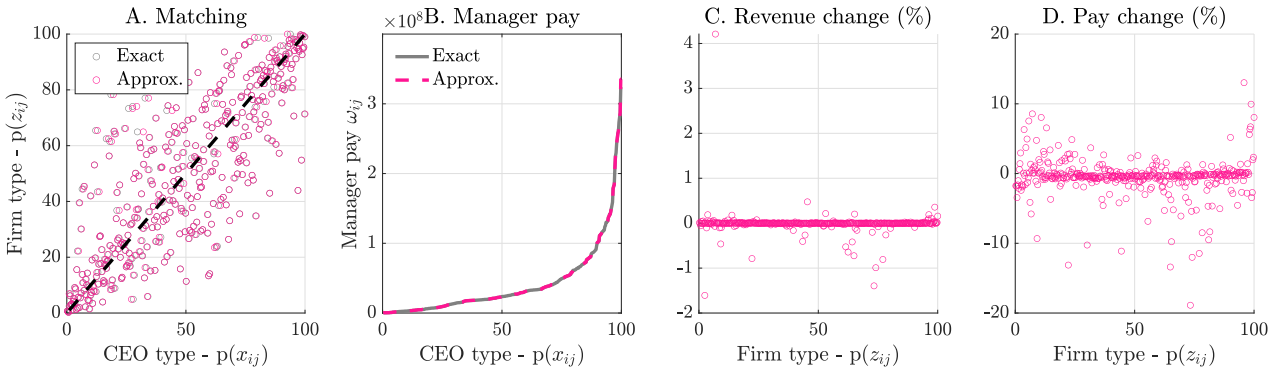


Figure C.1: Comparison: Exact and Approximate Stable Matching

Notes: We set $J = 100$ in this exercise. The set of parameter is taken from the estimates in 1994, 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 CEOs if they can get better off, until all of them satisfy the condition in Definition 1. Panel C and D reports 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.

within-market variance of markups, as the change in I_j influence all firms equally in the same market. Finally, a larger m_I creates some low-concentration markets with many tiny firms, which increases the variance in the firm sales distribution.

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 in the economy. As expected, a larger σ_I leads to a larger between-market variance of markups. Moreover, a larger difference across markets also makes the firm size distribution more dispersed. The effects on the markup level and its within-market variance are negligible.

Firm type - σ_z. The change in standard deviation of the z_{ij} influences both the variance and the level (because the distribution is lognormal) of firm types. First, a larger variance in firm types means it is more likely for all markets to draw superstar firms who exert more market power and charge high markups. This effect will pull the average markup up. Moreover, larger heterogeneity among firms will direct make the markup distribution more dispersed, which increases both the between and within-market variance. Lastly, the larger variance in the firm types distribution will naturally show up in the firm size distribution.

Market type - σ_{z_j}. The last parameter is the standard deviation of the market-level productivity shock, z_j. Since the markups are determined *within* each market according to equation (Appendix B.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_{z_j} will drive the variance of firm size up.

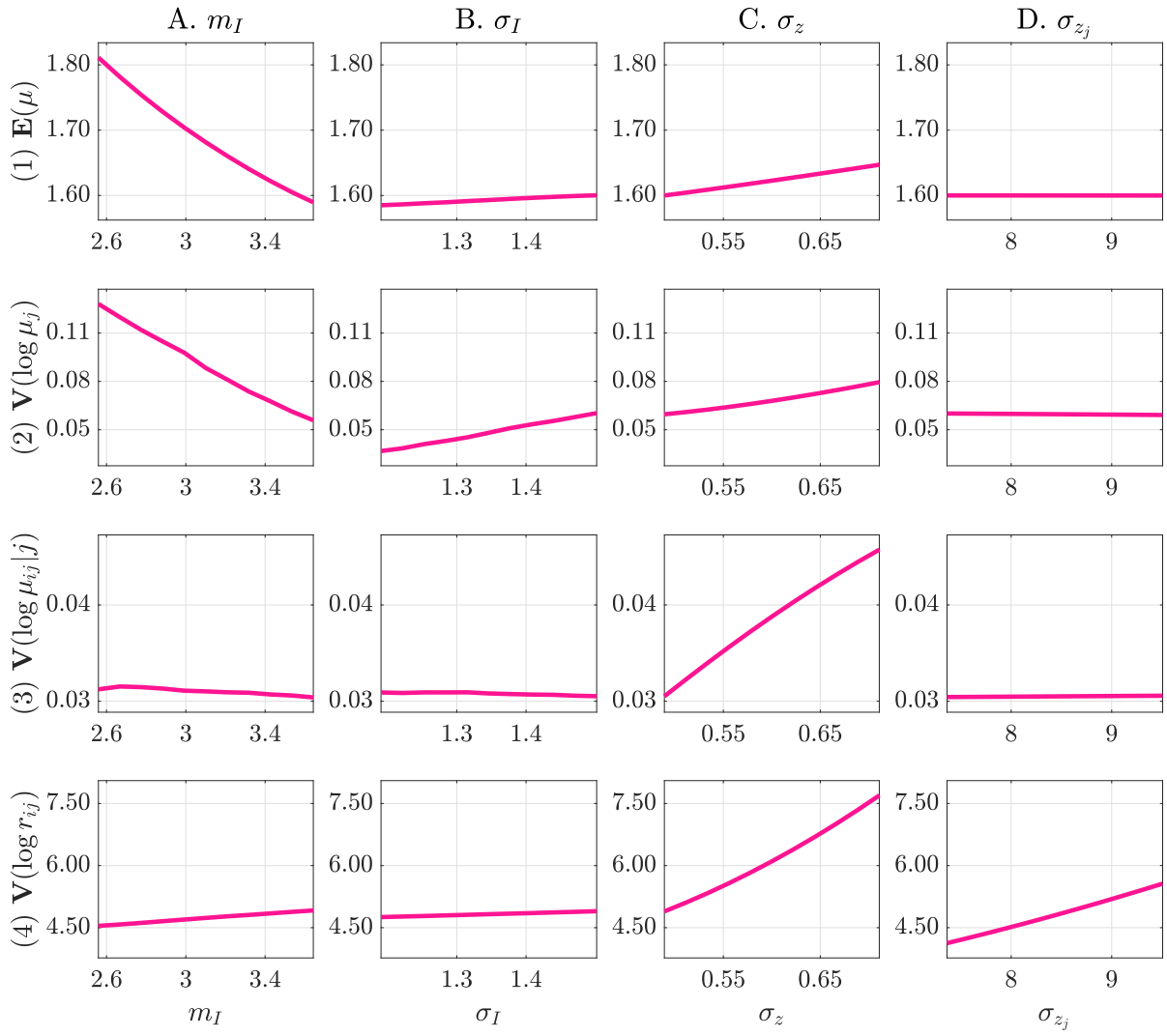


Figure C.2: Comparative static: firm side parameters

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.

Appendix C.3 Comparative static of manager parameters

Importance of managers - α. The importance of the manager is measured by the share of TFP α. Since the estimated α is tiny, changes in α will influence the sales of firms only marginally. As is shown by Proposition 1, an increase in α will proportionally raise the marginal contribution of managers for all firms. The presence of a constant, the reservation utility, in executive pay schedule means that shares of high-type managers will increase more than low-types. The top panel E in Figure 3 confirms with this insight: as α increases, so do manager salaries as a share of sales. An increase in α leads to lower variance of the salary share, an increase (less negative) in the correlation between manager's salary share and sales, and a slightly higher salary share for bottom 10% of firms.

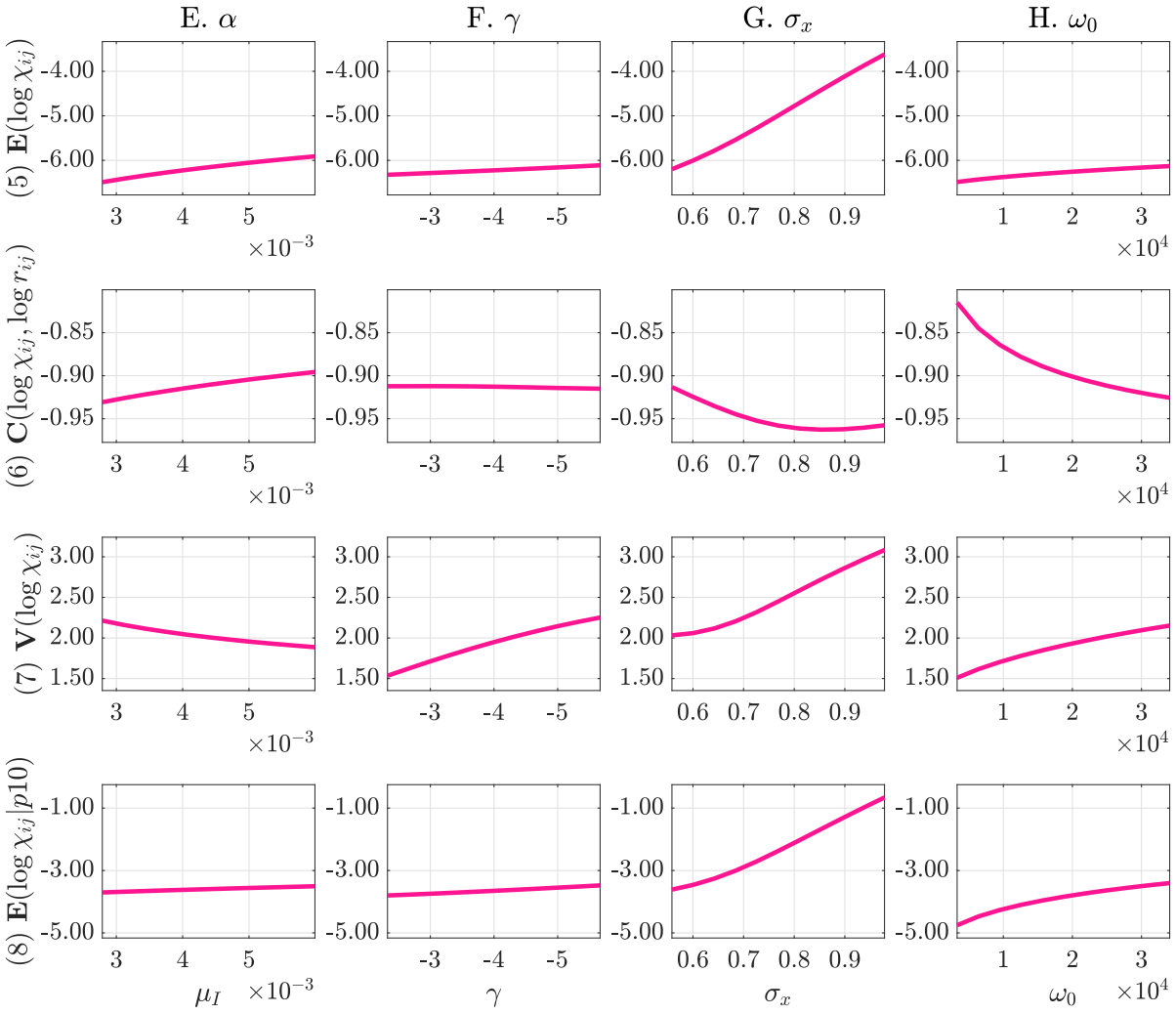


Figure C.3: Comparative static: manager parameters

Notes: In this exercise, we are moving manager parameters and check how the moments respond. In each column, we move only one parameter while fixing 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.

Complementarity - γ. The slope between log manager shares and log sales is flat when $\gamma \to 0$. When $\sigma_x > \sigma_z$, a decline in γ will give low-type managers ($x_{ij} < A_{ij} < z_{ij}$) larger shares while high-type ones ($x_{ij} > A_{ij} > z_{ij}$) smaller shares according to Equation (22), and vice versa. The numerical experiment in panel G of Figure 3 shows this exact idea. In this baseline economy, the dispersion in manager type is larger than the dispersion in firm type, so the more negative γ is, the more different manager shares will be between small and large firms. As a result, the correlation coefficient between these two objects get more negative when γ becomes more negative. This change also means a larger variance in manager shares. As for the level, a lower γ naturally increases the CEO shares for the bottom of firms. Moreover, although the large firms now have lower manager shares, the positive effect on small firms is dominating for the overall change because an increase in low-type manager's salary will also contribute to the

salaries of a better-type manager.

Manager types - σ_x. A larger dispersion in manager ability indicates that managers become more important, which will naturally lead to a higher managerial pay. As the panel F in Figure 3 shows, the managerial salary share will generally increase, while it rises faster for small firms because they have a smaller denominator (i.e., sales). Therefore, an increase in σ_x will increase the mean and variance in CEO shares, as well as make the correlation between CEO share and sales stronger.

Reservation utility - ω_0. Finally, the reservation utility changes nothing but shift the schedule of executive pay vertically. This constant shift in level will become a heterogenous effect in terms of manager share — small firms are, by definition, more vulnerable. In panel D of Figure 3, we see an obvious distinction among small firms but almost no difference among large ones when ω_0 increases from 10k to 50k. For our moments, it means a significant increase for the manager share among bottom of firms. It can also make the correlation between manager share and sales stronger, the variance of manager shares larger, and the overall average of manager share slightly larger.

Appendix C.4 Rescaling

This section documents the way we use the parameters $\{\overline{\varphi}, \overline{A}, \psi\}$ to match the average employee, the average unskilled wage, 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 estimating $\{\sigma_z, \sigma_{z_j}, m_I, \sigma_I, \sigma_x, \gamma, \alpha, \omega_0\}$. Therefore, we can do this rescaling *after* we estimate all those parameters.

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

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

The aggregate level of TFP, $\overline{A}$, can be pinned down by the wage level. For simplicity, denote

$$a_{ij} := z_j \left[\alpha x_{ij}^{\gamma} + (1-\alpha) z_{ij}^{\gamma}\right]^{\frac{1}{\gamma}},$$

which is known to us and gives $A_{ij} = \overline{A} a_{ij}$. 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 manager pay are proportional to $1/\psi$, based on which we can easily find the

right ψ. Finally, equation (B.7) leads to:

$$\frac{W}{P} = \frac{1}{\psi}\left[\frac{W/\zeta}{R/(1-\zeta)}\right]^{\zeta}\overline{A} \times \left[\left(\int_0^1 \left[\frac{1}{I_j}\sum_i \left(\frac{\mu_{ij}}{a_{ij}}\right)^{1-\eta}\right]^{\frac{1-\theta}{1-\eta}} dj\right)^{\frac{1}{1-\theta}}\right]^{-1}, \tag{C.2}$$

from which we can back out the TFP level $\overline{A}$.

Appendix C.5 Counterfactual: the influence from firm side

In this exercise, we fix the CEO-side parameters $\{\alpha, \sigma_x, \gamma, \omega_0\}$ at the estimates in 1994 and change firm-side parameters $\{m_I, \sigma_I, \sigma_z, \sigma_{z_j}\}$ annually. We only report CEO-side moments here, because firm-side moments are almost identical as Figure 4.

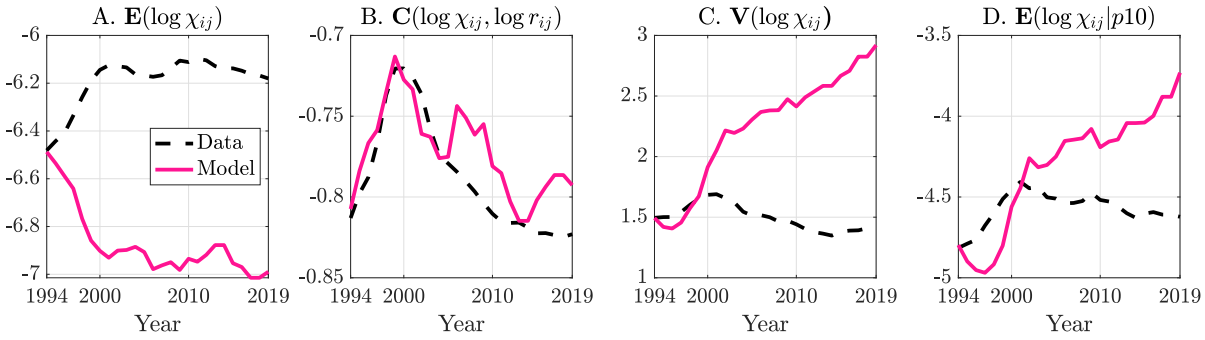


Figure C.4: Counterfactual moments: only change firm-side parameters

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