Manager Pay Inequality and Market Power*

Renjie Bao — Princeton†
Jan De Loecker — KU Leuven‡
Jan Eeckhout — UPF Barcelona§

November 2, 2023

Abstract

Manager pay has increased considerably since 1980, and so has inequality in manager pay. During the same period, there has been a sharp rise in market power. Besides the conventional role of managers to grow firm size and increase productivity, we acknowledge that managers also help firms gain more market power. We model how imperfect competition in product markets affects manager pay, and decompose the contribution to manager pay from firm size and market power. We find that market power contributes on average 45.2% to compensation. Most strikingly, there is significant heterogeneity across managers. Top managers are hired disproportionately by firms with market power, and they get rewarded for it: 80.3% of top manager pay in 2019 was due to market power. Our main conclusion is that the rise of market power is responsible for half of the increase in average manager pay, and for nearly all of the increase in manager pay inequality.

Keywords. Market Power in the Macro Economy. Manager Pay. Executive Compensation. Inequality. Markups. 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. This paper circulated earlier under the title "Are Managers Paid for Market Power?"

†renjie.bao@princeton.edu
‡jan.deloecker@kuleuven.be
§jan.eeckhout@upf.edu – ICREA-BSE-CREI

1 Introduction

Over the past four decades, there has been a significant increase in manager pay. Successful managers make other workers under their span of control more productive, and firms are willing to pay a premium to attract them. As firms grow larger and more profitable, the impact of managers becomes increasingly valuable, as their decisions have far-reaching consequences in the organization. In a competitive labor market, this leads to higher manager pay, which is the seminal insight of Gabaix and Landier (2008) and Terviö (2008) that the rise of the firm size can explain the increase in manager pay.

In this paper, we build on the insights from this literature by shedding new light on the microfoundation of how managers contribute to profitability. In addition to firm size, market power makes firms more profitable, both of which affect manager pay. Recent work documents that in the last four decades, there has been a rise in market power, and this evolution coincides remarkably with the rise in manager pay (see Figure 1, panel A and B, below).[1] Pay was relatively stable until the 1980s, when it started to rise sharply, more than doubling between 1994 and 2019. In addition to the increase in average compensation, there is a sharp increase in manager pay inequality, mainly driven by the longer and fatter right tail indicating an especially stark increase of pay for top managers (see Figure 1, C and D). We observe a similar pattern for markups: the variance of the markup distribution increases. We ask whether managers pay is not only determined by firm size, but also by market power, and analyze how do these two mechanisms jointly determine the distribution of manager pay over time.

Our objective is to decompose the sources of manager pay due to market power and those due to firm size. We seek to understand whether firms with market power pay managers higher salaries because of their ability to increase sales, or whether managers are able to extract some of the rents created by market power.[2] To examine the underlying mechanisms, we assume that markups and firm size are determined in an imperfectly competitive environment. There is strategic interaction in which oligopolistic firms exercise market power in the goods market, and managers are hired to contribute to their firms' productivity and hence their profits. Therefore, high managerial salaries are not only the result of large firm size but also reflect the competitive pressure on firms to gain market power by attracting top managerial talent.

Empirically, it is difficult to distinguish how market power and firm size affect manager pay. Firms that have more market power are usually bigger in size. But firms can also be big because they have better technologies.[3] The correlation between markups and manager pay therefore does not elucidate our understanding of the causal determinants, due to, amongst other, reverse causality and omitted-variable bias. The complexity of the relationship between market power, firm size, and executive pay underscores the importance of using structural methods to disentangle these effects.

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

[2] For tractability, in the baseline analysis we abstract from the role of agency and incentive pay, which has contributes to manager pay as well. In Appendix B.4 we extend the model as in Edmans and Gabaix (2011) to allow for incentive pay and show that agency problems, while relevant, do not alter the insights about the effect of market power on manager pay (see also the discussion in Section 3.2).

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

We therefore build a model with a small number of competitors in each market, in an economy with many of these small markets as in Atkeson and Burstein (2008). In these markets, the distribution of productivities among firms and the number of competitors determine the degree of market power. In line with the standard theory of oligopolistic competition, fewer competitors and more dispersed productivities lead to more market power. The distribution of market power is uneven, with more productive firms competing by offering lower prices, which yields a higher market share. However, due to *incomplete pass-through* of cost savings, these productive firms do not fully pass on all their productivity gains to the customer, resulting in higher markups and increased profits.

And here comes in the role of the manager. Managers raise the productivity of firms in the sense of Lucas (1978) span of control.[4] As in the canonical matching model of Gabaix and Landier (2008) and Terviö (2008), total factor productivity (TFP) is determined by the complementary inputs of the manager ability and the firm type. Thus, hiring good managers can enhance a firm's productivity. But more than expanding production, firms that become more productive relative to their competitors will also charge higher markups rather than passing on all of the efficiency gain to consumers. In a competitive labor market, managers are therefore rewarded for increasing not only the size but also the market power of firms. Incomplete passthrough in conjunction with a competitive market for managers is the key mechanism we introduce to analyze the impact of market power on manager pay.

Our theoretical framework also provides insights into the inequality of manager pay. Through assortative matching, top-performing managers gravitate towards high productivity firms, while less talented executives manage lower productivity firms. The magnitude of market power increases as the difference in productivity across firms grows.[5] When high-productivity firms face less competition, they can pass on less of the productivity gains to customers, a view put forward initially by Sutton (1991, 2001). Since managers reinforce the dominant position of high-productivity firms, firms that vie for top-talented managers must provide them with compensation commensurate with their contribution to profits. The impact of market power on managers with the highest levels of ability is disproportionately large, resulting in a right-skewed pay distribution with a long tail.

We use executive compensation data from Compustat spanning from 1994 to 2019, and quantify the production technology and the underlying distributions of productivities by matching cross-sectional moments on sales, markups, and manager shares over time. Notably, despite not directly targeting the manager pay distribution during estimation, our quantitative model is capable of predicting overall 65.6% of pay from the data, and 86.4% of the growth since 1994, which validates the importance of our mechanisms for understanding the determination of manager pay.[6] Our model also replicates a long right tail in the income distribution of managers, which is the key feature of the empirical distribu-

[4]This setup is consistent with the view that what skilled managers do is to increase the productivity of the firm (see for example, Bloom, Sadun, and Van Reenen, 2016). We refer readers to section 3.2 for further discussion.

[5]Even if the number of firms is small, when firms are identical in TFP, they have identical profits and market shares. Instead, when one firm has higher TFP, it achieves higher profits, and it obtains a larger market share. In the limit, as one firm is a lot more productive than all competitors in the market, it effectively behaves as a monopolist and obtains a market share close to one even if there are multiple competitors.

[6]We can further interpret the rest part as other mechanisms that are ruled out in our discussion for tractability, such as the incentive pay for managers. We refer readers to section 3.2 for a complete discussion.

tion that determines manager pay inequality. These results serve as external validation of our theory and suggests that the model, despite its simplifying assumptions, provides a precise portrayal of the mechanism underlying executive wage determination.

We then use the quantitative model to decompose the sources of manager pay into market power and firm size. Within our model prediction, over the entire period, 45.2% of average manager pay can be ascribed to market power and the remaining proportion is due to firm size, which respectively explain 29.8% and 35.8% of the total manager pay we observe in the data. Over time, we attribute 55.6% of manager pay growth to market power and 44.4% to the firm size, accounting for 48.0% and 38.4% of pay growth in the data, respectively. We conclude that market power plays an increasingly important role in explaining the recent rise of manager pay.

Next, we focus on inequality in manager pay. Cross-sectionally, our quantitative results reveal significant heterogeneity within the manager pay distribution. For the top-ranked managers in 2019, market power accounts for 80.3% of their pay in the model and nearly all of their substantial pay growth since 1994. In contrast, for lower-ranked managers, pay and pay growth, if any, are primarily determined by the firm size component. This difference indicates that market power is the most prominent channel behind the spectacular rise of the pay of superstar managers, which leads to the observed increase in manager pay inequality. We also decompose the variance of manager pay over time and conclude that variance of the market power component is the most important factor for the rise of manager pay inequality, whose contribution increases from 27.2% in 1994 to 42.4% in 2019. The variance of the firm size component, on the contrary, is flat and does not contribute to the increase in inequality.

Finally, we run through a counterfactual experiment where we keep all parameters fixed at their 1994 values, and then feed in one or more estimated, year-specific parameters. We find that the most important force for the rise of both the average and inequality of manager pay is the increasing weight of manager ability in the production process. We estimate that a one percent increase in managerial ability on average leads to 1.60% increase in firm-level profits in 1994, which doubles to 3.16% in 2019. We also document a substantial welfare loss that would arise from mismatch between firms and managers. If managers were assigned randomly to firms, total output would fall by 2.39% in 1994 and by 14.21% in 2019. These results highlight the increasingly important role managers play in the economy.

Our main conclusion is that top managers are hired disproportionately by firms with market power, and they get rewarded for it, increasingly so. And while our focus due to data availability is on CEOs, the same logic applies to all managers who supervise other workers and to other professionals for whom sorting and superstar pay is a key determinant. And because one fifth of the workers supervise other workers, these findings have macroeconomic implications, especially at the top percentiles of the income distribution.

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

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

Our paper bridges these literatures on firm size and manager pay on the one hand, and firm size and market power on the other. We model market power in the tradition of the general equilibrium model of Atkeson and Burstein (2008), which allows for endogenous markups, a flexible market structure and firm heterogeneity. The theoretical novelty is to add a two-sided matching framework to this model with oligopolistic competition and endogenous markups in general equilibrium. Our analysis framework is also related to Jung and Subramanian (2017, 2021), who check the relationship between CEO compensation and product market competition. While their works are built on Dixit and Stiglitz (1977) with monopolistic competition and exogenous markups, we examine from a new perspective that managers are paid because they allow firms to exert larger market power.

For simplicity, we abstract from incentive provision.[7] Our work complements the work that studies the effect of product market competition on incentive provision and optimal incentive contracts (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. The inefficiency from imperfect competition in the output market leads to rent extraction, where the manager and the owner of the firm join forces to extract rents from customers and competitors.[8]

Other recent studies also consider managerial compensation in a general equilibrium setup. Acemoglu, Akcigit, and Celik (2022) focuses on the choice between incremental and radical innovation, and investigates the sorting of managers of different ages and human capital across firms. Celik and Tian (2017) builds a general equilibrium with an agency problem to study the joint dynamics of corporate governance, managerial compensation, and disruptive innovations. As far as we know, no other work offers a theoretical and quantitative examination of the role of market power for manager compensation

[7]See Section 3.2 for more discussion on risk aversion and agency issue. We also provide a theoretical framework in Appendix B.4 demonstrating that this assumption will not alter our key insights.

[8]In a sense, this is in line with the rent extraction in Bebchuk et al. (2002), but rather than extraction by the manager from owners, it is by manager and owners from customers and competitors.

in general equilibrium.

Finally, there is also a growing literature linking economy-wide inequality to market power. Using micro data from the US Census, Deb et al. (2022a) document the effect of market power on the skill premium and the wage level of all workers. Kaplan and Zoch (2020) analyze the productivity of different occupations and the effect of markups. And Fernández-Villaverde, Mandelman, Yu, and Zanetti (2021) focus on the complementarities between firms and customers, which fosters market concentration, monopsony power, and wage inequality.

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 Stylized Facts

Data. We use data from Compustat throughout the paper.[9] 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.[10] 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.[11] 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.

Motivating facts: why do we need market power? We motivate our analysis by showcasing the necessity of introducing endogenous markups in interpreting the rise of manager pay. The strategic interaction between firms is the key concept that is absent in the canonical theory of executive compensation such as Gabaix and Landier (2008) and Terviö (2008). In their framework, firms hire managers with no incentive to compete for market power. Although their assumption is desirable to keep the model solution tractable, we find that the absence of endogenous market power can lead to unsolved puzzles in the data.

We first investigate the aggregate correlation between manager pay and markups. Figure 1.A depicts the evolution over time of average manager pay and average markups, and shows that the increase

[9]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.

[10]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.

[11]Details are documented in Figure A.1 of Appendix A.2, which is also mentioned in Terviö (2008).

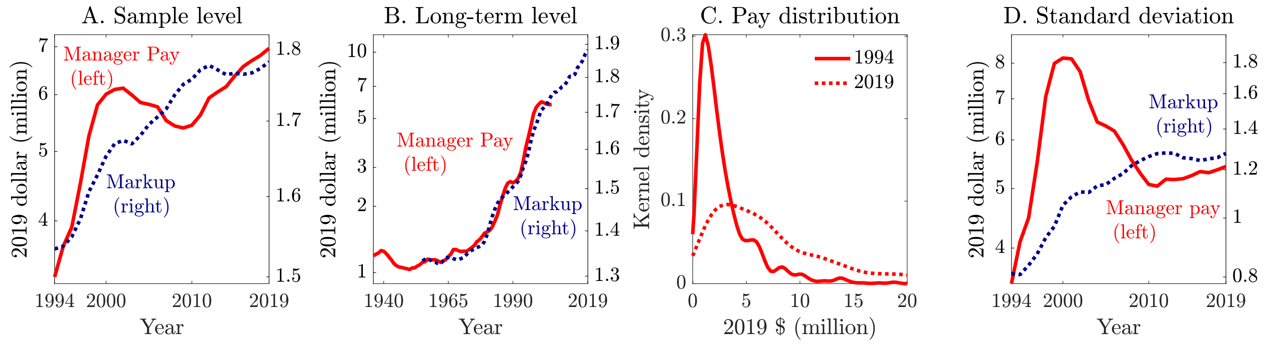


Figure 1: The evolution of manager pay and markups

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. Panel C reports the kernel density of manager pay in 1994 and 2019. Finally, panel D plots the corresponding standard deviations. All of the time series plots are in 2019 million dollars, in log scale, and in five-year centered moving average.

in average manager pay correlates with the rise of average 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 by 25 percentage points. In Figure 1.B, we show the same series for markups for a longer time period (starting in 1955) and for executive compensation. 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 average manager pay increases sharply. The year 1980 is also when markups start to increase. Inspection of the figure shows that there is a positive correlation between the average markup and average manager pay between 1955 and 2005. Furthermore, we document a consistent increase in manager pay inequality, which coincides with the rising markup heterogeneity documented in De Loecker et al. (2020). In panel C of Figure 1, we plot the kernel density of manager pay distribution and find that the increase in inequality is mainly due to the longer and thicker right tail. In panel D, we further show that the standard deviation of both manager pay and markup has been increasing from 1994 to 2019, with a hump in the former sequence coming from the 2000 dot-com bubble.

Looking into the micro data, we directly examine the effect of markups on manager pay with consideration of firm size in Table 1. We use various measures for firm size, including sales, costs of goods sold (COGS), and employment, while markups are obtained at firm-year level using the production approach from De Loecker et al. (2020).[12,13] The conventional wisdom that size plays an important role in managers' salary determination is confirmed by all regression specifications. On average, a one

[12]The recent work by Traina (2018), Basu (2019), Syverson (2019), Bond, Hashemi, Kaplan, and Zoch (2021) and De Ridder, Grassi, and Morzenti (2022) has brought to the attention of the research community important methodological aspects of production function estimation. 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 the production function estimation to obtain markups, De Loecker et al. (2020) 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).

[13]We also find that our quantitative results are robust to different measures of markups, such as those obtained with the demand approach from Deb et al. (2022b) where markups are estimated from a structural demand and supply model without estimating a production function.

Table 1: Motivating regression: Manager pay, own firm size, and markup

	log Manager Pay						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Firm size							
log Sales	0.395	0.389					
	(0.009)	(0.010)					
log COGS			0.331	0.387			
			(0.009)	(0.009)			
log Employment					0.300	0.298	
					(0.009)	(0.009)	
Market power							
log Markup		0.305		0.678		0.361	0.310
		(0.015)		(0.029)		(0.029)	(0.030)
Fixed effects							
Firm	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓
Adj. R-squared	0.665	0.667	0.657	0.667	0.652	0.655	0.637
Observations	34,148	33,150	34,148	33,150	34,148	33,150	33,150

Notes: The robust standard errors under heteroskedasticity are reported in the parenthesis. In all seven specifications, we include constant and additionally control for the firm and year fixed effects. All the results are robust if we instead control for industry-year fixed effects where an industry is defined by the 4-digit NAICS code.

percent increase in size for the same firm will lead to an increase in manager pay by 0.30% to 0.40%. Interestingly, conditional on size, we also find a significant contribution of markups from columns (2), (4) and (6). Depending on how we define firm size, a single percent increase in the markup causes a 0.31%, 0.68%, and 0.36% increase in pay, respectively. Moreover, the magnitude of the size effect does not decline after we control for markups in the regression, which suggests that the channel of market power seems to operate alongside the channel of firm size in determining manager pay.

We also provide indirect evidence of the role that markups play, in a regression exercise that replicates Gabaix and Landier (2008), in Appendix A.3. Key to our approach is that market power in the output market affects the hiring decision of managers by firms. In particular, firms have incentives to compete for a higher markup when markups are endogenous. In the absence of endogenous markups, firm size has similar effects on the compensation of managers regardless of which markets they are from, and which firms they are competing with. In the economies of Gabaix and Landier (2008) and Terviö (2008), for example, the match surplus depends, by assumption, only on firms' own characteristics.[14] Instead, we find strong evidence that interactions across firms within an industry plays a role in determining manager pay, which indirectly demonstrates the importance of market power.[15]

[14] Of course, markups can be exogenous and independent of competitors too. Recent work by Jung and Subramanian (2021) for example introduces monopolistic competition, but markups are exogenous since there is no strategic interaction as firms are monopolist in each market.

[15] Markups reflect both demand-side heterogeneity and strategic interactions among firms in a given market, and we

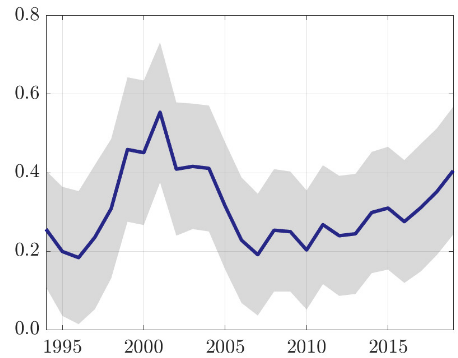


Figure 2: The elasticity of markups on manager pay over time

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

Finally, we also investigate the dynamic effects of market power on manager pay by including interactions between year dummies and markups. We consider the following specification:

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

for firm i in year t and where we assume that the residual e_{it} is independent of markups after controlling the fixed effects δ_i and κ_t. Figure 2 shows the evolution of the elasticity of markup on manager pay β_t over time. This elasticity is positive and significant, indicating that a higher markup correlates with higher manager pay. Moreover, we see a spike during the dot-com boom and an increase in the importance of market power after the Great Recession.

All the evidence in this section reinforces the central tenet of this paper: endogenous markups play a role in determining manager pay. That said, we are aware of the concern that this reduced-form analysis faces a number of serious identification problems. The limited availability of data and instruments 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 of manager pay that builds on the classic insights from the literature that links pay to firm size but also embeds strategic interaction between firms. We then structurally estimate the model using the data that we have analyzed in this section and disentangle the effects of firm size and market power.

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). We will introduce the model setup in section 3.1, where the main

propose a model that allows for both sources of markup heterogeneity to impact manager pay.

assumptions are discussed in section 3.2. Then, section 3.3 solves the model and section 3.4 further explores mechanisms that determine equilibrium manager pay. In section 3.5, it is demonstrated through two specific cases that our theory is capable of producing a comprehensive range of outcomes, thereby establishing the basis for our subsequent quantitative analysis.

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 $F(x)$.[16] 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.[17] 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:

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

where c_{ij} is the consumption of good ij, c_j is the consumption aggregate of market j, and C is the economy-wide aggregate of consumption. 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.[18] We represent the household's preferences with the following utility function over the consumption

[16]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.

[17]The measure J is endogenous, which is determined by $M = J \times \mathbb{E}(I_j)$. This normalization is harmless. All the results go through if we instead fix the measure of markets J and allow the measure of firms M to endogenously adjust.

[18]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.

bundle $\{c_{ij}\}$ that aggregates to C, and the supply of labor L:

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

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

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

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

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

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

$$A_{ij} = \mathcal{A}\left(x_{ij}, z_{ij}, A_j\right), \quad \text{with} \quad \mathcal{A}_x > 0, \ \mathcal{A}_z > 0, \ \text{and} \ \mathcal{A}_{xz} > 0. \tag{4}$$

We introduce managerial ability as an input that determines productivity, which can be interpreted as a Lucas (1978) model of span of control.[19] Like the classic literature, we also assume that managers and firms are complementary. We will specify a CES functional form when mapping this model into data in Section 4. Given the firm's TFP A_{ij}, the technology that determines the quantity of output y_{ij} as a function of inputs of production labor is linear:

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

[19] There is a large body of empirical literature documenting the importance of management for productivity (e.g. Ichniowski, Shaw, and Prennushi, 1995; Bertrand and Schoar, 2003). Most recently, Bloom, Sadun, and Van Reenen (2016) uses a structural analysis showing that management is indeed like a technology that raises TFP. Hence, manager ability is commonly interpreted as a TFP-enhancing (or equivalently, cost-reducing) technology in the literature (see also Jung and Subramanian, 2021; Acemoglu, Akcigit, and Celik, 2022). This is also consistent with the reverse channel championed by Sutton (1991, 2001), that firms create market power (whether it is through investment, or here through hiring skilled managers) by increasing the productivity of the firm. Kaplan and Zoch (2020) raises an alternative possibility that managers (they call it expansionary labor) may increase in product variety, which in our theoretical framework is equivalent to an increase in productivity (see for example, Deb et al., 2022a,b).

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

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

where $\widetilde{\pi}_{ij}$ is the firm's gross profit coming from the next period. We use the '$\sim$' to distinguish between gross profits $\widetilde{\pi}$ before paying the manager compensation, and net profits π after paying the manager compensation. Note that there is an externality in the problem (6), that the profit of the firm ij depends not only on its own TFP A_{ij} but also on the productivity of its competitors, $\boldsymbol{A}_{-ij}$.[20]

Once managers of type x and firms of type z_{ij} in markets A_j have matched, the firm's TFP A_{ij} is common knowledge to all in the economy. In stage 2, firms then Cournot compete in quantity y_{ij} with their rivals in the same market.[21] The firms make production decisions to maximize gross profits:

$$\max_{l_{ij}} \widetilde{\pi}_{ij} = p_{ij}y_{ij} - Wl_{ij}, \quad \text{s.t.} \quad y_{ij} = A_{ij}l_{ij}. \tag{7}$$

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

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

3.2 Discussion of model assumptions

We provide a complete list of the model variables in Table 2. For tractability, we make several model assumptions, which we discuss now.

Representative households. Our general equilibrium model builds up on representative households following Atkeson and Burstein (2008), and more fundamentally, the CES structure from Dixit and Stiglitz (1977). This assumption gives us well-behaving output demand and labor supply function. To maintain the representativeness of the households, we assume that households own a perfectly diversified stake in economy-wide manager income and profits. Note that although households are

[20]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. In general, for a treatment of matching games in the presence of externalities, see Chade and Eeckhout (2020).

[21]Cournot competition is not the crucial assumption. As is shown in Appendix D.2, all of our results extend when the firms Bertrand compete on price.

Table 2: Summary of the model variables

	Name	Meaning	Name	Meaning
Environment	θ	Elasticity of sub. across markets	η	Elasticity of sub. within a market
	J	Number of markets	I_j	Number of firms in market j
	$\overline{\varphi}$	Labor supply shifter	φ	Labor supply elasticity
	M	Measure of firms and managers	ω_0	Manager's reservation utility
	$F(\cdot)$	CDF of manager ability		
Firm/Good	x_{ij}	Manager ability	z_{ij}	Firm type
	A_{ij}	Productivity	l_{ij}	Employment
	c_{ij}	Consumption quantity	y_{ij}	Output quantity
	p_{ij}	Price	μ_{ij}	Markup
	$\widetilde{\pi}_{ij}$	Gross profit	π_{ij}	Net profit
	s_{ij}	Sales share (within a market)	r_{ij}	Sale (revenue)
	ω_{ij}	Manager pay	ε^p_{ij}	Price elasticity of demand
	ε^μ_{ij}	Markup elasticity of TFP	ε^l_{ij}	Employment elasticity of TFP
Market	c_j	CES aggregation of consumption	y_j	CES aggregation of output
	p_j	CES price index	μ_j	Average markup
	A_j	Market type		
Economy	C	CES aggregation of consumption	Y	CES aggregation of output
	P	CES price index (normalized)	L	Aggregation of labor
	Π	Aggregation of profits	Ω	Aggregation of manager pay
	W	Wage		

Note: The firm-level variables use subscript ij that indexes for the firm i in market j.

identical, we are still able to talk about the income inequality among managers *within* the households.[22] Likewise for profits. The reason for building a model with a representative household is to keep the analysis tractable. The innovation of this model comes from the heterogeneity on the production side (firms and managers) and not come from the preferences and goods demand.

Absence of agency problem. For tractability, we focus on the matching problem in the main analysis of this paper. Although the literature on agency has emphasized the importance of incentive provision and risk aversion in determining manager pay (for example, see Gayle, Golan, and Miller, 2015; Antón, Ederer, Giné, and Schmalz, 2021), recent analysis that combines matching and agency problems suggests that the matching component plays an important role in explaining the rise of manager pay and its cross-sectional distribution. For example, according to Edmans, Gabaix, and Landier (2009) and Edmans and Gabaix (2011), the rise of manager pay over time cannot be due to the economy-wide increases in risk. Moreover, by decomposing the CEO compensation into the matching component and

[22] Alternatively, we can interpret managers as another group of agents in the economy that is independent of the representative households with the same preferences, which will not change any of our theoretical and empirical results. By excluding managers from the households, we only need to rewrite the budget constraint in household problem (3). But since this budget constraint is always automatically satisfied by the transfer of profits, it is never binding, and hence this change will not influence any equilibrium outcome.

the incentive provision component, Chade and Eeckhout (2022) find that executives receive an incentive component that is remarkably constant in levels across the distribution of abilities. In Appendix B.4, we solve our baseline model model where in addition managers are risk averse and owners face an agency problem, à la Edmans and Gabaix (2011). We find that the incentive payment (such as stock options) that elicits effort and compensates for risk aversion also goes through the market power and firm size channels. Therefore, the assumption to leave out incentive provision, while relevant, does not alter the insights about the changes and inequality in manager pay.

Other roles of managers. There might be alternative ways other than productivity increases through which managers can benefit firms. For example, a successful manager might contribute by reducing fixed costs of operation, or managers may directly affect the extent of competition in the market via entry deterrence or mergers and acquisitions. Admitting the exclusion of these competing channels, we have chosen not to target manager pay in the estimation but rather let our quantitative model speak for how good the existing mechanisms are in explaining the observed data. In section 4.7, we show that our model can predict on average 65.6% of the data manager pay and 86.4% of its growth over the sample period, which establishes that the mechanisms we analyze are of first-order importance in determining manager pay.

General skill of managers. Following Gabaix and Landier (2008), we model manager ability by a one-dimensional general skill. There are good reasons to believe that managerial experience is industry or even firm-specific. At the same time, there is substantial mobility of managers across firms and industries. In particular, recent studies show an increased importance of general managerial skills over firm-specific human capital (e.g., Murphy and Zabojnik, 2004, 2007; Custódio, Ferreira, and Matos, 2013). Most recently, Dupuy, Kennes, and Lyng (2022) empirically examine a multidimensional matching model and conclude that CEO productivity is not higher in their firms or industries of initial employment, suggesting that firms value general CEO skills rather than industry or firm-specific skills.

Frictionless matching market. The matching market in our setting is without search friction. At the same time, there is substantial turnover among top managers, with an average tenure of two and a half years, which is shorter than the average job duration economy wide (4.5 years). What search frictions would introduce is a notion of mismatch: two-sided search would induce managers and firms to accept a less than ideal match (see for example, Shimer and Smith, 2000). In the real world there are all kinds of other frictions as well, such as information, learning,...[23] Information frictions would lead to ex-post mismatch upon revelation of the information, even though ex ante there is no mismatch in expectation (see for example, Chade and Eeckhout, 2022). In these examples, mismatch introduces noise around the frictionless allocation. Note that in our model we already have a similar form of "mismatch" due to the random realization of productivities of competitors in a market. As a result, there is no perfect

[23] See Cziraki and Jenter (2022) for evidence of frictions in the market for CEOs.

sorting of manager types of firm productivities.

Absence of monopsony power. For tractability, we assume the market for manager is perfectly competitive, which is therefore exempted from monopsony power. While excluding monopsony power has a direct impact on manager pay, recent work indicates that quantitatively the impact is small. Deb et al. (2022a,b) jointly estimate markups and markdowns based on the same structural framework from Atkeson and Burstein (2008), and find that while monopsony power exists, it matters significantly less than output market power. They find that markups have risen substantially drastically from 1997 to 2016, while markdowns are invariant over time. If we were to extrapolate those results to the manager market, then we can conclude that (1) monopsony power is quantitatively less important than output market power; and (2) omitting monopsony is likely to lead to little systematic bias explaining the growth of manager pay over time.

3.3 Solution

Stage 2. Production with market power

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

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

(a) Goods demand function:

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

where

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

(b) Labor supply function:

$$L = \overline{\varphi} W^{\varphi}. \tag{8}$$

Proof. See Appendix B.1. ■

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

$$p_{ij}(y_{ij})\left[1 + \frac{dp_{ij}}{dy_{ij}}\frac{y_{ij}}{p_{ij}}\right]\frac{dy_{ij}}{dl_{ij}} = W \quad \Leftrightarrow \quad p_{ij}\underbrace{\left(1+\varepsilon_{ij}^{P}\right)}_{\mu_{ij}^{-1}} A_{ij} = W. \tag{9}$$

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 (9). 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:

$$\mu_{ij} = \left[1 - \frac{1}{\theta} s_{ij} - \frac{1}{\eta}\left(1 - s_{ij}\right)\right]^{-1}, \tag{10}$$

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 (10) 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 (10), 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:

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

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

$$y_{ij} = \frac{1}{J}\frac{1}{I_j}\left(\frac{p_{ij}}{p_j}\right)^{-\eta}\left(\frac{p_j}{P}\right)^{-\theta} Y, \quad l_{ij} = \frac{y_{ij}}{A_{ij}}, \quad \text{and} \quad \widetilde{\pi}_{ij} = (\mu_{ij} - 1) W l_{ij}. \tag{11}$$

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

Stage 1. Matching Managers to Firms

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

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

If this condition is not satisfied for two firms, then both firms can be made better off by matching and redistributing the surplus. Furthermore, the complementarity between manager ability and firm type assumed in the technology (4) indicates that the matching output, $\widetilde{\pi}_{ij}$, is supermodular. In a classical matching model, supermodularity is sufficient for positive assortative matching (PAM) (see for example, Becker, 1973; Chade et al., 2017), but in the presence of the externality from imperfect competition, 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 have to rely on a computational algorithm to find it.[24]

Given the stable matching Γ, the firms' stage 1 optimization problem (6) yields the FOC:

$$\underbrace{\frac{\partial \widetilde{\pi}_{ij}}{\partial A_{ij}} \frac{\partial A_{ij}}{\partial x_{ij}}}_{\partial \pi_{ij} / \partial x_{ij}} = \frac{d}{dx} \omega(x_{ij}), \tag{12}$$

which requires the marginal benefit of hiring a higher ability manager (LHS) equals the marginal cost (RHS). It is instructive to point out that equation (12), joint with the gross profits (11), enables us to decompose the managers' *marginal* contribution to gross profits as follows.

Proposition 1 (Marginal Contribution of Managerial Ability) *The marginal contribution to gross profits of managerial ability can be decomposed as follows:*

$$\frac{\partial \widetilde{\pi}_{ij}}{\partial x_{ij}} = \left[\underbrace{\frac{\partial \mu_{ij}}{\partial A_{ij}} W l_{ij}}_{\text{Market power channel}} + \underbrace{(\mu_{ij} - 1) W \frac{\partial l_{ij}}{\partial A_{ij}}}_{\text{Firm size channel}} \right] \frac{\partial A_{ij}}{\partial x_{ij}}. \tag{13}$$

Proposition 1 decomposes the marginal contribution of managerial ability to gross profits into two distinct channels.[25] First, holding firm size l_{ij} constant, hiring a better manager contributes to gross profits by allowing the firm to set a higher markup. We therefore interpret this margin as the *market power channel*. Another way to see this margin is through the pass-through rate. A better manager helps the firm reduce its marginal production cost W/A_{ij}. Due to incomplete pass-through, prices do not decline as fast as the marginal cost, which creates a larger markup and therefore leads to an increase in profitability. The second mechanism is through the conventional *firm size channel*. Holding the markup μ_{ij} constant, the firm benefits from a better manager by adjusting its size choice l_{ij} due to the complementarity in production between manager skills and employment.

Note that Proposition 1 relies on the specific way we write the gross profits in equation (11), i.e., $\widetilde{\pi}_{ij} = (\mu_{ij} - 1)\, W l_{ij}$. The underlying thought experiment is to consider profits as the product of two parts: (1) the marginal profit per dollar of inputs, that is, markup $\mu_{ij} - 1$; and (2) the total amount of variable inputs, $W l_{ij}$.[26] Alternatively, one might think of writing the gross profit as product of Lerner index, which is the marginal profit per dollar of revenue, and total revenue. Since revenues contain

[24] 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).

[25] Note that the decomposition is based on the different *margins* through which a better manager contributes to gross profits. Mathematically, it corresponds to the partial derivatives holding other channels constant in equation (13).

[26] This statement depends on the assumption of constant return to scale in production, which ensures the marginal profit per cost is identical to the average profit per cost.

information about prices (and hence market power), this specification will quantitatively overstate the importance of the firm size channel. For this reason, we focus on the decomposition (13) in the main body of this paper.[27]

Our theoretical contribution also lies in Proposition 1. We provide a micro foundation for matching output between managers and firms, which is absent in most literature in this field. Some recent papers try to rationalize this output using the monopolistic competition framework with exogenous markups (for example, Jung and Subramanian, 2017, 2021). Our innovation is to introduce the margin of market power and strategic interaction, which is the missing piece in classic theory of manager pay and will be shown to be quantitatively important.

Since the marginal contribution of managers to gross profits can be decomposed, then under the frictionless matching assumptions we made for the manager market, manager pay can similarly be decomposed in Proposition 2 by solving the differential equation (13).

Proposition 2 (Manager Pay) *Given stable matching Γ, the executive salary schedule $\omega(x)$ satisfies:*

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

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

Proposition 2 suggests that manager pay can be decomposed into two separate channels: the market power component and the firm size component, which comes directly from the gross profits equation (13). The first channel shows that, conditioning on firm size, 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 higher managerial ability. Given the allocation of managers to firms, these two components jointly determine the marginal product of each manager, which further pins down the manager pay schedule in a competitive labor market.

3.4 Determinants of manager pay

To understand the determinants of manager pay, we first investigate the market power channel, that is, how managers influence the firms' gross profits through markups. Using the implicit function theorem on the FOC (9), we can derive the markup elasticity of TFP:

$$\varepsilon^{\mu}_{ij} := \frac{\partial \mu_{ij}}{\partial A_{ij}} \frac{A_{ij}}{\mu_{ij}} = \underbrace{\left[\frac{(\eta - 1)(1 - \phi_{ij})}{1 + (\eta - 1)\left(\frac{1}{\theta} - \frac{1}{\eta}\right) \mu_{ij} s_{ij}} \right]}_{\frac{\partial s_{ij}}{\partial A_{ij}} \frac{A_{ij}}{s_{ij}},\ \downarrow \text{ in } A_{ij}} \times \underbrace{\left[\left(\frac{1}{\theta} - \frac{1}{\eta} \right) \mu_{ij} s_{ij} \right]}_{\frac{d\mu_{ij}}{ds_{ij}} \frac{s_{ij}}{\mu_{ij}},\ \uparrow \text{ in } A_{ij}} \in [0, 1)\,, \tag{14}$$

[27] In Appendix D.1, we show that our results are empirically robust between these two different interpretations.

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 (10). 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:

$$\varepsilon^{l}_{ij} := \frac{\partial l_{ij}}{\partial A_{ij}}\frac{A_{ij}}{l_{ij}} = \phi_{ij}\underbrace{\Big[\theta-1\Big]}_{\text{Monopoly}} + \left(1-\phi_{ij}\right)\underbrace{\left[\frac{\eta}{1+\left(\frac{1}{\theta}-\frac{1}{\eta}\right)(\eta-1)\,\mu_{ij}s_{ij}}-1\right]}_{\text{Strategic interaction, }\downarrow\text{ in }A_{ij}}, \tag{15}$$

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 3 (Elasticities of TFP) *The markup and firm size elasticities of TFP are given by equation* (14) *and* (15)*, respectively. They have following properties:*

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

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

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

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

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

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

We summarize the important properties of these elasticities in Proposition 3. 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 3 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.

3.5 Two special cases

To illustrate the mechanics of our model, we discuss two special cases, driven by the elasticity of substitution in demand θ and η.

Monopolistic competition: $\theta = \eta$. Each product has the same substitutability within a market and across different markets. The model thus reduces into a standard monopolistic competition framework as in Jung and Subramanian (2017, 2021). The typical feature of such a model is the lack of strategic interaction, where markups $\mu_{ij} = \theta/(\theta - 1)$ are determined exogenously by the elasticity θ. A direct implication is that the markup elasticity of TFP is zero, i.e., the markup is constant no matter which CEO the firm hires. We thus conclude in this case that all the manager pay comes from the firm size channel.

Perfect competition within a market: $\eta \to \infty$. In another extreme, goods are perfectly substitutable in a market, hence all the market power comes from imperfect competition across markets, i.e., $\mu_{ij} = \theta/(\theta - s_{ij})$. strategic interaction appears through the market share s_{ij}. By hiring a better manager, a firm is able to outperform its competitors and gain a larger sales share, which contributes to a larger profit margin via higher markups. Thus, the markup elasticity is positive and managers get paid for their contribution on market power.

Our theoretical framework covers a wide range of settings with endogenous market power that lead to different implications that the role market power can play in determining manager pay. We now turn to the quantitative exercise in section 4 to take the model to the data.

4 Quantitative Exercise

We quantify the model *year by year* using Simulated Method of Moments in this part. Section 4.1 documents the strategy we implement to solve the matching problem. We further map our theory to the data by generalizing the production function in section 4.2. In section 4.3, we parametrize the model. The identification strategy is presented in section 4.4, based on which we estimate the parameters in section 4.5. We then investigate some key properties of the matching equilibrium in section 4.6. Finally, we validate our quantitative model by comparing the distribution of manager pay, markups, and sales predicted by the model against the data in sections 4.7 and 4.8.

4.1 Matching algorithm

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

In order to solve for the equilibrium matching, we use an algorithm that yields an approximate stable matching. Our algorithm uses a proxy for positive sorting between manager types and firm conditional profitability. The firm type now is no longer a sufficient statistic of the ranking of firms because the profitability of a firm also depends on its competitors' types. Instead, we construct the ranking by assigning all firms with the average manager and calculating the marginal product of the manager to each firm. This approach gives us a good proxy for firm conditional profitability taking into account the externality across firms, based on which we construct a PAM thanks to the complementarity between firms and managers. Specifically, we follow these steps:

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

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

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

4.2 Specify production technology

In the quantitative exercise, we use the CES specification for the TFP function (4):

$$A_{ij} = A_j \left[\alpha x_{ij}^{\gamma} + (1-\alpha) z_{ij}^{\gamma} \right]^{\frac{1}{\gamma}} . \tag{16}$$

Both the manager ability x_{ij} and the firm type z_{ij} determine the TFP of the firm, while A_j is a market-level Hicks-neutral technology. The share α measures the importance of the manager relative to the firm type. The expression (16) allows for a CES functional form where γ is the constant elasticity of substitution between manager ability and firm type. For example, when $\gamma < 1$, managers and firms become complementary. This CES form allows for a flexible specification of the TFP technology. When $\gamma = 0$, the expression (16) 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.

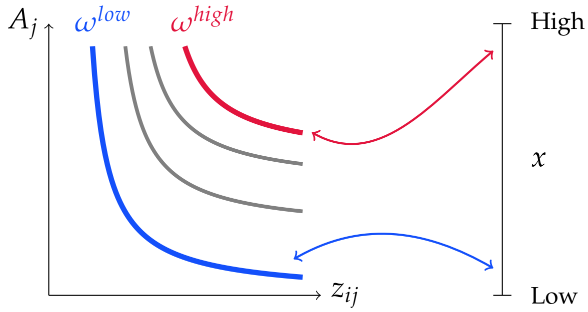


Figure 3: Matching of Managers to firm-market pairs (z_{ij}, A_j) with iso-wage curves

With this specification, we can characterize the stable matching from Proposition 2. The match surplus is generally increasing in z_{ij} and A_j, though not always due to the externalities from competition in the market. The same firm type z_{ij} will make lower (higher) profits if all competitors z_{-ij} are high (low) types. In the absence of those externalities, the matching pattern of managers x to pairs (z_{ij}, A_j) is illustrated in Figure 3. High type managers match with high z_{ij} firms in high A_j markets. But there is a trade-off as managers get the same wage for pairs with (low z_{ij}, high A_j) and (high z_{ij}, low A_j). This results in indifference maps that correspond to iso-wage curves for the manager. Given the match surplus (gross profits) is complementary in x and (z_{ij}, A_j), those indifference curves are ordered in the equilibrium matching from high x to low x as illustrated in the Figure. When there are externalities, these indifference maps are "noisy" in the sense that they depend on the realization of productivities in a given market. In our quantitative analysis in Section 4.6, we plot the kernel of those indifference maps derived in the presence of externalities and confirm that high ability managers are more likely to match with high-type firms in both z_{ij} and A_j.

Furthermore, in order to reconcile our technology with the data, where we observe intermediate inputs and capital, we follow the standard way in De Loecker et al. (2021) and extend our production function into a more general but tractable 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} is introduced 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.

This extension of the production function is an accounting adjustment of the data with capital and intermediate inputs and does not change the insights from the labor-only theory. It is necessary to map the theory to the data from Compustat and ExecuComp. Using the labor-only production function would lead to underestimation of the firm size effect as we overlook the material and capital costs. Lemma 3 further proves that there is a one-to-one mapping between this generalization and the labor-only model and we do not gain or lose any insights from this adjustment.

Lemma 3 *The production function (17) can be equivalently expressed by a labor-only production function:*

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

The decomposition of manager pay can be therefore written as:

$$\omega(x_{ij}) = \omega_0 + \frac{1}{\psi\zeta}\int_{\underline{x}}^{x_{ij}} \left[\underbrace{\frac{\partial \mu_{i'j'}}{\partial \widehat{A}_{i'j'}} W l_{i'j'}}_{\textit{Markup channel}} + \underbrace{\left(\mu_{i'j'} - 1\right) W \frac{\partial l_{i'j'}}{\partial \widehat{A}_{i'j'}}}_{\textit{Firm size channel}}\right] \times \left[\frac{\partial \widehat{A}_{i'j'}}{\partial x_{i'j'}}\right] dx_{i'j'}. \tag{18}$$

Proof. See Appendix B.5. ■

As each single firm cannot influence aggregate wage W, it will take the input-adjusted TFP, $\widehat{A}_{ij}$, as given. In the marginal cost expression, 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. The manager pay (18) is therefore also scaled by these two inputs share. 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. We conclude that while this accounting adjustment is quantitatively important, qualitatively it does not affect our results.

4.3 Parametrization

Endogenously estimated parameters. We assume that the distribution of manager type $F(x_{ij})$, firm type $G(z_{ij})$, and market type $H(A_j)$ are independent and lognormal. This rules out any negative realizations and has been shown to be consistent with the productivity distribution in the data.[28] Furthermore, as we will endogenously estimate $\{\alpha, \gamma\}$, we are unable to distinguish between $F(x_{ij})$ and $G(z_{ij})$. Being aware that the distribution of manager ability should be relatively stable over time, we normalize its distribution throughout the quantitative exercise to $\log x_{ij} \sim \mathcal{N}(-0.5, 1)$ such that the mean of x_{ij} is 1.[29] Moreover, we assume that the mean of z_{ij} is also normalized to 1. Its standard deviation σ_z will determine the lognormal distribution of z_{ij}. The market component A_j therefore captures the TFP

[28] For example, using Longitudinal Business Database (LBD) data, Deb et al. (2022a) estimate the firm-level productivity distribution and find that it follows the pattern of lognormal.

[29] Observe that we could equally estimate the distribution parameters μ_x, σ_x of the lognormal distribution of $x, \mathcal{N}(\mu_x, \sigma_x)$. In that case, we would not be able to separately identify α. If we fixed α, then the technological change as currently measured by α would be measured by the changing distribution of x. This would not affect our results nor the interpretation, as in both cases managers become more productive. It would lead to a philosophical discussion whether the increase in manager productivity is embodied in the manager's skill, or whether it is determined by better technology to which the identically skilled manager has access. The truth is probably somewhere in between.

Table 3: Endogenous, estimated parameters (time-varying)

	Parameter	Meaning
I. Match	α	The importance of manager relative to firm type
	γ	The elasticity of substitutes between manager and firm type
II. Market	m_I σ_I	Market structure $I_j \sim \mathcal{N}\left(m_I, \sigma_I^2\right)$, $I_j \in \mathbb{N}_+ \cap [1, 10]$
III. Firm	σ_z	Standard deviation of firm type z_{ij}
	m_A	Mean of market-level productivity A_j
	σ_A	Standard deviation of market-level productivity A_j

level of firms, whose distribution is determined by its mean and standard deviation, m_A and σ_A. To mimic the continuum of markets in the simulation, we set the number of markets equal to $J = 10,000$.[30] Furthermore, we assume that the number of firms in each market, I_j, is random to capture the heterogeneity across markets that we see in the data: I_j is an integer drawn exogenously from a truncated normal distribution $\mathcal{N}\left(m_I, \sigma_I^2\right)$ within the range $[1, 10]$.[31,32] To summarize, Table 3 lists the endogenous parameters that we estimate. They are organized in three categories: I. Match; II. Market; III. Firm.

Exogenously calibrated parameters. In addition, we take some exogenous parameters from the literature or calculate them directly from the data. Those are listed in Table 4. 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.[33] We obtain the elasticity of labor supply, φ, from the meta study Chetty, Guren, Manoli, and Weber (2011), and we calibrate the intercept $\overline{\varphi}$ year by year using the labor supply specification (8) and average employment and wage from the Compustat data. Given the Cobb-Douglas specification (17), the elasticity ζ is equal to the input share at equilibrium and is quite stable across years, so we compute it directly from the Compustat data. Finally, we calibrate the reservation utility of managers ω_0 by the first percentile of manager pay in each year. The yearly calibrated parameters are reported in Figure 4.

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

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

[32] An alternative way to introduce between-market heterogeneity is to have market-specific $\sigma_{z,j}$. This setting is conceptually equivalent to the dispersion in market structure. When $\sigma_{z,j}$ increases in one market, small firms will get a tiny share from the market, which (in an extreme case) is as if they stop operating and exiting the market. Our results are robust between these two setups.

[33] In section 5.5 and Appendix D.3, we show that our quantitative results are robust for different values of (θ, η). All our insights continue to hold when we use $\theta = 1.5$ and $\eta = 10.0$ from Atkeson and Burstein (2008).

Table 4: Exogenously calibrated parameters

I. Exogenously Fixed Parameters				II. Calibrated From Compustat Data			
	Meaning	Value	Source		Meaning	Value	Data moment
η	Within-sector elasticity of demand	5.75	De Loecker et al. (2021)	ζ	Elasticity of labor and material	0.88	Labor + intermediates in variable cost
θ	Between-sector elasticity of demand	1.20	De Loecker et al. (2021)	ψ	Labor share in labor plus material	0.33	Labor in labor plus intermediates
R	User cost of capital	1.16	De Loecker et al. (2021)	ω_0	Reservation utility of managers	Yearly	Log diff b/t 1st pct and mean of manager pay
φ	Labor supply elasticity	0.25	Chetty et al. (2011)	$\overline{\varphi}$	Labor shifter	Yearly	Employment-wage$^{\varphi}$ ratio

Notes: Parameters ω_0 and $\overline{\varphi}$ are calibrated yearly; their values are reported in the time series plot in Figure 4.

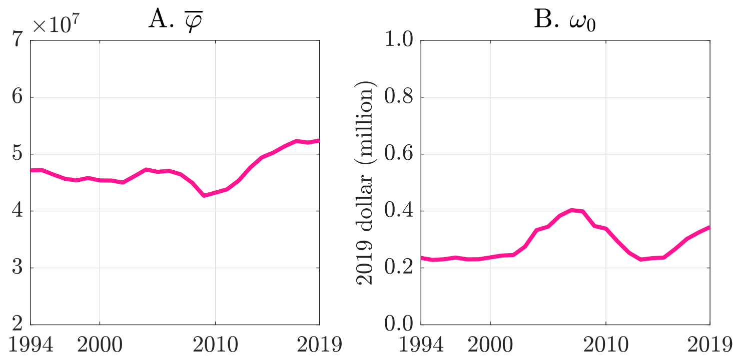


Figure 4: Calibrated parameters

Notes: The time series for both parameters is plotted with five-year centered moving average.

4.4 Identification

To capture the evolution of executive compensation and markups, we estimate the set of parameters listed in Table 3 that best matches the key moments of the data. We estimate the model annually: because the model is static, the estimates in different years are completely independent. We identify the endogenous parameters by minimizing the objective function:

$$\min_{\boldsymbol{\vartheta}} \ \mathcal{G}(\boldsymbol{\vartheta}) := \left(\widehat{\boldsymbol{M}} - \boldsymbol{M}(\boldsymbol{\vartheta})\right)' \boldsymbol{W}^{-1} \left(\widehat{\boldsymbol{M}} - \boldsymbol{M}(\boldsymbol{\vartheta})\right) \quad , \quad \boldsymbol{\vartheta} := \{\alpha, \gamma, m_I, \sigma_I, \sigma_z, m_A, \sigma_A\}, \tag{19}$$

where $\widehat{\boldsymbol{M}}$ is a vector of data moments and $\boldsymbol{M}(\boldsymbol{\vartheta})$ are their model counterpart given a set of parameters $\boldsymbol{\vartheta}$. The matrix $\boldsymbol{W}$ is the inverse of the variance-covariance matrix of the data moments.[34]

Table 5 lists the 7 moments that we target. The targeted moments, like the parameters, can be categorized into the same four groups, those corresponding to the matching, to the market, and to the firm. While all parameters affect all moments in this general equilibrium model, in the table we also list the corresponding key parameter that affects each of the moments most directly. Next, we

[34] Because our model is exactly identified, the choice of the weighting matrix is not crucial.

Table 5: Targeted Moments

		Moment	Key Parameter(s)
I. Match	Average salary share	$\mathbb{E}(\log \chi_{ij})$	α
	Sales elasticity of salary share	$\mathbb{K} := \partial \log \chi_{ij} / \partial \log r_{ij}$	γ
II. Market	Average markup	$\mathbb{E}(\mu_{ij})$	m_I
	Variance markup (between)	$\mathbb{V}(\log \mu_j)$	σ_I
III. Firm	Variance markup (within)	$\mathbb{V}(\log \mu_{ij} \| j)$	σ_z
	Average worker's wage	$\mathbb{E}(W)$	m_A
	Variance sales	$\mathbb{V}(\log r_{ij})$	σ_A

Notes: We base all our moments on the data discussed in Section 2. For the construction of empirical moments, we take the direct observations of revenues, employment and CEO compensation from the data. We estimate markups 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. An industry (market) is defined as four-digit NAICS code.

motivate our choice of the targeted moments. We also refer further to Appendix C.2, where we report the comparative statics prediction of how the parameters affect the selected model moments.

I. Match. We motivate our choice of moments on the matching side by showing how executive compensations are determined by $\{\alpha, \gamma\}$. Notice that manager ability x_{ij} influences gross profits exclusively through TFP A_{ij}. The expression below, which comes from the CES technology function (16), further gives us an intuitive way to understand the payoff share of managers:

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

Assume for now that there is no reservation utility nor market power. Then in a Cobb-Douglas world (i.e., $\gamma = 0$), the manager share will be constant and equal to α, which is commonly assumed in many matching literature (for example, Becker, 1973). The bigger α is, the more managers get. We therefore use the average log share of manager salary out of total sales, which we define as:

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

While α pins down the average salary share of the manager, the salary share is not a constant in the data, as is shown in the panel A of Figure 5. This implies the case when γ is non-zero. We therefore use the cross-sectional slope of the linear prediction of $\log \chi_{ij}$ on $\log r_{ij}$, i.e., the sales elasticity of salary share, to inform us about the elasticity of substitution, γ. Panel B and C of Figure 5 reiterates the logic of our choice of parameters by plotting the relationship between $\log \chi_{ij}$ and $\log r_{ij}$ when each of the parameters $\{\alpha, \gamma\}$ change.

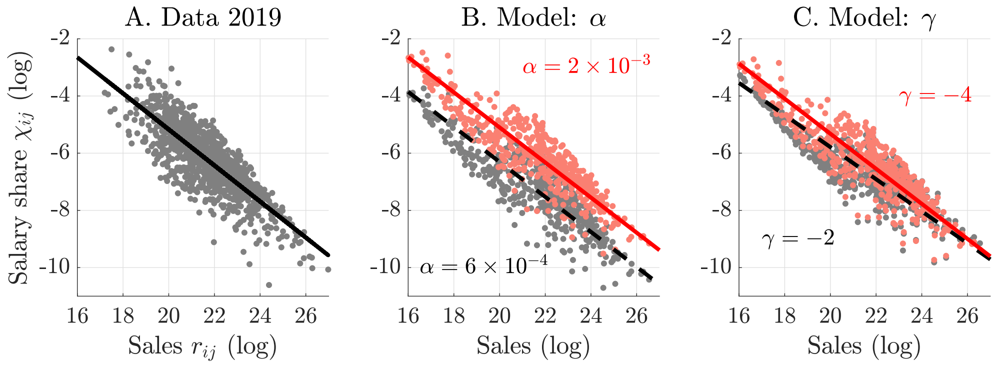
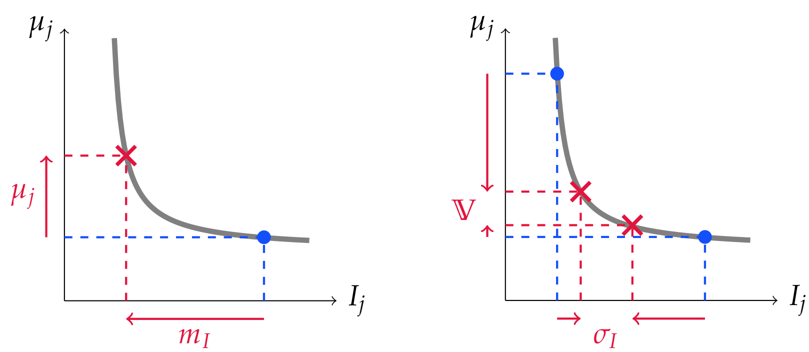


Figure 5: Identification of parameters in category "I. Match"

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



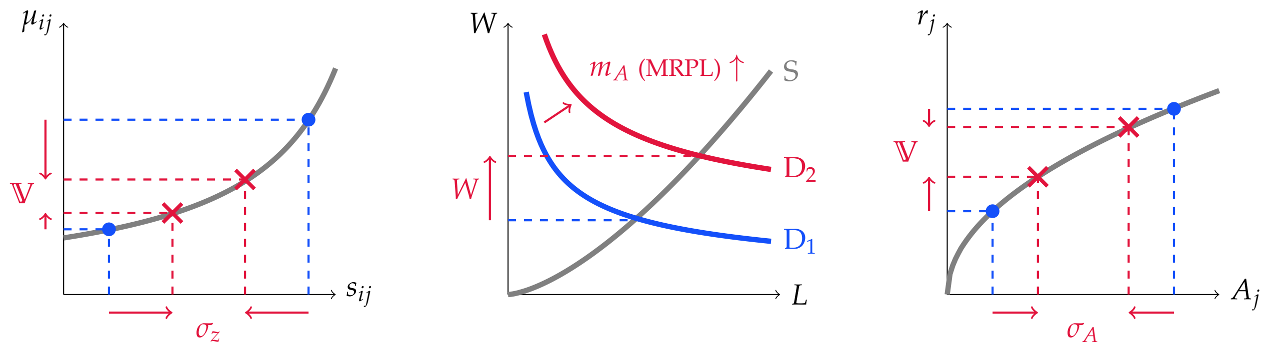
(a) Change in m_I (b) Change in σ_I

Figure 6: Identification of parameters in category "II. Market"

Notes: This figure shows the determinant of markups in a representative economy where firms have the same TFP. From Equation (10), we have: $\mu_{ij} = \left[1 - \frac{1}{\eta} - \left(\frac{1}{\theta} - \frac{1}{\eta}\right)\frac{1}{I_j}\right]^{-1}$ that is declining in I_j. The two panels demonstrate how the markup will respond when m_I and σ_I decline (from blue dots to red crosses), respectively.

II. Market. Equation (10) indicates a systematic relationship between the average markups and the number of firms in each market. In a representative economy where firms are identical, Figure 6a shows that markups will increase monotonically as I_j decreases, which helps us identify the average number of firms m_I.[35] Furthermore, because the number of firms differs in different markets, this monotonicity also makes the distribution of markups *across* markets informative on σ_I. Figure 6b illustrates that, when I_j gets less dispersed, market-level markups μ_j also become more concentrated. Therefore, we will exploit the between-market variance of markups to identify σ_I.

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



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

Figure 7: Identification of parameters in category "III. Firm"

III. Firm. The variance of markups *within* each market μ_{ij} is in turn determined by the variance in firm type σ_z.[36] As Figure 7a shows, a smaller σ_z will reduce the difference in s_{ij}, which eventually reduces the within-market variance of markups according to Equation (10). On the other hand, the panel B shows that the level of A_j influences the marginal revenue product of labor (MRPL), which shifts the labor demand function and eventually determines worker's wage. Finally, as the revenue is monotonically increasing over productivity, less dispersion in A_j leads to smaller variance in revenue, which becomes a good target for us to identify σ_A. This idea is shown in Figure 7c.

4.5 Estimation

We estimate the seven endogenous parameters jointly, in a separate estimation each year. Figure 8 shows the estimated parameters and how they evolve over time, while Figure 9 reports the close fit of the model moments to those in the data. To further validate our estimation, in Figure **??** we plot the manager pay distribution generated by the model, which matches the data distribution remarkably well in all years, even though we do not directly target the pay distribution.

I. Match. We first report the parameters that correspond to the match, $\{\alpha, \gamma\}$, in the first column of Figure 8. Estimates of α, which measure the relative importance of managers, are around 0.1% all the time. Although the estimated values appear small, we show in section 5.4 that managers play important roles for both the individual firm and the whole economy. Moreover, we find that α is generally increasing over time, suggesting that managers play an increasingly important role. This result is consistent with the finding of Garicano and Rossi-Hansberg (2006, 2015) that better communication technology effectively relaxes the time constraint of managers by allowing them to deal with more tasks.[37] The

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

[37] The parameter α an be interpreted as a residual term that reflects the relative importance of managers. There can be deeper factors that influence the evolution of this parameter, such as the advancements in communication technology mentioned here. Though interesting, these factors are not the focus of our analysis, so we abstract from them and capture those effect in a single parameter α.

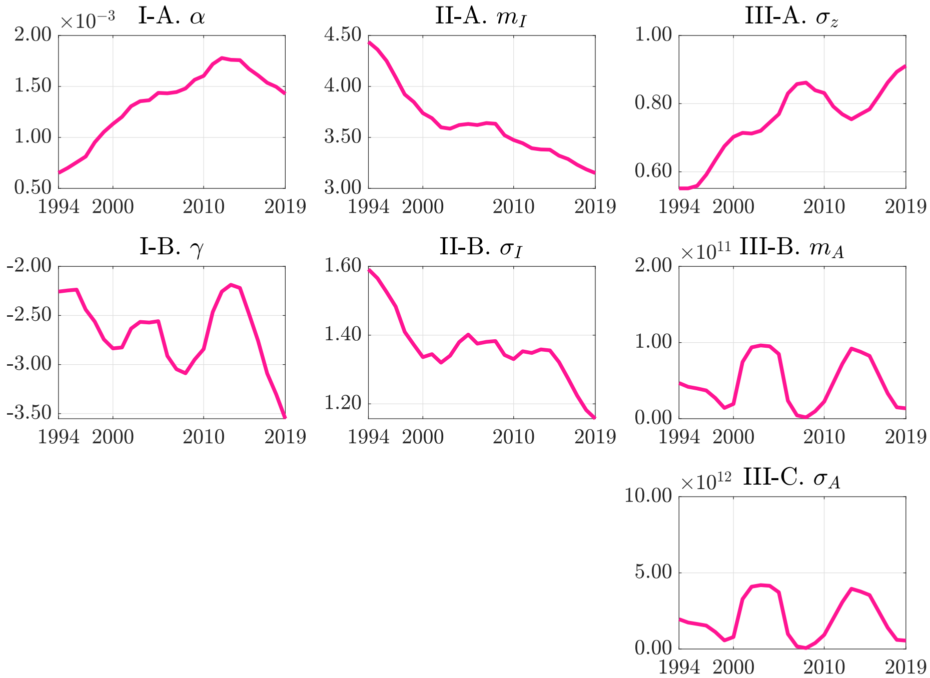


Figure 8: Parameters: I. Match, II. Market, and III. Firm

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

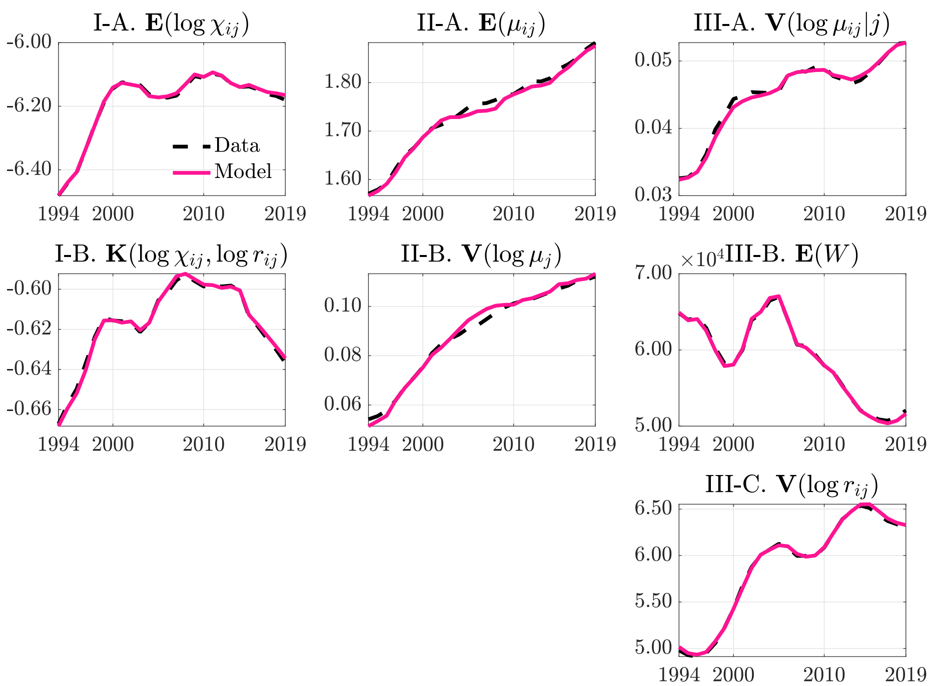


Figure 9: Targeted moments: I. Match, II. Market, and III. Firm

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

estimated elasticity of substitution γ is negative, which confirms the complementarity between firms and managers that is commonly assumed in the literature. Furthermore, γ was relatively stable, and then sharply declined from -2.22 in 2014 to -3.55 in 2019. This trend corresponds to the increasingly negative correlation between salary share and sales that is shown in Panel I-B of Figure 9 after 2014. Therefore, managers have recently become more complementary to firms.

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

III. Firm. The results of our estimation also suggest an increasing dispersion in firm type. Panel III-A of Figure 8 shows that its standard deviation σ_z increases from 0.51 to 0.77. This change mainly contributes to the increase in the variance of the log markups within and between markets. The same trend is documented in other literature as well (see for example, De Loecker et al., 2021; Deb et al., 2022a). One implication of this quantitative result is the rise of superstar firms, which is consistent with the findings of Autor, Dorn, Katz, Patterson, and Van Reenen (2020). Moreover, we also find that the average annual production worker wage is slightly decreasing in this sample, from \$65.8K to \$59.3K, which is consistent with the real wage stagnation of production workers in the economy. The overall decline in m_A matches this trend. We also document a huge difference across markets σ_A, which comes from the huge variance in sales and is within our expectation. Aggregating across widely different sectors implies there are huge productivity differences, say between labor-intensive sectors such as retail and sectors such as biotech.

4.6 Matching

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

Figure 10 shows how managers are matched with firms. Panel A reports the manager's iso-wage curves, which are consistent with the theoretical prediction in Figure 3. Basically, higher-type managers can earn more by working for firms with higher type z_{ij} and A_j. Panel B to D support these insights by showing the correlation between managers' type on the one hand, and firm type z_{ij}, market productivity A_j, and markups μ_{ij}. Because there are multiple dimensions and because there are externalities,

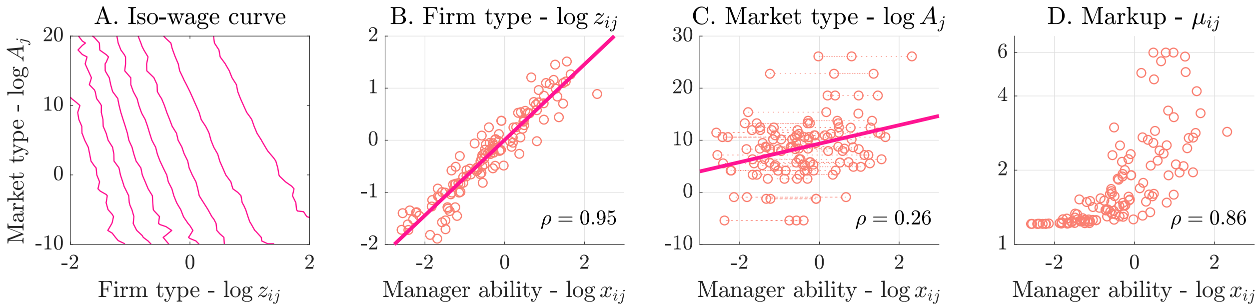


Figure 10: Matching: managers and firms in 2019

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

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-markup firms. Moreover, consistent with the data, we observe that manager ability is more closely correlated to firm type than the market productivity, which suggests that managers are mainly hired for competition within markets. This phenomenon is increasingly significant over time as the correlation within markets increases from 0.81 in 1994 to 0.95 in 2019.[38] The last panel reinforces this point by showing that better managers are in general hired by firms with larger market power.

In addition, we can also check the relationship between the type of CEOs and the elasticity of TFP on markup ε^{μ}_{ij} and on employment ε^{l}_{ij}, which has been discussed in Proposition 3. Figure 11 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 profit through the markup. In contrast, the employment elasticity is decreasing in manager type and may even be negative for some high-ability managers. Top managers in top firms hire less labor, which is consistent with the lower labor shares in superstar firms.[39] These different elasticities drive the heterogeneity in salaries between manager types, which is a topic that we will further elaborate on in Section 5.1.

4.7 Distribution of manager pay: model vs. data

Manager pay is the central object in our analysis, yet we do not directly target it in the estimation. This leaves rooms for us to validate how accurate our theory is and how much variation of manager pay in the data can be predicted by the channels highlighted in this paper. Inspiringly, our model can replicate the quantitative features of increasing manager pay and its dispersion, which lays foundation for our subsequent analysis.

[38] See Appendix C.4 for a time-series plot of these rank correlation coefficients.

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

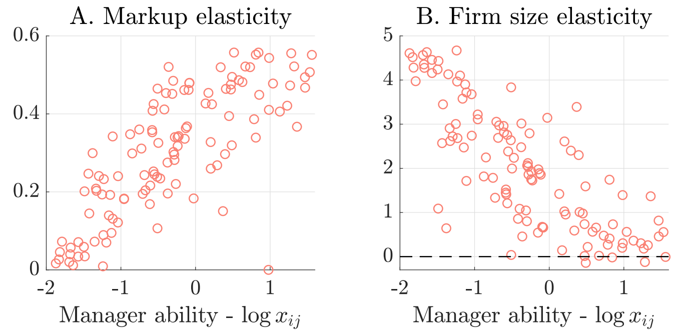


Figure 11: Matching: managers and elasticities in 2019

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

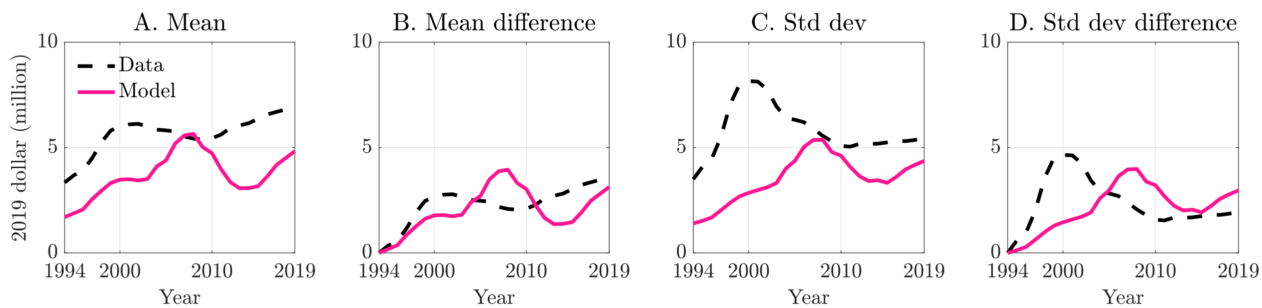


Figure 12: Mean and standard deviation of manager pay distribution: data and model prediction

Notes: The data and model sequences are both plotted in five year centered moving average.

In Figure 12 panels A and B, we compare both the level of manager pay and its growth since 1994 predicted by our model against the data counterparts. We find that our theory is able to explain on average 65.6% of the manager pay across the whole sample period. The average manager salary increases from \$3.34 million in 1994 to \$6.96 million in 2019, whereas the model counterpart increases from \$1.70 million to \$4.83 million. More remarkably, 86.4% of the increase in average manager pay from 1994 to 2019 (\$3.13 million in \$3.62 million) can be accounted for by the two channels we study.[40]

We also check the explanatory power of our theory on manager income inequality by comparing the standard deviation from the model to the data. Panel C of Figure 12 shows that overall 61.9% of the standard deviation in manager pay can be explained within our model. The standard deviation in the data is \$3.50 million in 1994 and \$5.43 million in 2019, while the numbers predicted by our model are \$1.40 million and \$4.37 million, respectively. Furthermore, the panel D indicates that our theory is also able to replicate the overall increase in the inequality of manager pay. Recall that we do not use any information on the manager pay distribution in our estimation.

We also plot the density of manager pay in the first two panels of Figure 13. Understanding that our theory could not explain everything in the level and variance of manager pay distribution, we find the model is still able to capture the shape of the empirical manager pay distribution. Specifically, we

[40]We interpret the systematic gap between our predictions and the data as other mechanisms that are ruled out in our analysis, such as the incentive payment. We refer reads to section 3.2 for a complete discussion.

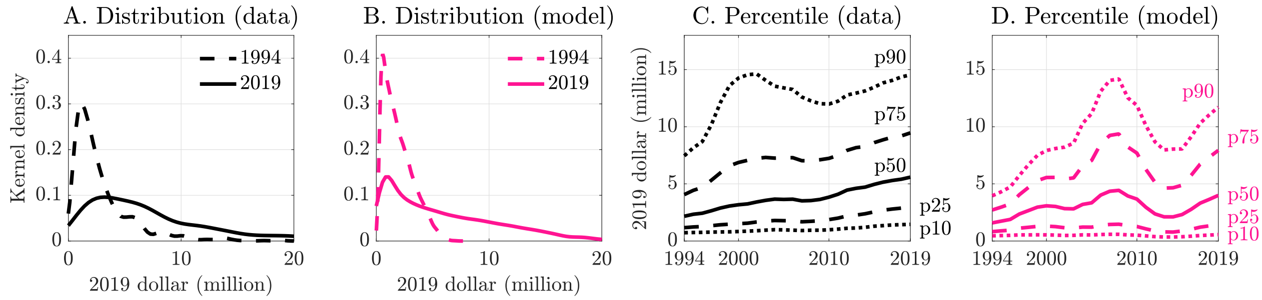


Figure 13: Distribution of manager pay: data and model prediction

Notes: Panel A and B show the kernel distribution of manager pay in the data and the model, respectively. Panel C and D report the evolution of the 10th, 25th, 50th, 75th, and 90th percentiles of the manager pay distribution in both data and model.

manage to replicate the right fat-tail of the pay distribution, which is the key feature of manager pay according to the superstar effects highlighted by Scheuer and Werning (2017). The same conclusion can be drawn from looking into the evolution of different percentiles in panels C and D, where we find that the income of the bottom managers has barely increased, while the most talented managers have experienced a sizable rise in their salaries.

The fact that our theory is able to replicate a major part of the first two moments of manager pay distribution as well as its shape from the data validates the quantitative model. In the remainder, we focus our analysis on the manager pay distribution within the quantitative model, which sheds important light on understanding of the real-world determinants of the rise in manager pay and its inequality. Before, we briefly analyze the markup and sales distributions.

4.8 Distribution of markup and sale: model vs. data

We further validate our model and estimates by comparing the distributions of markups and sales in the model and data. These two distribution are key for our purpose as they are measures for market power and firm size, respectively.[41] The results are shown in Appendix C.5, which suggest that our model matches the overall distribution of markups and sales in the data well. Only the 10th percentile of the markup and sales distributions are off in the model due to the lower bound of markups imposed by the CES demand system.

5 Main Results

With the model estimates in hand, we now analyze the different determinants of manager pay, which are summarized in Figure 14. Our main focus is on the contribution to manager pay from two channels: market power and firm size. In section 5.1, we study the rise of average manager pay. We then analyze the increasing inequality of manager pay in section 5.2. In section 5.3, we single out the direct effect of

[41] We do not compare the distribution of variable costs such as wage bill, which is the formal definition of firm size in this paper. The reason is that there are many missing data of wage bill in Compustat sample.

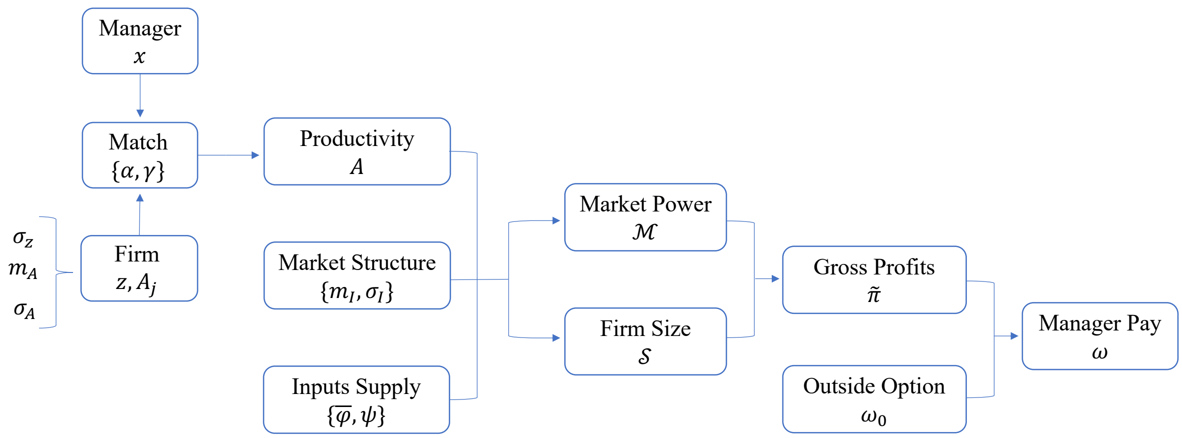


Figure 14: Determinants of Manager Salaries

each primitive parameter on manager pay and its inequality using a counterfactual experiment, which shows that the contribution of manager skill to productivity, α, plays a major role. In section 5.4, we investigate further the impact of managers in firms and in the whole economy. Finally, we discuss a set of robustness exercises in section 5.5. For label-wise simplicity, in our plots we will represent manager pay, market power and firm size using symbols Ω, $\mathcal{M}$, and $\mathcal{S}$, respectively.

5.1 The rise of manager pay

Our theory allows us to decompose equilibrium manager pay in our model into two channels: market power and firm size. We will start our analysis with a decomposition on the margin based on Proposition 1, which requires the minimum level of assumptions. Then, by putting the same structure on the manager market as Gabaix and Landier (2008) and Terviö (2008), we extend our decomposition exercise into the level of manager pay according to Proposition 2.

The marginal contribution of manager pay. We first find that market power is quantitatively important for the *marginal contribution* to manager pay, and increasingly so over time. The results build a basic picture on how the marginal dollar of manager pay is composited with the channels of market power and firm size, both across time and across managers with different abilities. Panel A of Figure 15 reports the time-series decomposition of marginal manager pay, where we yearly attribute the average marginal payment across managers to the market power and the firm size channels. It shows that the average contribution of the market power channel has been steadily increasing, from 36.4% in 1994 to 46.4% in 2019. We also see a robust result that top managers benefit more from market power. In panel B of Figure 15, we plot the share of market power channel in marginal manager pay as a function of managerial ability, which is in general increasing. Indeed, for the bottom manager, all the marginal salary comes through the firm size channel, while almost all the top manager's marginal pay comes

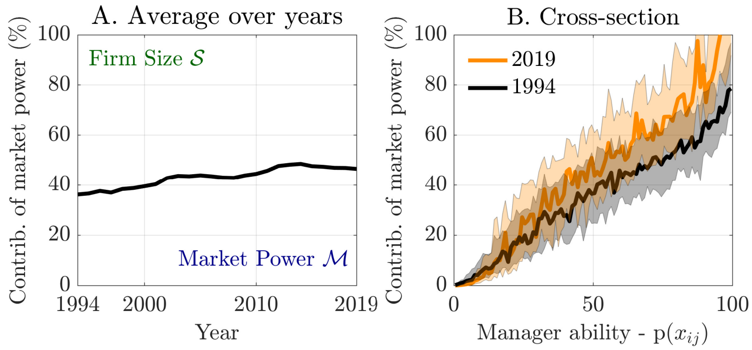


Figure 15: The marginal contribution of market power on manager pay

Notes: This figure reports the decomposition of manager pay at the margin according to Proposition 1. In panel A, we plot the average (across managers) share of market power channel in determining the marginal manager pay for each year, i.e., (markup channel)/(markup channel + firm size channel). The plot takes five year centered moving average. Panel B plots the cross-sectional distribution of the share of market power in marginal manager pay for 1994 and 2019. We put percentiles of manager ability on the x-axis and plot the kernel median smoother as the solid lines. The shaded part indicates the area between the first and third quartiles of the market power share distribution that conditions on manager ability.

from the market power channel.[42] This finding suggests that, on the margin, a higher-ability manager gets rewarded more from the extra market power he or she creates than the marginally larger firm size.

The level of manager pay. To learn more about the effects on the level of manager pay, we rely on the matching structure on the manager market and try to decompose the manager pay according to Proposition 2. In Figure 16, we plot the contribution to equilibrium manager pay of the market power and firm size channels.

Consistent with the results on the marginal contribution of manager pay, panel 16.A shows that both market power and firm size effects play important roles in determining executive salaries. Over the sample period, the model predicted manager pay (net of reservation utility) increases from \$2.70 million to \$4.83 million, where the market power effect increases from \$0.62 million to \$2.36 million and the firm size effect increases from \$1.08 million to \$2.47 million. Panel 16.B further shows that market power and firm size respectively contribute 45.2% and 54.8% to our model prediction of total manager pay, which explains 29.8% and 35.8% of what we observe in the data. Moreover, we document a relatively increasing contribution from the market power channel, which rises from 36.7% in 1994 to 48.9% in 2019.

In addition, we can also decompose the change of manager pay over time and attribute it to each channel. Panel 16.C shows the cumulative change in average manager pay and its components relative to the baseline year 1994. During the whole sample period, the model predicted manager pay increases by \$3.13 million, of which \$1.74 million is due to the increase in market power and \$1.39 million due to the firm size effect. Panel 16.D further shows that overall market power channel contributes to the growth in model by 55.6%, which accounts for 48.0% of growth in executive compensation shown in

[42]For some top managers, the firm size channel may even be negative when the market power share is greater than one, which means their employers have a tendency to reduce size on that margin. This model feature accounts for the very few cases where we see the share of market power component being greater than 100%.

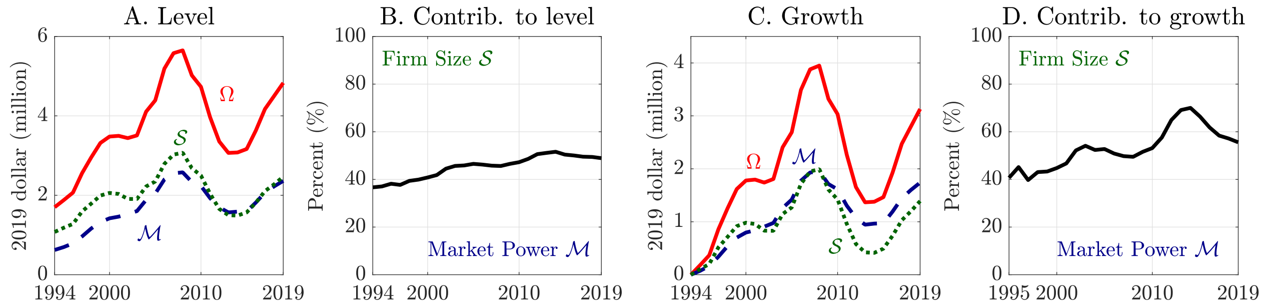


Figure 16: Manager pay decomposition into market power and firm size, by year

Notes: The capital letters Ω, $\mathcal{S}$ and $\mathcal{M}$ represents for manager pay, firm size channel, and market power channel, respectively. 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. In panel B and D, we compute and plot the contribution of firm size and market power to the level and growth of manager pay from the data. All results plotted are five-year moving averages.

the data. On the other hand, the firm size channel takes the remaining 44.4% of model growth, which explains 38.4% of growth in data.

5.2 The rise of manager pay inequality

Our decomposition exercise also allows us to examine the inequality in manager pay. We first look into the cross-sectional distribution of manager pay and its overall growth though the lens of the market power and firm size channels that are consistent with Proposition 3. We then check the underlying distribution of the two components. Finally, we study the evolution of this inequality over time and decompose the variance of manager pay.

Distribution of manager pay and its growth. We now detail how the channels of market power and firm size contribute to the distribution of manager pay. In the theory, Proposition 3 predicts that for small, low TFP firms, the firm size channel dominates the market power channel, while the importance of the market power channel should generally increase in firms' revenues. To understand this mechanism, we first analyze heterogeneity in the cross-section of a representative year 2019 and of the overall growth from 1994 to 2019.

In panel A of Figure 17, we plot the salary (net of reservation utility) of each percentile of managers, as well as the corresponding decomposition of the effects of market power and firm size in 2019. It shows that the schedule of manager pay is convex, as is predicted by the superstar effects of the executive profession. Furthermore, a key difference between the two components is that the effect of market power is convex while the firm size effect is concave in manager ability. Consequently, for the lowest type managers, almost all of their salary comes from the firm size effect, while the market power channel becomes increasingly important when the manager is more talented. This pattern is shown in Figure 17.B, where we plot the percentage contribution of the two components on the manager pay predicted by our model. For the top-ability managers, 80.3% of their salaries is due to market power.[43]

[43]Observe also a peculiar feature of the largest firms in our model. There is a sharp decrease in the firm size effect among

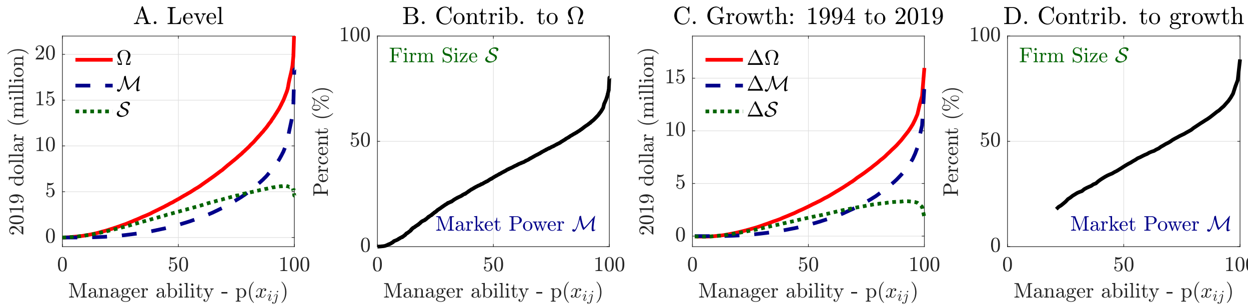


Figure 17: Cross-sectional distribution of manager pay and its decomposition

Notes: The capital letters Ω, $\mathcal{S}$ and $\mathcal{M}$ represents for manager pay, firm size channel, and market power channel, respectively. Panel A plots the model predicted distribution of manager pay and its decomposition for the year 2019. Panel B shows the percentage contribution of market power and firm size components to the model manager pay. Panel C and D plot the growth of manager pay from 1994 to 2019 across managers and decompose it into the two channels. The manager pay for the bottom CEOs drops from 1994 to 2019, so we only show the percentage contribution of market power and firm size in panel D for the percentiles of CEOs whose salary has increased.

This discrepancy contributes to the huge inequality in manager pay.

We also investigate heterogeneity in the growth of manager pay from 1994 to 2019. In Figure 17.C, we report the growth of manager pay per percentile of manager ability. The convexity indicates that the income increase of high-ability managers is disproportionally higher than the less abled ones, which marks an enlarging inequality among managers. The same feature is documented in the manager pay distribution that we studied earlier in Figure 13. The decomposition exercise offers an explanation that the high-ability managers benefit much more than the low-ranked ones from the larger increase in the effect of market power. This logic is confirmed in panel D of Figure 17 that not just the level, but also the change in manager pay is mainly driven by the market power channel for the top managers and by the firm size channel for those ranked at the bottom.

Distribution of market power and firm size components. We further report the distribution of market power and firm size components in Figure 18. The market power component in panel A shows a similar pattern to Pareto distribution with a thick right tail, while the firm size component in panel B distributes more uniformly. This difference suggests that, although both channels have increased by a similar amount over the sample period, the market power channel is the main force that drives the right tail of manager pay distribution. Furthermore, we plot the time series of multiple percentiles for the two components in Figure 18 panel C and D. Consistently, we find that the distribution of market power component gets increasingly dispersed over time, highlighted by a sharp rise for the top-ability managers. By contrast, the evolution of the firm size component is more uniform and contribute relatively smaller to the overall inequality among managers.

the very top managers. This is because the best managers are matched with superstar, but not monopolistic, firms whose employment elasticity of TFP (equation (15)) is negative. This insight is also confirmed by Figure 11 that the employment elasticity is negative for some high-ability managers.

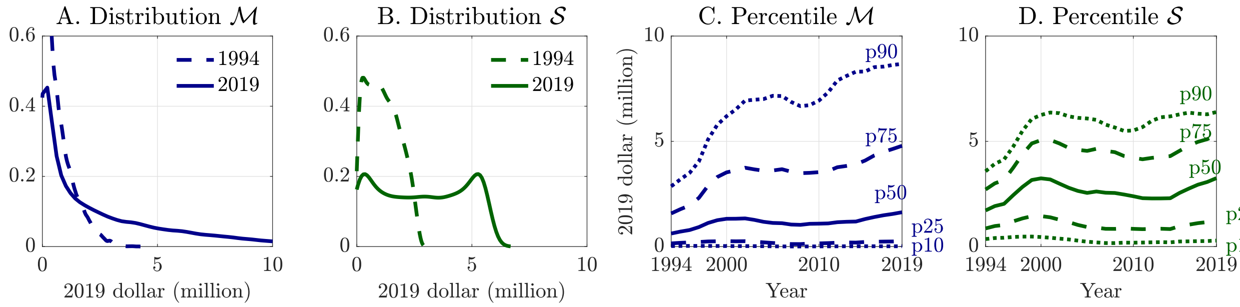


Figure 18: Distribution of manager pay growth from 1994 and 2019

Notes: In panel A and B, we plot the distribution of the two components, market power and firm size, from the manager pay decomposition for year 1994 and 2019. We then plot the evolution of the 10th, 25th, 50th, 75th, and 90th percentiles for the distribution of market power and firm size components in manager pay in panel C and D.

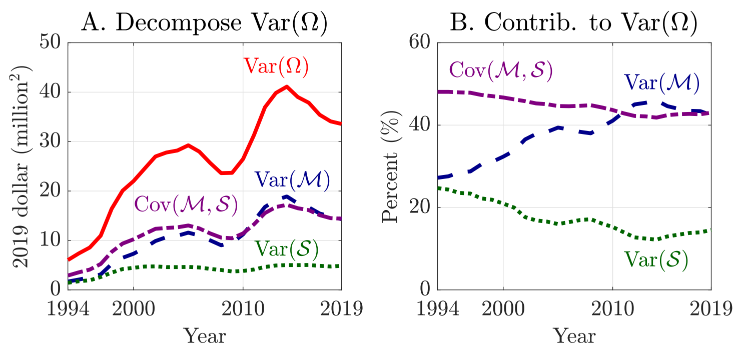


Figure 19: Time series of manager pay inequality and its decomposition

Notes: We decompose the variance of manager pay into different parts and report them in panel A, including the variance of market power component, the variance of firm size component, and the covariance term. Panel B calculates the contribution of each part to the gross manager pay inequality. All the sequences are plotted with five-year centered moving average.

Variance decomposition. Finally, our framework allows us to decompose the variance of manager pay distribution into the variance of market power component, the variance of firm size component, and the covariance between the two components. The results are reported in Figure 19. We find that the rise of manager pay inequality is mainly driven by the rising variance in the market power channel and the interaction term, while the variance of firm size component remains fairly flat. Relatively speaking, the variance of market power component has been significantly more important in determining manager inequality, whose contribution increases from 27.2% in 1994 to 42.4%, while the contribution from the firm size channel and the covariance term are both declining. We thus conclude that market power is the most important component that contributes to the enlarging inequality in manager pay.

5.3 Counterfactual: factor decomposition

Empowered by our structural model, we can also analyze the contribution of each primitive parameter to manager pay through the channels of market power and firm size. To do this, we keep all parameters fixed at their 1994 values, and then feed in one or more estimated, year-specific parameters, plotting the cumulative changes in the effects of market power and firm size on manager pay and its inequal-

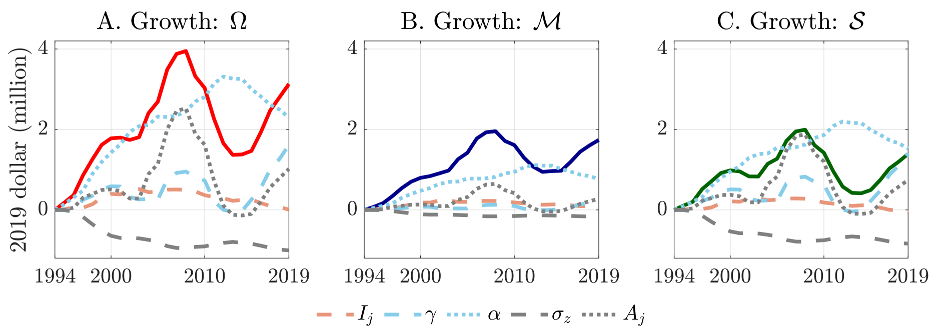


Figure 20: Factor decomposition: The rise of manager pay

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 induced manager pay, market power component, and firm size component, respectively. Parameters in the same category defined in Table 5 are marked by the same color. For each panel, we choose the corresponding 1994 value as the reference point and plot the cumulative change from this point in each counterfactual economy. We bundle $\{m_I, \sigma_I\}$ into I_j because they jointly characterize the market structure distribution, and so does $\{m_A, \sigma_A\}$ into A_j. The solid line in each figure corresponds to the baseline sequence from our yearly estimated model. All the results are plotted in five-year centered moving average.

ity. Throughout this exercise, we will focus on five sets of parameters: market structure $\{m_I, \sigma_I\}$, the complementarity between managers and firms γ, the importance of managers α, the dispersion of firm type σ_z, and the distribution of market type $\{m_A, \sigma_A\}$. 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.

Manager pay. We first check the counterfactual impact of the primitive parameters on the growth of manager pay in Figure 20. In panel A, we decompose the gross change in the manager pay (the red, solid line) into five primitives. The biggest contribution comes from the increasing importance of managers, α, which alone can raise average manager pay by \$2.29 million, explaining 73.2% of the whole growth predicted by our model. Moreover, the complementarity parameter γ and the overall distribution of market-level productivity shifter $\{m_A, \sigma_A\}$ also prove to be important, each of which directly contributes to \$1.62 million and \$1.02 million of increase in manager pay. The latter one also appears to be responsible for the hump increase during the 2008 Great Recession. On the other hand, we find the dispersion of firm type σ_z plays a negative role that drives down manager pay by \$1.01 million. The impact from change in market structure is relatively negligible.

In panels B and C of Figure 20, we further dig into the impact of the two channels, market power and firm size, which have similar weights in determining average manager pay. Our results suggest that the increase in the market power component is largely driven by the change in α and other sets of parameters remain relatively silent. For the firm size component, α again is the most important driving force, but we also find other sets of parameters like γ, $\{m_A, \sigma_A\}$, and σ_z play active roles. We conclude that the parameter α contributes to the manager pay through both market power and firm size channels, while other parameters mainly function through the firm size one.

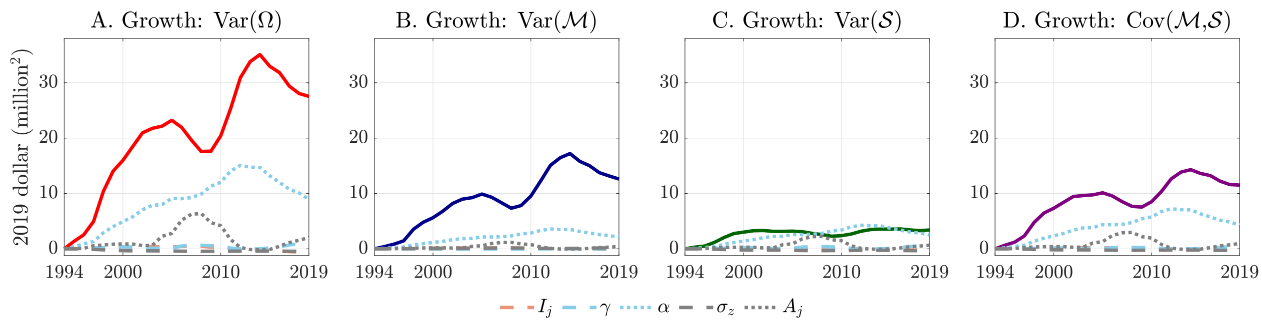


Figure 21: Factor decomposition: The rise of inequality

Notes: We set 1994 estimates as our baseline parameters. In each case, we only change a certain set of parameters, solve the economy, and report the induced variance in manager pay, market power component, and firm size component, as well as the covariance term, respectively. Parameters in the same category defined in Table 5 are marked by the same color. For each panel, we choose the corresponding 1994 value as the reference point and plot the cumulative change from this point in each counterfactual economy. We bundle $\{m_I, \sigma_I\}$ into I_j because they jointly characterize the market structure distribution, and so does $\{m_A, \sigma_A\}$ into A_j. The solid line in each figure corresponds to the baseline sequence from our yearly estimated model. All the results are plotted in five-year centered moving average.

Manager inequality. We perform the same decomposition on the inequality of manager pay in Figure 21. We report the counterfactual results for variance of manager pay in panel A, which we then further decomposes into the variance of the market power component, of the firm size component, and their covariance in panels B to D. Among all the five sets of primitives, we only document an active effect from the parameter α. The evolution of manager importance can directly explain 32.4% of the gross rise in the variance of manager pay, which can be attributed into 16.7% in the variance of market power component, 74.4% in the variance of firm size component, and 37.2% in the covariance term. The large part of remaining unexplained growth in manager pay inequality comes through the interaction among different primitives.

5.4 The importance of managers

Section 5.3 suggests that the parameter α, which measures the importance of manager skill, is the key parameter that accounts for a majority fraction of increase in both the level and inequality of manager pay. It is therefore worthwhile to investigate deeper what the contribution of the manager is for each firm and for the whole economy.

Importance of managers to firms in partial equilibrium. We first check the partial equilibrium impact from managers to firms, that is, the effect of increasing a single manager's ability on his/her employer holding everything else equal. In the first two panels of Figure 22, we report the profit elasticity of manager ability in the cross-section and over time. Panel A shows that there is strong heterogeneity depending on the sales of the firm. In 2019, the profit for the first-percentile firm can increase by 51.0% if its manager becomes one percent better, while the same shock will only benefit the median firm by 0.51%, and the top-percentile firm by 0.01%. This distributional pattern is very robust across different years. In panel B, we report the aggregate partial equilibrium effect as the average elasticity of manager

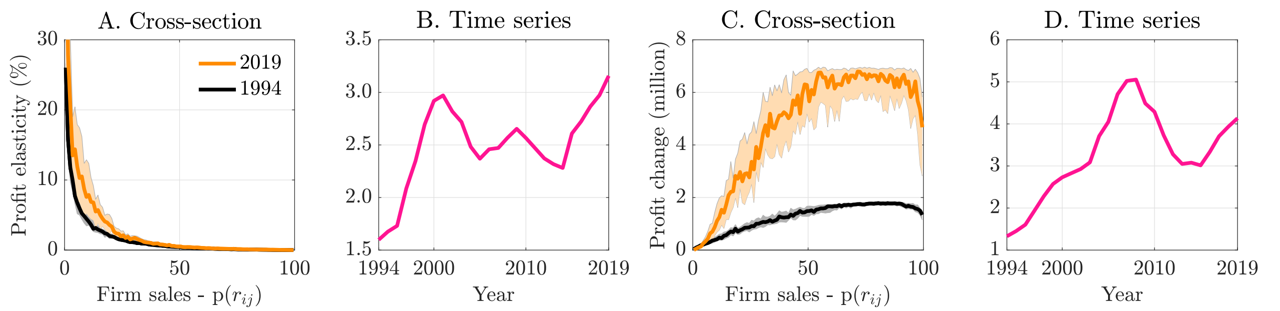


Figure 22: Effects of one-percent manager ability increase on firm profits

Notes: In panel A and C, we report the cross-sectional distribution and the mean evolution of profit elasticity of manager ability, i.e., $(d\pi_{ij}/\pi_{ij})/(dx_{ij}/x_{ij})$ under our model notation. We rank firms by their sales on the x-axis and plot the median elasticity/change within each percentile. The shaded part indicates the area between the first and third quartiles of the corresponding objects within each percentile. In panel B and D, we report the change in profits in reaction to a 1% increase in manager ability, i.e., $d\pi_{ij}/(dx_{ij}/x_{ij})$. All the time series sequences are plotted in five-year centered moving average.

ability on firm profit across all firms, i.e., $\mathbb{E}[\frac{d\pi_{ij}/\pi_{ij}}{dx_{ij}/x_{ij}}]$. The results immediately suggest that managers are important for firm profitability, consistent with empirical findings such as Bennedsen, Pérez-González, and Wolfenzon (2020). Moreover, their importance has been rising over the sample period. In 1994, a single percent increase in manager ability will on average lead to 1.60% of increase in profits, which has almost been doubled to 3.16% in 2019.

Furthermore, for those big firms we claim that a low profit elasticity does not mean managers are unimportant. Specifically, we calculate and plot the partial equilibrium profit change at the firm level when facing a one-percent increase in manager ability in panel C and D of Figure 22. We find that the absolute benefit to firms of such a managerial ability increase is in general increasing with sales. While the absolute increase in profit is small for low-sale firms, the medium and the large ones do benefit tremendously from this shock, whose effect is nearly $2 million in 1994 and above $6 million in 2019. In terms of time series, we also document an increase in the average effect of raising manager ability by 1%, which rises from $1.33 million in 1994 to $4.14 million in 2019.

Importance of managers to the economy in general equilibrium. With the general equilibrium effect in mind, we further quantify the importance of managers to the whole economy by running two counterfactual experiments: doubling managerial ability for *all* managers and randomly assigning managers to firms. Results are reported in Figure 23.

In panel A, we find that the economy will benefit from doubling every manager's ability z_{ij}. Specifically, output will increase 0.013% in 1994 and 0.028% in 2019, showing an increasing trend across time. This general equilibrium effect is much smaller than the partial equilibrium effect we identify in Figure 22.B for two reasons. First, our partial equilibrium analysis on individual firm level rules out the negative externality through competitions. Firms will produce less when their competitors become more productive due to strategic interaction within a market, which could dampen the gain from better manager ability. Second, big firms are more important in the GDP calculation than the small or medium-sized ones, meaning that we are assigning higher weights to firms who have a lower profit

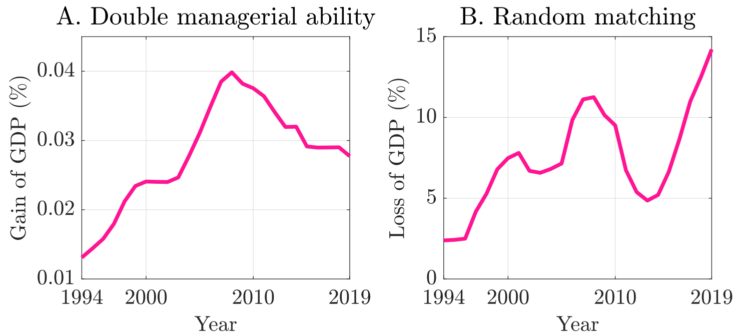


Figure 23: Counterfactual: Importance of managers to the economy

Notes: We report counterfactual changes of GDP in relative to its value in the baseline economy. In panel A, we proportionally double the ability of all managers. In panel B, we randomly assign managers to firms. All results are plotted in five-year centered moving average.

elasticity when studying this aggregate effect.

We also demonstrate the increasing importance of managers by examining the output loss due to mismatch. In Figure 23 panel B, we find that randomly assigning managers to firms will induce a significant loss in GDP compared to the equilibrium under stable matching, which ranges from 2.39% in 1994 to 14.21% in 2019. From the perspective of matching efficiency, this result suggests that managers have large implications on the economy-wide efficiency, and this impact is becoming larger over time.

5.5 Robustness

Measuring market power in different ways. The literature has documented the rise of market power from various perspectives, including the rising markups, the higher market concentration, and the higher profit rates.[44] In this paper, we treat markups as the measure of market power and estimate our model matching moments from the markup distribution. Our results are similar when we use the markups estimated by Deb et al. (2022b). They use a structural model instead of the production function approach and Census data for the universe of firms instead of Compustat, which generates a markup distribution that is similar to the one using the production function approach. It is worth noting that, although we mainly focus on the markup distribution during estimation, our estimated model is also able to replicate the rise in market concentration and profit rates. Hence, our framework is consistent with various observations related to market power.

Quantitatively, we can also measure market power by the Lerner index, which is $1 - 1/\text{Markup}$. In Appendix D.1, we replicate our main exercises by decomposing the margin, level and distribution of manager pay into the channel of Lerner index (market power) and revenues (firm size).[45] The results using the Lerner index show trivially that the results are identical to those using the markup. After all, the Lerner index is a monotone transformation of the markup. We also include in the Appendix the

[44]See Syverson (2019), De Loecker et al. (2020), Bond, Hashemi, Kaplan, and Zoch (2021), and De Ridder, Grassi, and Morzenti (2022) for discussions on methods including production function estimation, the use of concentration measures, structural estimation,...

[45]The detailed decomposition expression is documented in Appendix D.1 as well.

outcome of an exercise where we naively – though wrongly – interpret the impact of the Lerner index as being different from the impact of the markup.

Bertrand competition. An alternative way to model oligopolistic competition is to let firms set prices (Bertrand) instead of quantities (Cournot). In Appendix D.2, we replicate our main results under Bertrand competition and demonstrate the robustness. Indeed, we see that market power becomes more important across time, whose contribution to the manager pay margin (level) has been increasing from 26.2% (26.8%) in 1994 to 53.4% (56.9%) in 2019. The cross-sectional decomposition of manager pay distribution shows the same pattern where the top managers' pay is determined predominantly by the market power channel.

Elasticities of demand. In our main analysis, we calibrate the parameters that determine the demand elasticity $(\theta, \eta) = (1.20, 5.75)$, based on the estimates from De Loecker et al. (2021). In Appendix D.3, we redo our quantification exercise with the elasticity $(\theta, \eta) = (1.50, 10.00)$, used by Atkeson and Burstein (2008) and show that our results are qualitatively robust over the different sets of elasticity of demand. We find that market power contributes to 43.4% of manager pay in 1994 and 51.5% in 2019, and these demand parameters also generates a similar pattern across managers. This is not a surprise because as long as competition is imperfect, market power will play a role in determining manager pay irrespective of the demand.

6 Conclusion

Market power in the goods market distorts the efficient allocation of resources. In this paper, we show that market power also distorts manager pay, as managers are paid in part for market power, due to the sorting of managers into top firms. Without market power, superstar managers would earn less. Currently, managers are paid to create profits, and profits derive from higher value of the firm as well as more market power. Better managers grow the firm which increases value, but they also increase market power, which is inefficient.

The main insight of this paper is to decompose the contribution of market power to manager pay as distinct from firm size. We estimate the model using data on executive compensation and verify that our quantitative model, without using information on the manager pay distribution, can explain the majority of the level and almost all the growth of manager pay in the data. Within the model prediction, 45.2% of manager pay is on average due to market power, growing from 36.7% in 1994 to 48.9% in 2019. Market power accounts for 55.6% of growth over this period.

Our analysis also reveals that market power channel is responsible for the rising inequality among managers. While almost all the salaries of the bottom managers are determined by the firm size channel, the market power channel contributes 80.3% of the payment for the very top managers. The best managers are hired by large, high markup firms where they create high profits for the shareholders, but disproportionately little additional value to the economy due to the incomplete pass-through. We find that the growth of their pay due to market power is even larger. The rising market power over time hence leads to a longer and thicker tail for the manager pay distribution on the right, resulting in a larger inequality.

The mechanism that we identify behind the reward structure of managers crucially hinges on the competitive pressures within a market. In the presence of imperfect competition, the most productive firms extract higher rents than the less productive firms. Because of the complementarity between manager ability and firm productivity, the most productive firms can widen the gap even more by hiring a highly skilled manager. This increases their markups even further. The less productive firms have low markups and hence have little to gain from hiring a superstar manager. Because there is competition for managers, all top firms in their own market who benefit from having a top manager will bid up the top wages. Managers at top firms are paid predominantly for increasing the gap between their direct competitors.

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

Online 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 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.

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}.

Appendix A.3 Replication of Gabaix and Landier (2008)

To test the role of interaction within a market plays in determining manager pay, we follow the spirit of the regression analysis in Table 2 of Gabaix and Landier (2008) and regress manager pay in year $t+1$ on firm size, which is measured by Sales and COGS in this exercise, as well as the baseline firm size (the 250th largest firm) in year t.

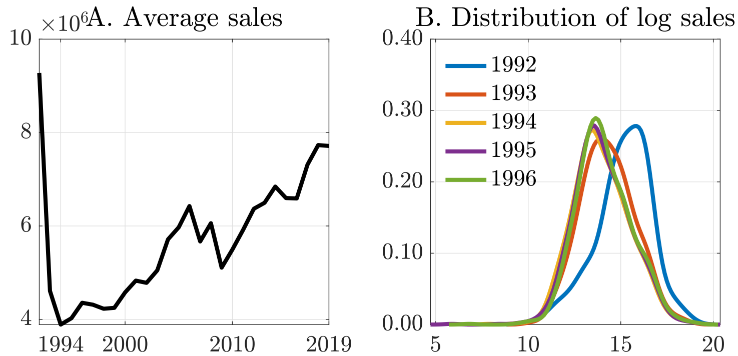


Figure A.1: Sample selection in 1992 and 1993

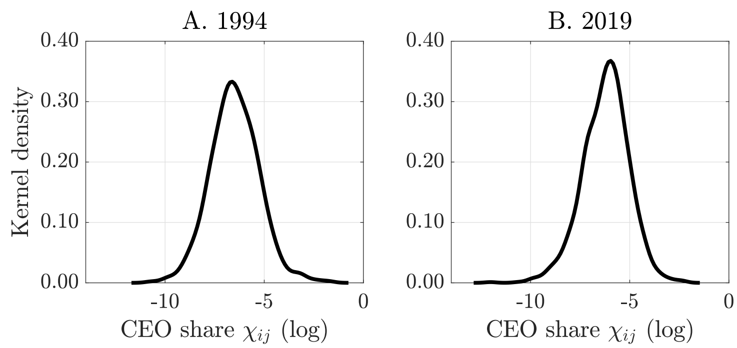


Figure A.2: Normality of log Manager share log χ_{ij}

We make three main changes in our replication exercise. First, we expand the sample size by including observations until year 2020. All results are robust when we restrict the sample period to the one used in Gabaix and Landier (2008). Second, we measure firm size by either their sales or cogs, while the latter one is consistent with our structural method. Third, industries are defined at a finer level based on four-digit NAICS code, which provides a more accurate measure of market segment.

The results are reported in Table A.1. We first confirm the conventional wisdom that manager compensation is increasing with firm size, as the coefficients on both measures are robustly positive for all specifications. Interestingly, we also find that this correlation between manager pay and firm size becomes significantly stronger after we control for market fixed effects.[46] We read this result as follows: a manager will get more rewards from a larger firm relative to its direct competitors than a larger firm relative to the economy. This further suggests that an important piece of strategic interaction within a market is missing in the canonical theory of manager pay. We hence use endogenous markups to address this issue in our paper.

[46]The exception is in specification (5) and (6) when we restrict our sample to the top 500 firms in each year, where our market definition is too fine and we lack within-market variation to identify the correlation between manager pay and sales.

Table A.1: Motivating regressions: Manager pay, own firm size, and reference firm size

	log manager pay							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Top 1000				Top 500			
log sales	0.377	0.417			0.333	0.349		
	(0.009)	(0.010)			(0.017)	(0.018)		
	(0.008)	(0.007)			(0.016)	(0.013)		
log cogs			0.326	0.389			0.311	0.356
			(0.009)	(0.009)			(0.016)	(0.015)
			(0.007)	(0.006)			(0.014)	(0.013)
log sales of firm #250	0.585	0.520			0.603	0.535		
	(0.035)	(0.033)			(0.048)	(0.044)		
	(0.097)	(0.095)			(0.125)	(0.127)		
log cogs of firm #250			0.601	0.528			0.623	0.537
			(0.039)	(0.035)			(0.050)	(0.044)
			(0.113)	(0.110)			(0.132)	(0.132)
Industry fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.346	0.452	0.290	0.431	0.230	0.394	0.207	0.396
Observations	25,937	25,937	25,937	25,937	12,974	12,974	12,974	12,974

Notes: We measure firm size by either sales or cogs. In the three sets of exercises, we select each year the top $n \in \{500, 1000\}$ largest firms in terms of the corresponding measure of firm size at year $t-1$. The size of the 250th largest firm is constant over firms in the same year, so it effectively plays the role of year fixed effects. The industries are defined on four-digit NAICS codes. We report standard errors clustered at the firm level (first line) and at the year level (second line).

Appendix B Model appendix

Appendix B.1 Lemma 1: household solution

Recall the household problem:

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

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

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

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

which incurs first order condition:

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

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

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

The FOC gives:

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

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

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

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

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

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

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

Appendix B.2 Lemma 2: sub-game equilibrium

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

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

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:

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

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 $1/I_j$ and $1/J$ neutralize the effect of love of variety — it prevents the change in I_j and J from directly influencing equilibrium wage. As a result, all changes in wages W are due to the evolution of markups and productivities.

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:

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

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 3: markup and firm size elasticities of TFP

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

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

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

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

Sum them up with the sales weight, we get:

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

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

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

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

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

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

from which we get:

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

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

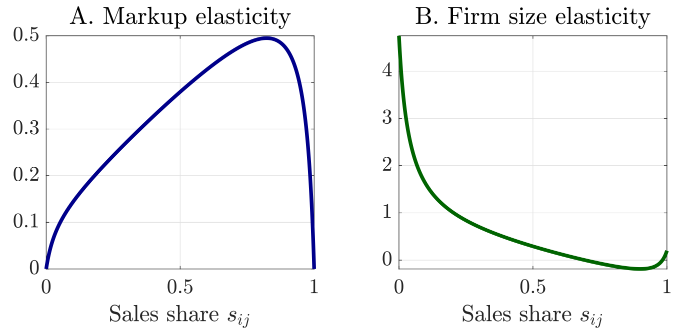


Figure B.1: Markup and employment elasticity of TFP

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

Appendix B.4 Extension: agency issue

In this section, we introduce risk aversion and an agency problem into our matching framework à la Edmans and Gabaix (2011) (henceforth, EG). We rederive the main theoretical predictions of our baseline model, based on which we will reach the conclusion that ignoring agency issue does not affect the decomposition of manager pay into the effect of market power and firm size.

We follow the setup and notations from the baseline model. In addition, we assume managers have CRRA utility function:

$$U(b,a) = \begin{cases} \frac{\left(be^{-g(a)}\right)^{1-\Phi}}{1-\Phi} & \text{for } \Phi \neq 1 \\ \ln b - g(a) & \text{for } \Phi = 1 \end{cases}$$

where b denotes the realized compensation and $a \in [\underline{a}, \overline{a}]$ denotes the effort level. In this specification, $\Phi \geq 0$ is the relative risk aversion that is essential for introducing the agency problem. The term $g(a)$ captures the disutility of effort. Effort enters the gross profits in a multiplicative way:

$$\widehat{\pi} = \frac{\widetilde{\pi} e^{a - \overline{a} + \iota}}{\mathbb{E}\left[e^{\iota}\right]},$$

where $\widetilde{\pi}$ is the baseline gross profit defined in the main body, ι is mean-zero noise with standard deviation σ and bounded interval support, and $\mathbb{E}[e^{\iota}]$ normalizes the matching output to ensure that it does not depend on the noise distribution. Note that we introduce the effort and shock in a multiplicative way that will not influence the output market competition, just like if it were a profit taxes. We assume the manager privately observes ι before choosing a, but after signing the contract. Hence, the manager remains exposed to risk.

A key assumption of EG is that the baseline matching outcome $\widetilde{\pi}$ should be sufficiently large, or alternatively the cost of effort and the risk should be sufficiently small, such that the maximum productive effort $\overline{a}$ becomes optimal for the firm, because the benefits of eliciting effort outweigh the costs.

Under this assumption, the matching outcome on the equilibrium path is:

$$\widehat{\pi} = \frac{\widetilde{\pi} e^{\iota}}{\mathbb{E}\left[e^{\iota}\right]}.$$

Given this setup, we can replicate the analysis by EG, which leads to simple, closed form expression for the optimal contract.

Claim (Proposition 1 in EG) *Let $\underline{u}$ be the reservation utility of the manager. The optimal contract pays the manager an amount b defined by*

$$\ln b = \Lambda \ln \widehat{\pi} + K, \tag{B.12}$$

where $\Lambda := g'(\overline{a})$ is the marginal cost of effort and K is a constant that makes the participation constraint bind, that is,

$$\mathbb{E}\left[\frac{\left(be^{-g(\overline{a})}\right)^{1-\Phi}}{(1-\Phi)}\right] = \underline{u}.$$

The optimal contract for firms can thus be implemented by giving the manager $\Lambda\omega$ of stock and $(1-\Lambda)\omega$ of cash, given the amount of expected payment ω.

Proof. See Edmans and Gabaix (2011). ■

Furthermore, given this contract, we can write the risk premium demanded by a manager as $\overline{\Phi}\left(\Lambda^2\sigma^2\right)/2$, where we define

$$\overline{\Phi}\left(\sigma^2\right) = 2\left(\ln \mathbb{E}\left[e^{\iota}\right] - \frac{1}{1-\Phi}\ln \mathbb{E}\left[e^{(1-\Phi)\iota}\right]\right).$$

The expected utility of the manager can hence be written as:

$$U = \mathbb{E}\left[\frac{\left(be^{-g(\overline{a})}\right)^{1-\Phi}}{1-\Phi}\right] = \frac{\left[\omega e^{-g(\overline{a})} e^{-\overline{\Phi}\left(\Lambda^2\sigma_n^2\right)/2}\right]^{1-\Phi}}{1-\Phi} := \frac{\left(\omega e^{-\tau}\right)^{1-\Phi}}{1-\Phi}$$

where $\tau := g(\overline{a}) + \overline{\Phi}\left(\Lambda^2\sigma^2\right)/2$ is the "equivalent variation" and U is the certainty equivalence of the manager under this contract with expected compensation of ω. Therefore, we can define $v := \omega e^{-\tau}$ as the effective wage of the manager.

In the matching market, firm ij's problem then becomes:

$$\begin{aligned}
\max_x \pi_{ij} &= \mathbb{E}\left[\widehat{\pi}_{ij}\left(A_{ij}|A_{-ij}\right) - v(x)\, e^{\tau}\right] \\
&= \widetilde{\pi}_{ij}\left(A_{ij}|A_{-ij}\right) - v(x)\, e^{\tau} \\
&= e^{\chi}\left[\underbrace{\widetilde{\pi}_{ij}\left(A_{ij}|A_{-ij}\right) e^{-\tau}}_{\text{Effective matching output}} - v(x)\right],
\end{aligned}$$

which incurs the FOC:

$$e^{-\tau}\frac{\partial\widetilde{\pi}_{ij}}{\partial A_{ij}}\frac{\partial A_{ij}}{\partial x_{ij}}=\frac{d}{dx}v\left(x_{ij}\right). \tag{B.13}$$

As before, we can numerically find the stable matching and solve for the equilibrium effective wage schedule $v(x)$ and do the same decomposition exercise as in the benchmark model. We now replicate the first two main propositions in the presence of agency issue, whereas the Proposition 3 is unchanged.

Proposition 1' *The marginal contribution to gross effective profits of managerial ability can be decomposed as follows:*

$$\frac{\partial}{\partial x_{ij}}\left(\widetilde{\pi}_{ij}e^{-\tau}\right)=\left[\underbrace{\frac{\partial\mu_{ij}}{\partial A_{ij}}Wl_{ij}}_{\text{Markup channel}}+\underbrace{(\mu_{ij}-1)W\frac{\partial l_{ij}}{\partial A_{ij}}}_{\text{Firm Size channel}}\right]\frac{\partial A_{ij}}{\partial x_{ij}}e^{-\tau}. \tag{B.14}$$

Proposition 2' *Given stable matching Γ, the executive effective salary schedule $v(x)$ satisfies:*

$$v(x_{ij})=v_0+e^{-\tau}\int_{\underline{x}}^{x_{ij}}\left[\underbrace{\frac{\partial\mu_{i'j'}}{\partial A_{i'j'}}Wl_{i'j'}}_{\text{Markup channel}}+\underbrace{\left(\mu_{i'j'}-1\right)W\frac{\partial l_{i'j'}}{\partial A_{i'j'}}}_{\text{Firm size channel}}\right]\times\left[\frac{\partial A_{i'j'}}{\partial x_{i'j'}}\right]dx_{i'j'},$$

where v_0 is the reservation utility that determines the effective wage for the lowest-type manager.

The results in this section show that introducing risk aversion and incentive provision in a multiplicative way does not change the key insights demonstrated in this paper. The intuition is that, although managers are additionally compensated for effort elicitation and risk aversion, these compensation also goes through the two channels and can hence be attributed to market power and firm size. In the current setup where all firms have identical τ, we can derive the same results because everything is simply scaled by a constant $e^{-\tau}$. This framework also allows us to introduce heterogenous risk σ_{ij}^2 and effort cost $g_{ij}(a)$, which can lead to richer heterogeneity in the quantitative exercise, yet it does not change the key mechanism through which market power determines manager pay.

Appendix B.5 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:

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

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 $P^m = W$.

Moreover, solving this cost minimization problem gives us the marginal cost of production:

$$
mc_{ij} = \frac{1}{\psi}\frac{1}{\zeta}\frac{W}{\widehat{A}_{ij}}, \tag{B.16}
$$

which further leads to the gross profit:

$$
\widetilde{\pi}_{ij} = (\mu_{ij}-1) mc_{ij} y_{ij} = \frac{1}{\psi}\frac{1}{\zeta}(\mu_{ij}-1) W l_{ij}. \tag{B.17}
$$

Compared to the labor-only model, the gross profit (B.17) is scaled by the production elasticity of material and capital, which indicates the final decomposition of manager pay in equation (18).

Appendix C Quantification

Appendix C.1 Verifying the efficiency of the approximate algorithm

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

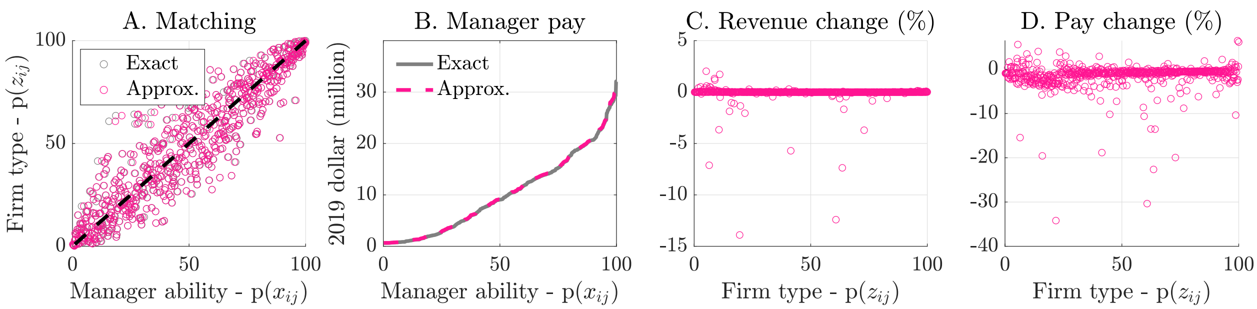


Figure C.1: Comparison: Exact and Approximate Stable Matching

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

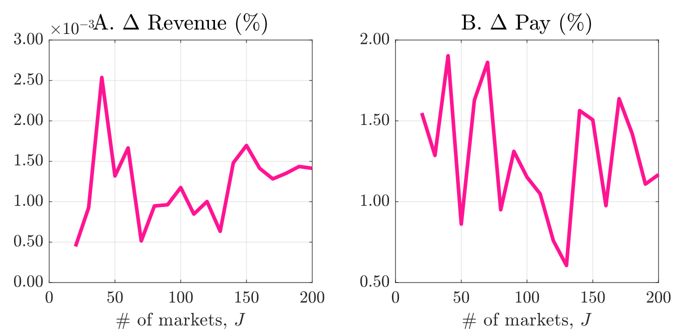


Figure C.2: Robustness of Approximate Stable Matching over J

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

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

Appendix C.2 Comparative static

Category I. Match

Importance of managers - α. Figure C.3 reports the comparative static results for $\{\alpha, \gamma\}$. The importance of the manager is measured by the share of the manager α. As is shown by Proposition 2, an increase in α will proportionally raise the marginal contribution of managers for all firms. This leads to the two conclusions regarding moments: first, the average salary share of managers will increase; and second, the slope of salary share on sales will be constant.

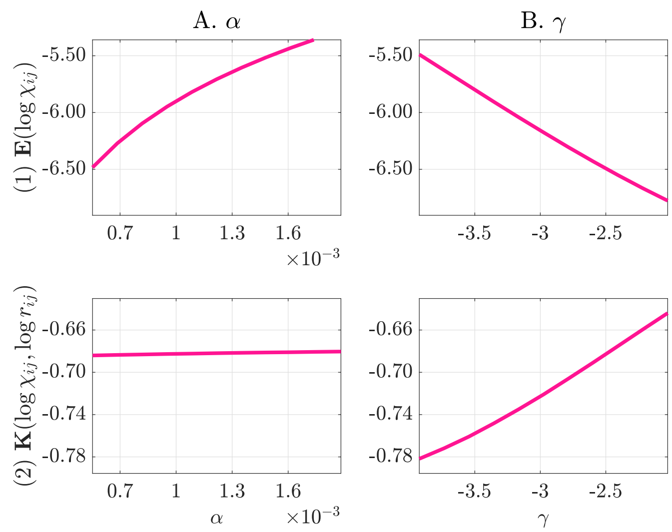


Figure C.3: Comparative static: I. Match

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

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

Category II. Market

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

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

Category III. Firm

STANDARD DEVIATION OF FIRM TYPE - σ_z. Figure C.5 presents the comparative static over firm-level parameters. The change in standard deviation of the z_{ij} influences mainly the variance of firm types.

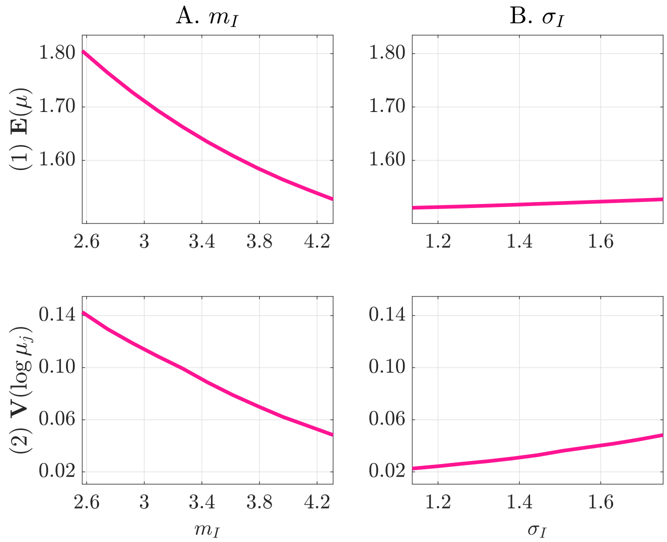


Figure C.4: Comparative static: II. Market

Larger heterogeneity among firms will direct make the markup distribution more dispersed within each market. Moreover, as we fix the mean of z_{ij} to 1, changes in its standard deviation will not heavily influence the level of technology, and thus the worker's wage. Finally, this increase will also naturally show up in the increasing variance of the revenue distribution.

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

STANDARD DEVIATION OF MARKET PRODUCTIVITY - σ_A. The last parameter is the standard deviation of the market-level productivity shock, A_j. Since the markups are determined *within* each market according to Lemma 2, this market-level shock will not influence the markup distribution at all. Therefore, its only effect is on the firm size distribution. By making firms more different across markets, a larger σ_A will drive the variance of firm size up. This intuition is confirmed by the column three in Figure C.5. Finally, σ_A has a slightly positive impact on W because an increase in the standard deviation of a lognormal distribution will also contribute to a larger expectation. A higher TFP level hence leads to higher wages, as is shown in Panel 2.C.

Appendix C.3 Rescaling

We simply take the reservation utility ω_0 from data. This section documents the way we use the parameters $\{\overline{\varphi}, \psi\}$ to match the average employee and the average manager pay from model to the data. Note

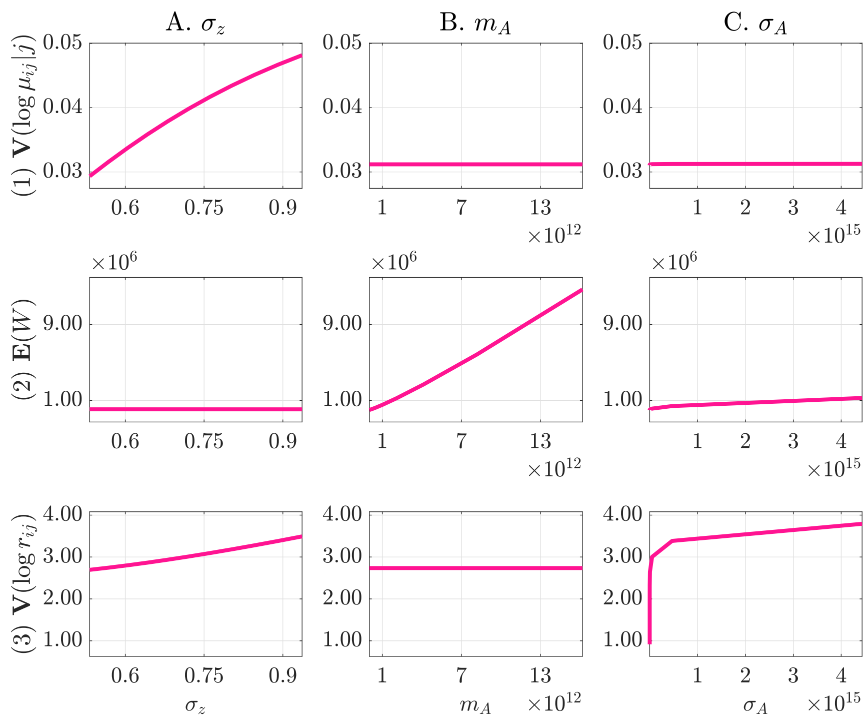


Figure C.5: Comparative static: III. Firm

that the constant return to scale allows us to rescale the model without influencing any other moments we targeted in the first three categories.

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

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

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

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

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

Appendix C.4 Matching correlation over time

In this section, we show the Spearman rank correlation coefficient of firm and market types, x_{ij} and A_j, with manager ability, z_{ij}, over time. These coefficients correspond to the numbers reported in Panel B and C of Figure 10. Figure C.6 specifies a clear trend that manager ability is getting more and more correlated with firm type than market type. It suggests that managers are hired by firms increasingly for competition within a market over time.

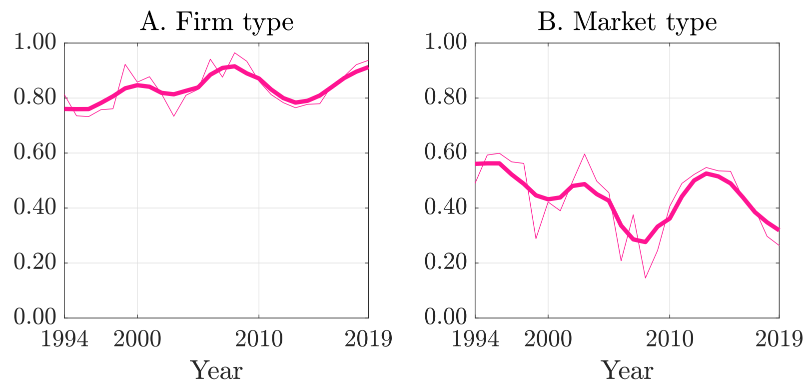


Figure C.6: The Spearman rank correlation coefficient with manager ability over time

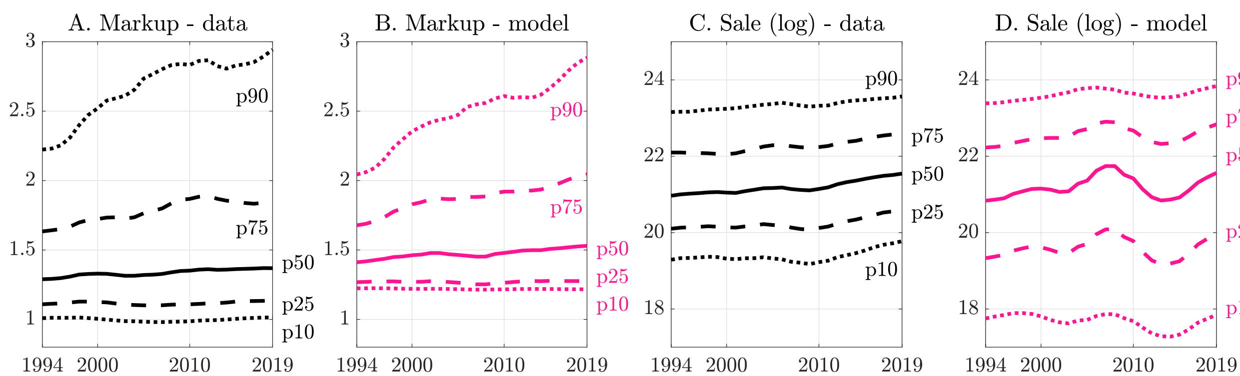


Figure C.7: Model prediction of markups and sales distribution

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

Appendix C.5 Distribution of markups and sales

Figure C.7 reports the 10th, 25th, 50th, 75th, and 90th percentiles of markup and sale distribution in both data and model. The most parts (25th percentiles onwards) of both distribution in our model match well with the data, which provides a solid validation of our estimates. The left tails are off mainly due to the fact that markups in our model is bounded by $\eta/(\eta-1) \approx 1.21$, while the markup in the data have no lower bound. The bound on the markup distribution influences the left tail of sales distribution, which leads to some bias.

Appendix D Robustness

Appendix D.1 Revenue as a measure of firm size

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

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

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

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

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

which further gives us the way to decompose manager pay:

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

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

By the same token, if we interpret market power as the Lerner index $L_{ij} = 1 - \frac{1}{\mu_{ij}}$ instead of the markup, we would obtain the same result as when using revenue as the measure of firm size, since $\widetilde{\pi}_{ij} = \left(1 - \frac{1}{\mu_{ij}}\right) r_{ij} = L_{ij} r_{ij}$. But again, this is because revenue $r_{ij} = \mu W L_{ij}$ includes part of the markup channel. Therefore, trivially, if we measure the impact of the Lerner index L_{ij} but correct for the effect of L_{ij} on r_{ij}, we obtain the same result as the effect of the markup μ_{ij}. This follows immediately from the chain rule: $\frac{\partial L_{ij}}{\partial \mu_{ij}} = \frac{1}{\mu_{ij}^2}$.

Quantification. Nevertheless, we find that even when we are underestimating the market power effect, we still quantify a significant influence from it and see a robust increase of this effect over time. In Figure D.1, we replicate the marginal decomposition and find that the market power channel contributes for 22.7% of manager pay on the margin in 1994, and 25.3% in 2019. The distribution across manager ability is also heterogenous: almost all the marginal manager pay comes from the firm size channel for bottom managers, while the top manager benefit nearly 40% on the margin in both 1994 and 2019.

Figure D.2 shows the decomposition of manager pay level. As we expect, the market power channel is less important in this case, which accounts for \$0.38 million in 1994 and \$1.25 million in 2019. Over time, the market power component still plays a slightly more important role, whose share in-

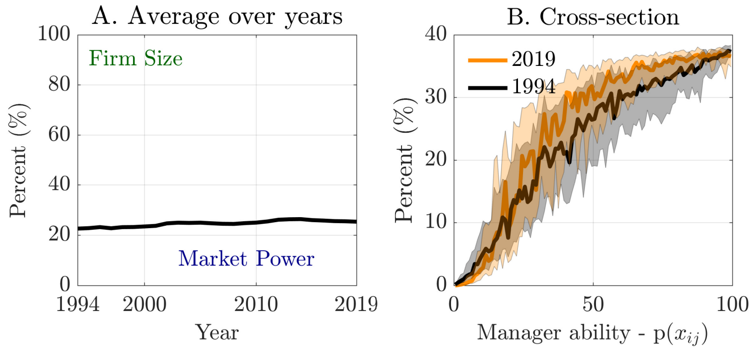


Figure D.1: The marginal contribution of market power on manager pay, Lerner index

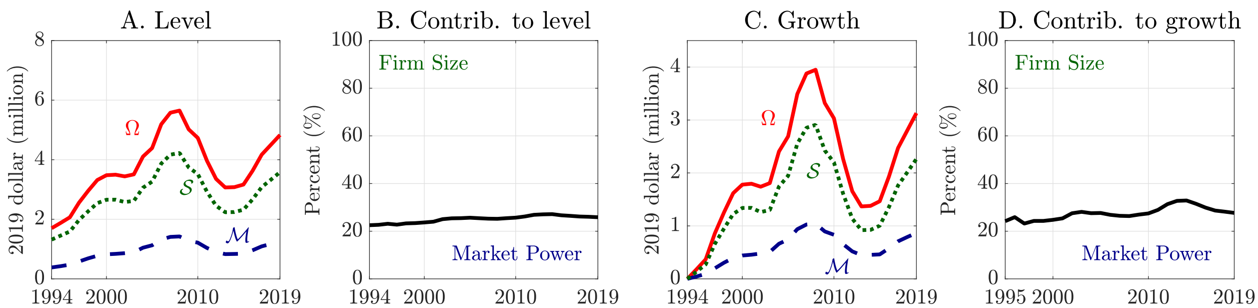


Figure D.2: Manager pay decomposition into market power and firm size by year, Lerner index

creases from 22.5% to 25.9%. Furthermore, Panel C and D show that market power contributes to the growth in manager pay by \$0.87 million (27.7% of the total growth). Our main results still hold in this specification, although this method actually underestimates the effect of market power.

We also revisit the results regarding distribution. Figure D.3 demonstrates that the heterogeneity in market power and firm size channels still hold true in this decomposition. Basically, market power contributes to the compensation of high-ability managers (30.7%) more than those low-ability ones, and so does its contribution to growth (31.3% for the top manager).

Appendix D.2 Bertrand equilibrium

In this section, we replicate our main exercises under the assumption that firms are competing in prices. We will first adjust our theory accordingly, then report the quantitative results.

Equilibrium under Bertrand. First of all, price competition will lead to different demand elasticities, and hence different markups than quantity competition. To see this, the firms problem in stage 2, i.e., equation (7), becomes:

$$\max_{p_{ij}} \widetilde{\pi}_{ij} = p_{ij} y_{ij} - W l_{ij}, \tag{D.3}$$

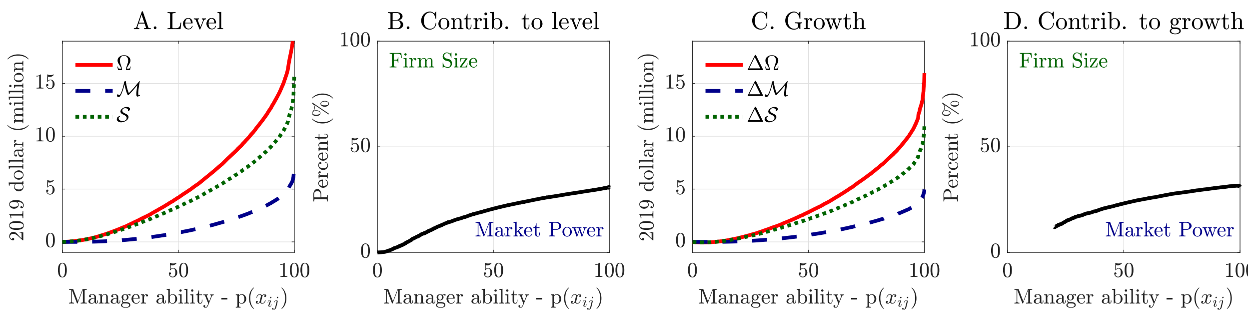


Figure D.3: Distribution of manager pay and its decomposition, Lerner index

which incurs FOC:

$$\left[1+\frac{\partial y_{ij}}{\partial p_{ij}}\frac{p_{ij}}{y_{ij}}\right] y_{ij} = \frac{W}{A_{ij}}\frac{\partial y_{ij}}{\partial p_{ij}} \quad \Leftrightarrow \quad \mu_{ij} = \frac{-\eta+(\eta-\theta)\,s_{ij}}{1-\eta+(\eta-\theta)\,s_{ij}}.$$

The subgame equilibrium of stage two can be solved in the same way but instead using this new FOC.

As firms are competing in a different ways, the decomposition of manager pay has to be adjusted as well. Following the same approach, we can derive markup and firm size elasticities of TFP:

$$\frac{\partial \mu_{ij}}{\partial A_{ij}}\frac{A_{ij}}{\mu_{ij}} = \underbrace{\left[\frac{(\eta-1)\,(1-\phi_{ij})}{1+(\eta-1)\,(\eta-\theta)\,\mu_{ij}s_{ij}/\,\left[\eta-(\eta-\theta)\,s_{ij}\right]^2}\right]}_{\frac{\partial s_{ij}}{\partial A_{ij}}\frac{A_{ij}}{s_{ij}}} \times \underbrace{\left[\frac{(\eta-\theta)\,\mu_{ij}s_{ij}}{\left[\eta-(\eta-\theta)\,s_{ij}\right]^2}\right]}_{\frac{\partial \mu_{ij}}{\partial s_{ij}}\frac{s_{ij}}{\mu_{ij}}} \tag{D.4}$$

$$\frac{\partial l_{ij}}{\partial A_{ij}}\frac{A_{ij}}{l_{ij}} = \phi_{ij}\underbrace{\left[\theta-1\right]}_{\text{Monopoly}} + (1-\phi_{ij})\underbrace{\left[\frac{\eta}{1+(\eta-1)\,(\eta-\theta)\,\mu_{ij}s_{ij}/\,\left[\eta-(\eta-\theta)\,s_{ij}\right]^2}-1\right]}_{\text{Strategic interaction, }\downarrow\text{ in }A_{ij}} \tag{D.5}$$

where

$$\phi_{ij} := \left[\frac{s_{ij}}{1+\frac{\mu_{ij}(\eta-1)(\eta-\theta)s_{ij}}{\left[\eta-(\eta-\theta)s_{ij}\right]^2}}\right] \Bigg/ \left[\sum_{i'}\frac{s_{i'j}}{1+\frac{\mu_{i'j}(\eta-1)(\eta-\theta)s_{i'j}}{\left[\eta-(\eta-\theta)s_{i'j}\right]^2}}\right].$$

All of our theoretical results remain robust when switching to the Bertrand equilibrium.

Quantification. We report the quantitative exercise under the Bertrand equilibrium. Using the time-series estimates of parameters shown in Figure 8, we decompose manager pay into the market power and firm size channels both across years and in crosssection. We report the marginal decomposition in Figure D.4, where we observe the same patterns as in Cournot competition. Figure D.5 shows that, under Bertrand competition, the market power channel contributes to manager pay by 26.8% in 1994 and 56.9% in 2019, which indicates an even larger increase across time compared to the results under Cournot setup. In Figure D.6, we show that at crosssection level our results are also robust. In 2019, almost all of the top manager pay is due to market power, while the bottom manager pay comes mainly

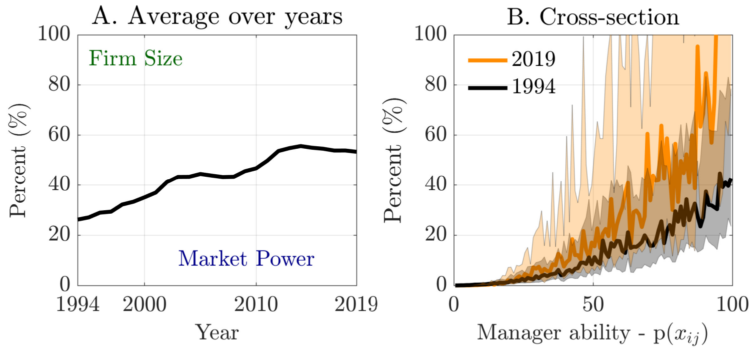


Figure D.4: The marginal contribution of market power on manager pay, Bertrand

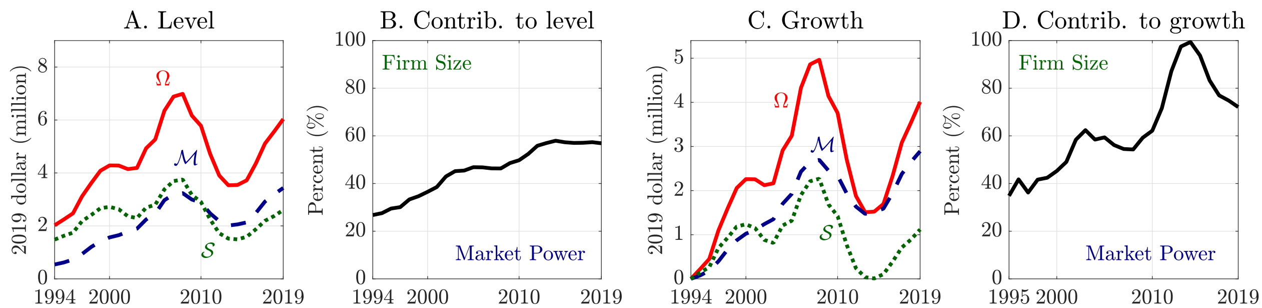


Figure D.5: Manager pay decomposition into market power and firm size (Bertrand), by year

from the firm size channel. This heterogeneity also shows up in the growth of the manager pay.

Appendix D.3 Output elasticity (θ, η) from Atkeson and Burstein (2008)

In this section, we redo our quantification exercise using the output elasticity in Atkeson and Burstein (2008), that is, $(\theta, \eta) = (1.5, 10.0)$. We reestimate the endogenous model parameters using the same set of data moments, based on which we generate our main decomposition results.

We first replicate the decomposition of marginal manager pay in Figure D.7. We can draw the same conclusions under as what we get in our main paper. First, the market power share has been increasing from 43.0% in 1994 to 51.3% in 2019. We also see an increasing relationship between market power share and manager ability. The reason for the sharp decline for top managers in 2019 is that there are some monopolists firm in the economy who hire top managers. However, since they are the only firm producing in their markets, their markups are exogenously given by the elasticity $\frac{\theta}{\theta-1}$ like a standard CES structure. Hence, those top managers contribute little to the market power, which drives the market power share down on the right tail.

The decomposition of manager pay level over time in Figure D.8 generates exactly the same insights. We see an increasing contribution from the market power channel to the manager pay, and this channel also contributes a lot to the growth of manager pay over time.

Finally, we report the exercise on the heterogeneity among managers in Figure D.9. Same insights

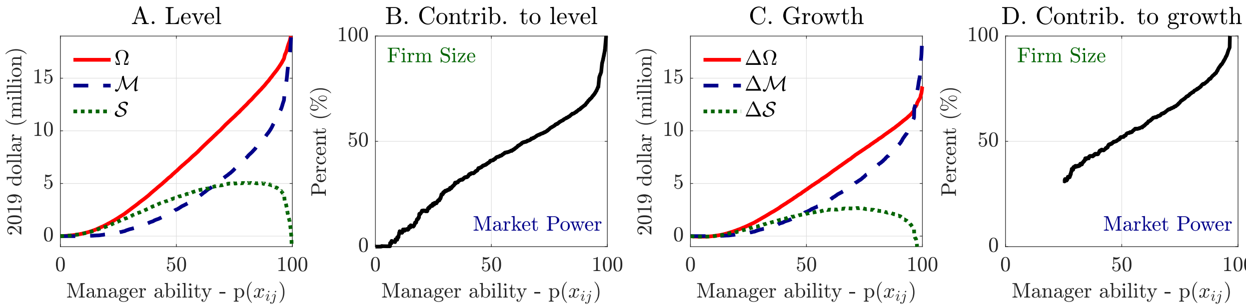


Figure D.6: Distribution of manager pay and its decomposition: Bertrand

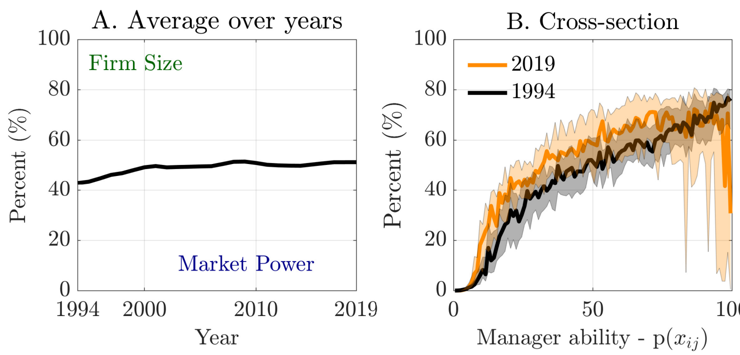


Figure D.7: The marginal contribution of market power on manager pay, with $(\theta, \eta) = (1.5, 10)$

are generated, that the market power channel matters more for the high-ability managers. Again, the sharp decline of the contribution of market power (share) for the very top managers comes from the fact that more monopolists firms are generated in the economy.

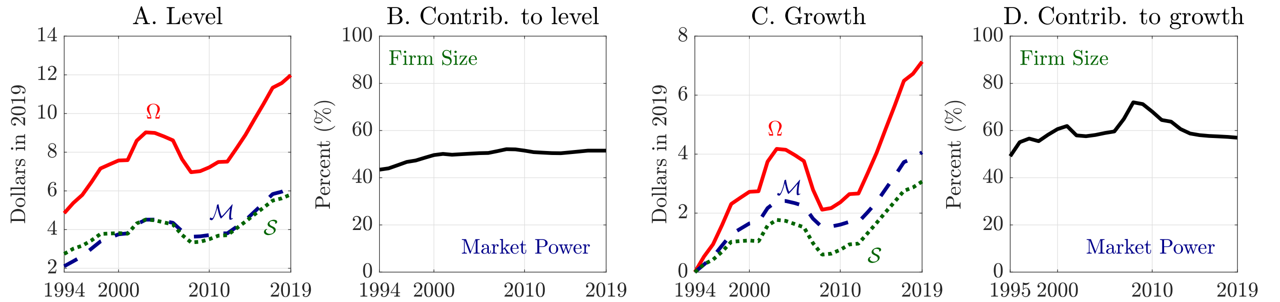


Figure D.8: Manager pay decomposition into market power and firm size, by year with $(\theta, \eta) = (1.5, 10)$

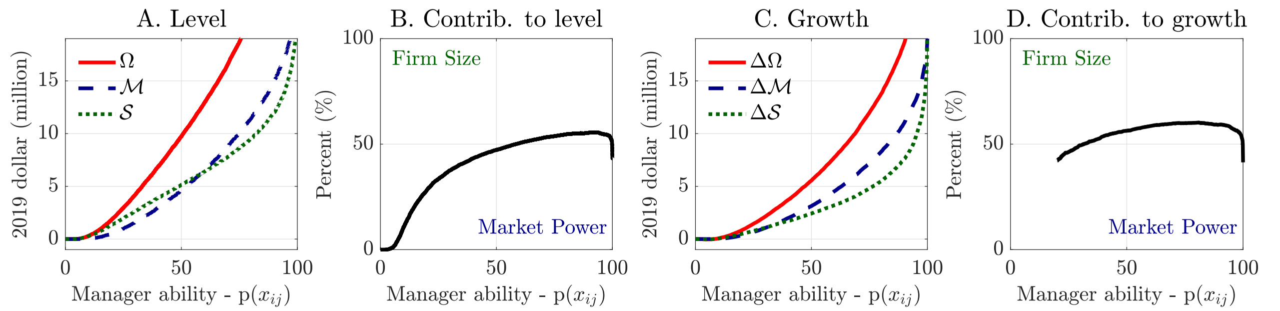


Figure D.9: Distribution of manager pay and its decomposition, with $(\theta, \eta) = (1.5, 10)$

References

ACEMOGLU, D., U. AKCIGIT, AND M. A. CELIK (2022): "Radical and incremental innovation: The roles of firms, managers, and innovators," *American Economic Journal: Macroeconomics*, 14, 199–249.

AGGARWAL, R. K. AND A. A. SAMWICK (1999): "Executive Compensation, Strategic Competition, and Relative Performance Evaluation: Theory and Evidence," *The Journal of Finance*, 54, 1999–2043.

ANTÓN, M., F. EDERER, M. GINÉ, AND M. C. SCHMALZ (2021): "Common Ownership, Competition, and Top Management Incentives," Mimeo.

ATKESON, A. AND A. BURSTEIN (2008): "Pricing-to-Market, Trade Costs, and International Relative Prices," *American Economic Review*, 98, 1998–2031.

AUTOR, D., D. DORN, L. F. KATZ, C. PATTERSON, AND J. VAN REENEN (2020): "The Fall of the Labor Share and the Rise of Superstar Firms," *Quarterly Journal of Economics*, 135, 645–709.

BARKAI, S. (2019): "Declining Labor and Capital Shares," *Journal of Finance, Forthcoming*.

BASU, S. (2019): "Are Price-Cost Markups Rising in the United States? A Discussion of the Evidence," *Journal of Economic Perspectives*, 33, 3–22.

BEBCHUK, L. A., J. M. FRIED, AND D. I. WALKER (2002): "Managerial Power and Rent Extraction in the Design of Executive Compensation," *The University of Chicago Law Review*, 69, 751–846.

BECKER, G. (1973): "A Theory of Marriage: Part I," *Journal Political Economy*, 81, 831–846.

BENNEDSEN, M., F. PÉREZ-GONZÁLEZ, AND D. WOLFENZON (2020): "Do CEOs matter? Evidence from hospitalization events," *The Journal of Finance*, 75, 1877–1911.

BERTRAND, M. AND A. SCHOAR (2003): "Managing with style: The effect of managers on firm policies," *The Quarterly journal of economics*, 118, 1169–1208.

BLOOM, N., R. SADUN, AND J. VAN REENEN (2016): "Management as a Technology?" Tech. rep., National Bureau of Economic Research.

BOND, S., A. HASHEMI, G. KAPLAN, AND P. ZOCH (2021): "Some Unpleasant Markup Arithmetic: Production Function Elasticities and Their Estimation from Production Data," *Journal of Monetary Economics*.

CELIK, M. A. AND X. TIAN (2017): "Agency frictions, managerial compensation, and disruptive innovations," *Managerial Compensation, and Disruptive Innovations (November 1, 2017)*.

CHADE, H. AND J. EECKHOUT (2020): "Competing Teams," *The Review of Economic Studies*, 87, 1134–1173.

——— (2022): "Do Incentives or Competition Determine Managers' Wages?" Mimeo.

CHADE, H., J. EECKHOUT, AND L. SMITH (2017): "Sorting Through Search and Matching Models in Economics," *Journal of Economic Literature*, 55, 493–544.

CHETTY, R., A. GUREN, D. MANOLI, AND A. WEBER (2011): "Are Micro and Macro Labor Supply Elasticities Consistent? A Review of Evidence on the Intensive and Extensive Margins," *American Economic Review*, 101, 471–75.

CUSTÓDIO, C., M. A. FERREIRA, AND P. MATOS (2013): "Generalists Versus Specialists: Lifetime Work Experience and Chief Executive Officer Pay," *Journal of Financial Economics*, 108, 471–492.

CZIRAKI, P. AND D. JENTER (2022): "The market for CEOs," *European Corporate Governance Institute–Finance Working Paper*.

DE LOECKER, J., J. EECKHOUT, AND S. MONGEY (2021): "Quantifying Market Power and Business Dynamism in the Macroeconomy," Working Paper 28761, National Bureau of Economic Research.

DE LOECKER, J., J. EECKHOUT, AND G. UNGER (2020): "The Rise of Market Power and the Macroeconomic Implications," *Quarterly Journal of Economics*, 135, 561–644.

DE RIDDER, M., B. GRASSI, AND G. MORZENTI (2022): "The Hitchhiker's Guide to Markup Estimation," Mimeo.

DEB, S., J. EECKHOUT, A. PATEL, AND L. WARREN (2022a): "Market Power and Wage Inequality," Tech. rep., UPF mimeo.

——— (2022b): "What drives wage stagnation: Monopsony or Monopoly?" *Journal of the European Economic Association*.

DIXIT, A. K. AND J. E. STIGLITZ (1977): "Monopolistic competition and optimum product diversity," *The American economic review*, 67, 297–308.

DUPUY, A., J. KENNES, AND R. S. LYNG (2022): "Job Amenities in the Market for CEOs," University of Toronto Mimeo.

EDMANS, A. AND X. GABAIX (2011): "The Effect of Risk on the CEO Market," *Review of Financial Studies*, 24, 2822–2863.

——— (2016): "Executive Compensation: A Modern Primer," *Journal of Economic Literature*, 54, 1232–87.

EDMANS, A., X. GABAIX, AND D. JENTER (2017): "Executive Compensation: A Survey of Theory and Evidence," *The Handbook of the Economics of Corporate Governance*, 1, 383–539.

EDMANS, A., X. GABAIX, AND A. LANDIER (2009): "A Multiplicative Model of Optimal CEO Incentives in Market Equilibrium," *The Review of Financial Studies*, 22.

EDMOND, C., V. MIDRIGAN, AND D. Y. XU (2019): "How Costly are Markups?" Tech. rep., National Bureau of Economic Research.

FALATO, A. AND D. KADYRZHANOVA (2012): "Optimal CEO Incentives and Industry Dynamics," Tech. rep., FEDS Working Paper.

FERNÁNDEZ-VILLAVERDE, J., F. MANDELMAN, Y. YU, AND F. ZANETTI (2021): "The "Matthew effect" and market concentration: Search complementarities and monopsony power," *Journal of Monetary Economics*, 121, 62–90.

FRYDMAN, C. AND R. E. SAKS (2010): "Executive Compensation: A New View From A Long-Term Perspective, 1936–2005," *The Review of Financial Studies*, 23, 2099–2138.

GABAIX, X. AND A. LANDIER (2008): "Why has CEO Pay Increased So Much?" *The Quarterly Journal of Economics*, 123, 49–100.

GABAIX, X., A. LANDIER, AND J. SAUVAGNAT (2014): "CEO Pay and Firm Size: An Update after the Crisis," *The Economic Journal*, 124, F40–F59.

GARICANO, L. AND E. ROSSI-HANSBERG (2006): "Organization and Inequality in a Knowledge Economy," *The Quarterly Journal of Economics*, 121, 1383–1435.

——— (2015): "Knowledge-based Hierarchies: Using Organizations to Understand the Economy," *Annual Reviews of Economics*, 7, 1–30.

GAYLE, G.-L., L. GOLAN, AND R. A. MILLER (2015): "Promotion, turnover, and compensation in the executive labor market," *Econometrica*, 83, 2293–2369.

GRASSI, B. (2017): "IO in IO: Competition and Volatility in Input-Output Networks," *Unpublished Manuscript, Bocconi University*.

GREEN, C. P., J. S. HEYWOOD, AND N. THEODOROPOULOS (2021): "Hierarchy and the Employer Size Effect on Wages: Evidence from Britain," *Economica*, 88, 671–696.

GRULLON, G., Y. LARKIN, AND R. MICHAELY (2016): "Are US Industries Becoming More Concentrated?" *Unpublished Working Paper*.

GUTIÉRREZ, G. AND T. PHILIPPON (2017): "Declining Competition and Investment in the US," Tech. rep., National Bureau of Economic Research.

HARTMAN-GLASER, B., H. LUSTIG, AND M. X. ZHANG (2016): "Capital Share Dynamics When Firms Insure Workers," Tech. rep., National Bureau of Economic Research.

ICHNIOWSKI, C., K. L. SHAW, AND G. PRENNUSHI (1995): "The effects of human resource management practices on productivity," .

JUNG, H. W. H. AND A. SUBRAMANIAN (2017): "CEO Talent, CEO Compensation, and Product Market Competition," *Journal of Financial Economics*, 125, 48–71.

——— (2021): "Search, Product Market Competition and CEO Pay," *Journal of Corporate Finance*, 69, 101981.

KAPLAN, G. AND P. ZOCH (2020): "Markups, Labor Market Inequality and the Nature of Work," Tech. rep., National Bureau of Economic Research.

KEHRIG, M. AND N. VINCENT (2017): "Growing Productivity without Growing Wages: The Micro-Level Anatomy of the Aggregate Labor Share Decline," Duke mimeo.

KLETTE, T. J. AND Z. GRILICHES (1996): "The Inconsistency of Common Scale Estimators when Output Prices are Unobserved and Endogenous," *Journal of Applied Econometrics*, 343–361.

LUCAS, R. E. (1978): "On the Size Distribution of Business Firms," *The Bell Journal of Economics*, 508–523.

MURPHY, K. J. AND J. ZABOJNIK (2004): "CEO Pay and Appointments: A Market-Based Explanation for Recent Trends," *American Economic Review*, 94, 192–196.

——— (2007): "Managerial Capital and the Market for CEOs," *Available at SSRN 984376*.

OLLEY, G. S. AND A. PAKES (1996): "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 1263–1297.

RAITH, M. (2003): "Competition, Risk, and Managerial Incentives," *American Economic Review*, 93, 1425–1436.

SCHEUER, F. AND I. WERNING (2017): "The Taxation of Superstars," *The Quarterly Journal of Economics*, 132, 211–270.

SCHMIDT, K. M. (1997): "Managerial Incentives and Product Market Competition," *The Review of Economic Studies*, 64, 191–213.

SHIMER, R. AND L. SMITH (2000): "Assortative Matching and Search," *Econometrica*, 68, 343–369.

SUTTON, J. (1991): *Sunk costs and market structure: Price competition, advertising, and the evolution of concentration*, MIT press.

——— (2001): *Technology and market structure: theory and history*, MIT press.

SYVERSON, C. (2019): "Macroeconomics and Market Power: Context, Implications, and Open Questions," *Journal of Economic Perspectives*, 33, 23–43.

TERVIÖ, M. (2008): "The Difference that CEOs Make: An Assignment Model Approach," *The American Economic Review*, 642–668.

TRAINA, J. (2018): "Is Aggregate Market Power Increasing? Production Trends using Financial Statements," Chicago Booth mimeo.