Manager Pay Inequality and Market Power*

RENJIE BAO
Princeton†

JAN DE LOECKER
KU Leuven‡

JAN EECKHOUT
UPF Barcelona§

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Abstract

Manager pay has increased considerably since 1980, and so has inequality in manager pay. Over the same period, there has been a sharp rise in market power. We start from the premise that the role of managers is to increase firm productivity. When markets are imperfectly competitive, productivity not only helps firm grow in size, productivity also affects market power. We model how imperfect competition in product markets affects manager pay, and break down the contributions of firm size and market power to compensation. We find that market power, on average, accounts for 45.2% of total manager pay. Notably, there is substantial variation across managers. Top managers are disproportionately employed by firms with market power, and they benefit from it: in 2019, 80.3% of top manager pay is attributable to market power. Our main conclusion is that rise of market power explains half of the increase in average manager pay, and nearly all of the increase in manager pay inequality.

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

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†renjie.bao@princeton.edu

‡jan.deloecker@kuleuven.be

§jan.eeckhout@upf.edu – ICREA-BSE-CREI

1 Introduction

Over the past four decades, manager pay has increased significantly. Successful managers enhance the productivity of those they supervise, and firms are willing to pay a premium to attract them. As firms grow larger and more profitable, the influence of managers becomes more valuable, given their far-reaching decisions within the organization. In a competitive labor market, these factors lead to higher manager pay, aligning with the key insight of Gabaix and Landier (2008) and Terviö (2008) that rising firm size can explain the increase in manager pay.

In this paper, we build on insights from the existing literature by offering new evidence on how managers contribute to profitability. Managers make firms more productive and depending on how firms compete, part of that productivity goes into selling more, and part goes into markups; both factors affect manager pay. Recent studies show that over the last four decades, market power has risen significantly, and this trend coincides closely with the increase in manager pay (see Figure 1, panels A and B).[1] Manager pay remained relatively stable until the 1980s, then began to rise sharply, more than doubling between 1994 and 2019. Along with this increase in average compensation, there has been a marked rise in manager pay inequality, driven mainly by the longer and heavier right tail, indicating a particularly steep increase for top managers (see Figure 1, panels C and D). A similar pattern appears in markups, whose distribution has also become more dispersed. We ask whether manager pay is determined not only by efficiency and firm size but also by market power, and we analyze how these two mechanisms jointly shape the distribution of manager pay over time.

Our goal is to disentangle the portion of manager pay attributable to market power from that arising from efficiency and firm size. Specifically, we aim to determine whether firms with market power pay managers higher salaries because these managers boost how much the firm sells, or whether managers help the firm capture some of the rents generated by market power.[2] Our central premise is that managers enhance efficiency. However, in doing so, they also influence a firm's market power because not all efficiency gains are passed on to customers. To examine these mechanisms, we assume that markups and firm size are determined in an imperfectly competitive environment with strategic interactions among oligopolistic firms. These firms exercise market power in the goods market and hire managers to increase productivity and profits. Because managers who improve productivity can also expand their firms' market power, managerial pay reflects not only firm size but also the extent to which firms gain market power by attracting top managerial talent.

Empirically, it is challenging to disentangle how market power and firm size affect manager pay. Firms with greater market power are typically larger. Large firms typically owe their size to superior technologies.[3] Consequently, the correlation between markups and manager pay alone does not clarify the causal determinants, particularly in light of issues such as reverse causality and omitted-variable bias. The complex interplay between market power, firm size, and manager pay underscores the need for structural methods to untangle these effects.

[1] See, among others, Grullon, Larkin, and Michaely (2019); Gutiérrez and Philippon (2017); De Loecker et al. (2020).

[2] For simplicity, our baseline analysis abstracts from agency and incentive pay, which also contribute to manager pay. In Appendix B.5, we extend the model in Edmans and Gabaix (2011) to include incentive pay and show that, while agency considerations are relevant, they do not alter our main conclusions regarding the effect of market power on manager pay (see also 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 charge high markups. See Autor, Dorn, Katz, Patterson, and Van Reenen (2020) and De Loecker et al. (2020).

We develop a model featuring a small number of competitors in each market, with many such markets across the economy, following Atkeson and Burstein (2008). In these markets, the distribution of firms' productivities and the number of competitors together determine the degree of market power. In line with standard oligopolistic competition theory, markets with fewer competitors display higher market power, and markets with more dispersed productivity also exhibit stronger market power. Moreover, irrespective of the number of firms, a highly productive firm's behavior can approach that of a monopolist in a Cournot setting if its productivity exceeds that of its competitors by a sufficient margin. These more productive firms compete by offering lower prices, thereby capturing a larger market share. However, because of incomplete pass-through of cost savings, they do not fully pass on their productivity gains to consumers, resulting in higher markups and increased profits.

Here, the manager plays a crucial role. Managers raise firms' productivity in the sense described by Lucas (1978)'s span of control, thereby increasing efficiency.[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 managerial ability and firm type. Thus, hiring talented managers boosts a firm's productivity and enhances efficiency. In addition to expanding production, firms that become more productive may also gain greater market power, especially if they become more productive relative to their competitors. This advantage allows more productive firms to charge higher markups rather than passing on all efficiency gains to consumers. In a competitive labor market, managers are rewarded not only for increasing firm size but also for enhancing market power by raising their firm's productivity *relative to that of rival firms*. Both effects – size and market power – boost profits, and both contribute to manager pay. Since these two effects arise through increases in the firm's productivity, they are jointly determined. The goal of our model is to decompose the contribution of each effect to manager pay.

Our theoretical framework also sheds light on the inequality of manager pay. Through assortative matching, highly skilled managers tend to cluster in firms with high productivity, while less talented executives gravitate toward firms with lower productivity. As productivity gaps between firms widen, market power grows correspondingly.[5] When high-productivity firms face limited competition, they pass on fewer of their efficiency gains to consumers – an idea originally proposed by Sutton (1991, 2001). Managers increase the productivity of the firm, and the nature of competition translates this productivity increase into firm size effects or markups. Firms must offer top-tier managers pay that reflects their contributions to profits through these two channels. Because the markup channel is most pronounced for large firms who hire the most capable managers, the pay distribution is right-skewed with a pronounced long tail.

We use executive compensation data from Compustat spanning 1994 to 2019 to quantify the production technology and the underlying distributions of productivities by matching cross-sectional moments for sales, markups, and managers' shares over time. Notably, although we do not explicitly target the manager pay distribution in our estimation, our quantitative model still captures 65.6% of observed

[4]This setup is consistent with the view that skilled managers increase a firm's productivity (see, for example, Bloom, Sadun, and Van Reenen, 2016). Refer to Section 3.2 for further details.

[5]Even if the number of firms is small, when they have the same TFP, firms also have identical profits and market shares. By contrast, when one firm has higher TFP, it secures higher profits and a larger market share. In the extreme, if one firm is significantly more productive than its competitors, it effectively behaves as a monopolist, capturing a market share close to one, even with multiple competitors.

pay, validating the importance of our mechanism for understanding how manager pay is determined.[6] Our model also reproduces the pronounced right tail observed in the empirical distribution of manager incomes – a key characteristic driving manager pay inequality. These findings thus provide external validation of our theory and suggest that, despite its simplifying assumptions, the model accurately captures the core mechanism behind the determination of manager pay.

We then employ the quantitative model to break down the components of manager pay into contributions from market power and firm size. Over the entire sample period, our model predicts that an average of 45.2% of manager pay stems from market power, while the remainder is explained by firm size. Over time, the model attributes 55.6% of the growth in manager pay to market power and 44.4% to firm size. We conclude that market power plays an increasingly significant role in explaining the recent increase in manager pay.

Our most striking findings concern the *inequality* of manager pay. In cross-sectional terms, our quantitative analysis shows considerable heterogeneity within the manager pay distribution. For top-ranked managers in 2019, market power accounts for 80.3% of their compensation in our model and explains nearly all of their large pay growth since 1994. By contrast, for lower-ranked managers, pay and any pay growth are primarily driven by firm size. This discrepancy underscores that market power is the predominant factor behind the spectacular rise in superstar manager pay, which fuels the observed increase in overall manager pay inequality. Furthermore, decomposing the variance of manager pay over time reveals that the variance of the market power component is the most significant source of rising manager pay inequality, increasing from 27.2% in 1994 to 42.4% in 2019. Meanwhile, the variance of the firm size component declines slightly, thus contributing little to the increase in manager pay inequality.

Finally, we conduct a counterfactual exercise where we fix all parameters at their 1994 values and then introduce one or more estimated, year-specific parameters. We find that the most influential factor driving both the rise in average manager pay and its increasing inequality is the growing importance of managerial ability in production. Our estimates suggest that a 1% increase in managerial ability boosts firm-level profits by 1.60% in 1994, a figure that nearly doubles to 3.16% in 2019. We also identify that sorting of managers and firms is important for efficiency and that there is a significant welfare loss resulting from the mismatch. If managers were randomly assigned to firms, total output would decline by 2.39% in 1994 and by 14.21% in 2019. These results underscore the expanding role managers play in the economy, chiefly in enhancing production efficiency. They also confirm the main conclusion in Gabaix and Landier (2008) and Terviö (2008) – that managers remain critical to efficient production.

Our main conclusion is that managers boost firms' efficiency, and their compensation reflects the efficiency gains they generate. At the same time, managers also affect the distribution of firm productivity relative to competitors, which influences market power. The most productive firms reap the largest profit increases by enhancing their productivity relative to rivals, thereby capturing efficiency gains rather than passing them on to customers. In a competitive labor market, these firms hire top managers, who are compensated accordingly.

Although our focus (due to data constraints) is on CEOs, the same logic applies to all managers responsible for overseeing other workers, as well as other professionals whose sorting and superstar pay play a major role in their earnings – such as top lawyers, coders, or consultants. Across the economy,

[6] We can interpret the remaining portion as resulting from other factors not included in our framework for simplicity, such as incentive pay for managers. See Section 3.2 for a full discussion.

one-fifth of workers supervise others, implying that our findings have important macroeconomic implications, particularly at the upper end 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 percolates into manager compensation. Managers contribute to firm productivity, and in the presence of imperfect competition, productivity affects both firm size and market power.[8]

By assuming that manager ability is an input factor in production, we build on a recent 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

[7]See Section 3.2 for more discussion on risk aversion and agency issue. We also provide a theoretical framework in Appendix B.5 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, there is rent extraction by manager and owners from customers and competitors.

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). Recent work by Dessein and Prat (2022) also considers management ability as an input in production, and they do so in a dynamic setting where managers build up capital, depending on the underlying firm type and the manager type. The role of manager ability as an input in production 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 product varieties, which in our theoretical framework is equivalent to an increase in productivity (see for example, Deb et al., 2022a,b). Finally, using German administrative data, Bender, Bloom, Card, Van Reenen, and Wolter (2018) find that the human capital of the managers contributes to firm productivity, more so than the human capital of employees. In addition, they find that better-managed firms pay a wage premium and they recruit and retain workers with higher average human capital.

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 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

2.1 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 (Standard & Poor's, 2025). We drop the finance, insurance, and real estate sectors (SIC between 6000 and 6799). The ExecuComp data set (1992–2019) has measures for

[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.

manager pay (Standard & Poor's, 2026). 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.

2.2 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 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 with an AKM-style regression that holds firm, manager, and year fixed effects.[12] 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

[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.3, which is also mentioned in Terviö (2008).

[12]The AKM-style mover design introduces additional sample selection to the ExecuComp data. In Appendix A.4, we report the regression table without manager fixed effects. All the results are robust. Note also that in column (0) we only have Year fixed effects and Sales as a regressor. The results confirm that a 10% increase in sales will lead to 3.73% increase in manager pay.

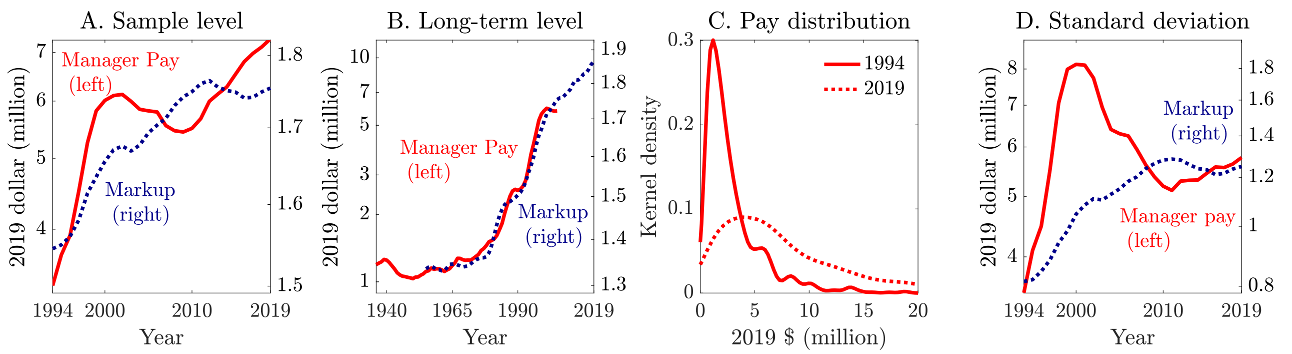


Figure 1: The evolution of manager pay and markups

Notes: Panel A plots average manager pay and average markups 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.

et al. (2020).[13][14] The conventional wisdom that size plays an important role in managers' salary determination is confirmed by all regression specifications. On average, a 10% percent increase in size for the same firm will lead to an increase in manager pay by 2.97% (column (6)) to 3.38% (column (1)). 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 an increase in pay between 0.35% and 0.71%. 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.

These regressions show that an increase in the markup by 10% leads to an increase in CEO pay by 4-7%. Since there is a variation in the range of the markup distribution between 1.2 and 6 in the model (similar in the data), there is a variation by factor 5. In other words, the increase in markups from the lowest markup firms to the highest markup firms leads manager pay to approximately increase by a factor of 2-3.5. We believe this magnitude is reasonable: the pay of the top manager who is hired in the highest markup firm would drop from \$80 million to the range \$23-40 million, when hired by a low markup firm, and the pay of the median manager would drop from \$5 million to the range \$1.5-2.5 million. Below, in the model we use for our baseline quantitative exercise, this elasticity is manager-specific. The estimated model suggests the salary of the top manager would drop from \$80 to \$16 million and that of the median manager from \$5 to \$2.5 million. Even thought there are several endogeneity issues with our regressions here – which is why we estimate a structural model below –, the predictions from the regressions and those of the model below are in the same ballpark.

In Figure 2, we plot the distribution of estimated fixed effects from specification (6) in Table 1. Panel

[13]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).

[14]We also find that our quantitative results are robust to different measures of markups, such as those obtained by Deb et al. (2022b) where markups are estimated from a structural model, with both output and input market power, and calibrated to the same demand specification as the current model).

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

	log Manager Pay								
	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm size									
log Sales	0.368	0.371	0.361						
	(0.011)	(0.044)	(0.044)						
log COGS				0.286	0.364				
				(0.042)	(0.044)				
log Employment						0.297	0.297		
						(0.046)	(0.045)		
Market power									
log Markup			0.352		0.710		0.421	0.418	
			(0.113)		(0.118)		(0.114)	(0.115)	
Fixed effects									
Firm		✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓	✓
Manager		✓	✓	✓	✓	✓	✓	✓	✓
Adj. R-squared	0.359	0.635	0.637	0.630	0.637	0.629	0.632	0.623	0.621
Observations	2,475	2,369	2,369	2,369	2,369	2,369	2,369	2,369	2,369

Notes: The robust standard errors under heteroskedasticity are reported in the parenthesis. We construct sample of CEOs who have switched jobs at least once during the sample period (1994-2019). A constant is included in all eight specifications. 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.

(a) and (b) display the manager and firm fixed effects (the black solid line), both of which closely follow a fitted Normal distribution (the pink, dashed line) and significantly contribute to manager pay variation. Panel (c) shows that the year fixed effects are close to 0. These findings guide our distributional assumptions in the quantitative exercise (notably lognormal distributions). Further, the variance decomposition shows that managerial ability accounts for 25.3% and firm type accounts for 12.0% of the total variance in log manager pay. This indicates that both dimensions play substantial roles in shaping compensation.

We also provide indirect evidence of the role that markups play, in a regression exercise that replicates Gabaix and Landier (2008), in Appendix A.5. 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 and the economy-wide distribution of firm characteristics, but not on the strategic interaction with competitors.[15] 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.[16]

We also investigate the dynamic effects of market power on manager pay by including interactions

[15]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.

[16]Markups reflect both demand-side heterogeneity and strategic interactions among firms in a given market, and we propose a model that allows for both sources of markup heterogeneity to impact manager pay.

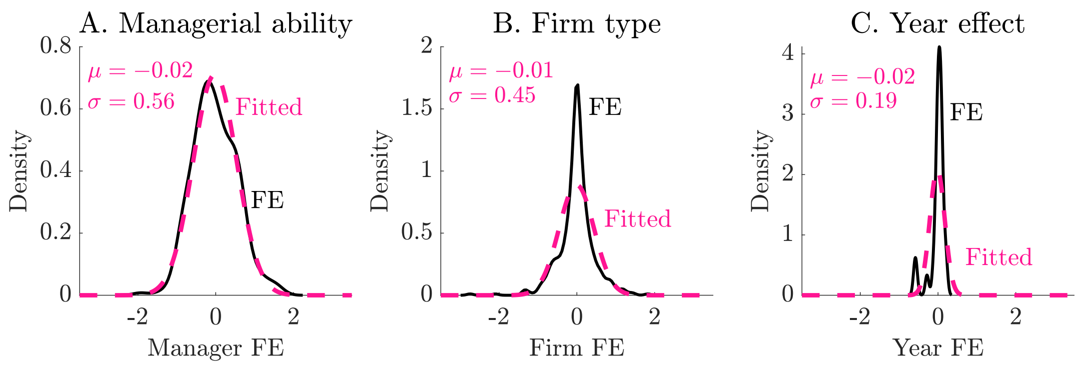


Figure 2: Distribution of manager, firm, and year fixed effects

Notes: The fixed effects are constructed from the AKM regression of log manager pay on log employment, log markup, and fixed effects of firms, managers, and years, which corresponds to the specification (6) in Table 1. In each panel, we report the kernel density (black, solid line) and its best-fitted normal distribution (pink, dashed line). The fitted mean and standard deviation are also reported.

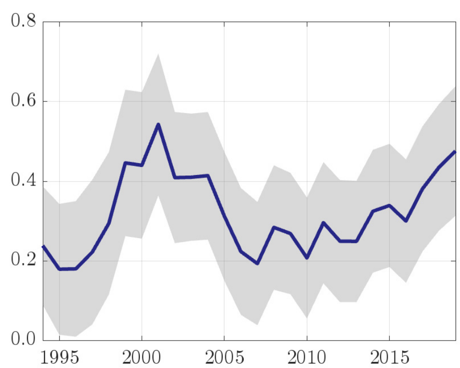


Figure 3: The elasticity of markups on manager pay over time

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.

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 3 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.[17]

One of the findings in the structural model below is that there is a marked variation in the contribution of market power to manager pay depending on the rank of the manager in the distribution of wages (or equivalently in the rank of the firms). There we find that the contribution to compensation of the highest ranked managers is up to 80% due to market power and 20% due to firm size, whereas the

[17] In Appendix C.8 we also analyze the AKM regressions on model simulated data with a dynamic effect. We find that our results are robust.

contribution of market power for the lowest ranked managers is close to zero. In order to link the AKM regressions to that finding, we run the regression analysis on the 50% highest paid managers. The results are reported in Table A.2 in Appendix A.4. The coefficient on markups for the different specifications is systematically around 50% higher than for the whole sample. At the same time, the coefficient on firm size is lower. This confirms our model prediction (below) that the market power channel is indeed stronger among managers in the top of the distribution.

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. Manager pay, markups and firm size are determined jointly and endogenously. While we find correlations between pay and markups and pay and size, this does not inform us about the causality nor the contribution of each component. Moreover, most of the variation is absorbed by the manager fixed effect, which includes a broad range of determinants. These regressions therefore underline the importance of a method that can isolate the effect of each of these components. In this paper, we use a structural approach and propose a theory of manager pay that builds on the classic insights from the literature that links pay to firm size, while also embedding 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 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 $F(x)$.[18][19] The market structure contains a continuum of markets with measure J, each indexed

[18]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.

[19] Consistent with Atkeson and Burstein (2008), we assume the measure of firms (and therefore managers) is a continuum for simplicity. This granularity of the distributions is not a crucial assumption for any of our results.

by $j \in [0, J]$. Each market j contains a finite number of I_j firms, where I_j varies by market j.[20] 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:

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

where c_{ij} is the consumption of good ij, c_j is the consumption aggregate of market j, and C is the economy-wide aggregate of consumption. 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.[21] We represent the household's preferences with the following utility function over the consumption bundle $\{c_{ij}\}$ that aggregates to C, and the supply of labor L:

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

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

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

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

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

[20] 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.

[21] 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.

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:[22]

$$A_{ij} = \mathcal{A}\left(x_{ij}, z_{ij}, A_j\right), \quad \text{with} \quad \mathcal{A}_x > 0,\ \mathcal{A}_z > 0,\ \text{and}\ \mathcal{A}_{xz} > 0. \tag{5}$$

We introduce managerial ability as an input that determines productivity, which can be interpreted as a Lucas (1978) model of span of control. 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:

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

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 $\omega\left(x\right)$ denotes the compensation function of manager type x. Therefore, the profit maximization problem for firm ij at this stage is:

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

where $\widetilde{\pi}_{ij}$ is the firm's gross profit coming from the next period. We use the '$\sim$' to distinguish between gross profits $\widetilde{\pi}$ before paying the manager compensation, and net profits π after paying the manager compensation. Note that there is an externality in the problem (7), that the profit of the firm ij depends not only on its own TFP A_{ij} but also on the productivity of its competitors, $\boldsymbol{A}_{-ij}$.[23]

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.[24] The firms make production decisions to maximize gross profits:

$$\max_{l_{ij}} \widetilde{\pi}_{ij} = p_{ij} y_{ij} - W l_{ij}, \quad \text{s.t.} \quad y_{ij} = A_{ij} l_{ij}. \tag{8}$$

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 $\omega\left(x\right)$ that specifies the salary for all managers and an assignment function Γ of man-

[22] Below in the quantitative exercise, we will use a Constant Elasticity of Substitution (CES) functional form, specified in equation (20).

[23] 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).

[24] Cournot competition is not the crucial assumption. As is shown in Appendix D.3, 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.

ager abilities to firm productivities that is measure preserving and that maximizes (7) of the matching game, taking as given the stage two subgame, which includes prices p_{ij}, the wage W, and employment l_{ij} that solve (8) 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 identical, we are still able to talk about the income inequality among managers *within* the households.[25] Likewise for profits. The reason for building a model with a representative household is to keep the analysis

[25] 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 (4). 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.

tractable. The innovation of this model comes from the heterogeneity on the production side (firms and managers) and not comes from the preferences and goods demand.

Nested-CES demand system. We assume nested-CES preference in our baseline quantitative model, but our results are robust to a general set of demand systems. In Appendix B.4, we show that our theoretical conclusion that both market power and firm size contribute to manager pay holds for a general demand system where market power is endogenously determined by productivity. We further demonstrate the robustness of our quantitative results by considering a Kimball demand system in Appendix D.6.

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 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.5, 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.

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, ...[26] 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 sorting of manager types of firm productivities.

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.

Substitutability of managers. The degree of substitutability of managers is a central aspect of our analysis. We assume a general substitutability pattern in the technology $\mathcal{A}\left(x_{ij}, z_{ij}, A_j\right)$ in equation (5), and in the quantitative exercise we assume a CES functional form where manager ability x and firm productivity z are imperfect substitutes, with an elasticity of substitution that we estimate below. We find the elasticity of substitution to be negative, indicating that manager ability and firm productivity are complements, and the degree of complementarity is increasing over time (the elasticity becomes more negative). It is worth noting that the estimated technology is more complementary even than Gabaix and Landier (2008), who have a technology function close to Cobb-Douglas, corresponding to an elasticity of substitution equal to zero.[27,28]

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

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

[27] In their notation, Gabaix and Landier (2008) assume the matching output is $a_0(1 + C \times T)$, where a_0 is the "baseline" earnings, C is a constant, and T is the manager's talent. This functional form is effectively a Cobb-Douglass specification plus a constant. Below, Figure 6 shows that the expenditure share of sales of manager salaries is not constant, suggesting that the technology is not Cobb-Douglas.

[28] The substitutability depends on the technology, but also on the distribution of abilities of managers. In the theory, the ability distribution is continuous, whereas in the numerical implementation as in the data, we use a discrete distribution. Because the underlying distribution of manager abilities in the quantitative exercise is lognormal, the top managers in the right tail are more spread out than the managers at the bottom. However, we find there is little effect of the discreteness in our analysis and for our results.

power; and (2) omitting monopsony is likely to lead to little systematic bias explaining the growth of manager pay over time.

The dynamic nature of manager impact. We model the production technology and the role of the manager as a static problem, where as in reality this is a dynamic problem. The main reason for our modeling choice is tractability. The dynamic choice involves solving a dynamic oligopoly problem, the complexity of which grows exponentially in the number of periods as we need to compute the present value of future strategic interaction. Moreover, the dynamic nature of the problem involves career concerns and job mobility, on which we are missing a lot of information when managers take up non-CEO positions or positions in privately held firms. Nonetheless, the static approximation is informative in the knowledge that 95.1% of managers have only one stint as CEO in our data set, and the duration is relatively short, on average four years. In Appendix C.8 we extend the AKM motivating regression in the simulated model to a dynamic setting and find that the empirical results in a dynamic setting are similar.

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* (4) *yields:*

(a) Goods demand function:

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

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:

$$L = \overline{\varphi} W^{\varphi}. \tag{9}$$

Proof. See Appendix B.1. ■

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

$$p_{ij}(y_{ij})\left[1 + \frac{dp_{ij}}{dy_{ij}}\frac{y_{ij}}{p_{ij}}\right]\frac{dy_{ij}}{dl_{ij}} = W \quad \Leftrightarrow \quad p_{ij}\underbrace{\left(1+\varepsilon_{ij}^{p}\right)}_{\mu_{ij}^{-1}} A_{ij} = W. \tag{10}$$

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 (10). 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:

$$\mu_{ij} = \left[1 - \frac{1}{\theta}s_{ij} - \frac{1}{\eta}\left(1 - s_{ij}\right)\right]^{-1}, \tag{11}$$

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 (11) 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 (11), 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:

$$y_{ij} = \frac{1}{J}\frac{1}{I_j}\left(\frac{p_{ij}}{p_j}\right)^{-\eta}\left(\frac{p_j}{P}\right)^{-\theta} Y, \quad l_{ij} = \frac{y_{ij}}{A_{ij}}, \quad \textit{and} \quad \widetilde{\pi}_{ij} = (\mu_{ij} - 1)Wl_{ij}. \tag{12}$$

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 (5) indicates that the matching output, $\widetilde{\pi}_{ij}$, is supermodular. In a classical matching model, supermodularity is sufficient for positive assortative matching (PAM) (see for example, Becker, 1973; Chade et al., 2017), but in the presence of the externality from 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.[29]

Given the stable matching Γ, the firms' stage 1 optimization problem (7) yields the FOC:

$$\underbrace{\frac{\partial \widetilde{\pi}_{ij}}{\partial A_{ij}} \frac{\partial A_{ij}}{\partial x_{ij}}}_{\partial \pi_{ij}/\partial x_{ij}} = \frac{d}{dx}\omega(x_{ij}), \tag{13}$$

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 (13), joint with the gross profits (12), 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:*

$$\frac{\partial \widetilde{\pi}_{ij}}{\partial x_{ij}} = \left[\underbrace{\frac{\partial \mu_{ij}}{\partial A_{ij}} W l_{ij}}_{\textit{Market power channel}} + \underbrace{(\mu_{ij} - 1) W \frac{\partial l_{ij}}{\partial A_{ij}}}_{\textit{Firm size channel}} \right] \frac{\partial A_{ij}}{\partial x_{ij}}. \tag{14}$$

Proposition 1 decomposes the marginal contribution of managerial ability to gross profits into two distinct channels.[30] 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 (12), i.e., $\widetilde{\pi}_{ij} = \left(\mu_{ij} - 1\right) W l_{ij}$. 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, $W l_{ij}$.[31] 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 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 (14) in the main body of this paper.[32]

[29] 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 for one-to-one matching with externalities between the matched firms, see as Chade and Eeckhout (2020).

[30] 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 (14).

[31] 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.

[32] In Appendix D.2, we show that our results are empirically robust between these two different interpretations.

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 (14).

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

$$\omega(x_{ij}) = \omega_0 + \int_{\underline{x}}^{x_{ij}} \left[\underbrace{\frac{\partial \mu_{i'j'}}{\partial A_{i'j'}} W l_{i'j'}}_{\text{Markup channel}} + \underbrace{\left(\mu_{i'j'} - 1\right) W \frac{\partial l_{i'j'}}{\partial A_{i'j'}}}_{\text{Firm size channel}} \right] \times \left[\frac{\partial A_{i'j'}}{\partial x_{i'j'}} \right] dx_{i'j'}, \tag{15}$$

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 (14). 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 (10), we can derive the markup elasticity of TFP:

$$\varepsilon^{\mu}_{ij} := \frac{\partial \mu_{ij}}{\partial A_{ij}} \frac{A_{ij}}{\mu_{ij}} = \underbrace{\left[\frac{(\eta - 1)\left(1 - \phi_{ij}\right)}{1 + (\eta - 1)\left(\frac{1}{\theta} - \frac{1}{\eta}\right) \mu_{ij} s_{ij}} \right]}_{\frac{\partial s_{ij}}{\partial A_{ij}} \frac{A_{ij}}{s_{ij}},\ \downarrow \text{ in } A_{ij}} \times \underbrace{\left[\left(\frac{1}{\theta} - \frac{1}{\eta} \right) \mu_{ij} s_{ij} \right]}_{\frac{d\mu_{ij}}{ds_{ij}} \frac{s_{ij}}{\mu_{ij}},\ \uparrow \text{ in } A_{ij}} \in [0, 1)\,, \tag{16}$$

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 (11). Thus, although higher TFP always contributes to a higher markup, the size of the markup elasticity depends on the trade-off between these two opposing effects.

Similarly, we can write the firm size channel as:

$$\varepsilon_{ij}^{l} := \frac{\partial l_{ij}}{\partial A_{ij}} \frac{A_{ij}}{l_{ij}} = \phi_{ij} \underbrace{\left[\theta - 1\right]}_{\text{Monopoly}} + (1 - \phi_{ij}) \underbrace{\left[\frac{\eta}{1 + \left(\frac{1}{\theta} - \frac{1}{\eta}\right)(\eta - 1)\,\mu_{ij} s_{ij}} - 1\right]}_{\text{Strategic interaction, } \downarrow \text{ in } A_{ij}}, \tag{17}$$

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* (16) *and* (17)*, respectively. They have following properties:*

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

$$\lim_{s_{ij} \to 0} \varepsilon_{ij}^{\mu} = \lim_{s_{ij} \to 1} \varepsilon_{ij}^{\mu} = 0; \tag{18}$$

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

$$\lim_{s_{ij} \to 0} \varepsilon_{ij}^{l} = \eta - 1 > 0 \quad \textit{and} \quad \lim_{s_{ij} \to 1} \varepsilon_{ij}^{l} = \theta - 1 > 0. \tag{19}$$

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

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

We summarize the important properties of these elasticities in Proposition 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 encompasses 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 (see Appendix B.4 for the setup with a general demand system). In the robustness section 5.5, we also explore models with alternative demand systems and market structures and evaluate those models quantitatively. 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 estimated model by comparing its prediction with data in sections 4.7.

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 a solution that takes 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. We also test the performance of our approximation algorithm with different initial manager type in step (a), which justifies the selection of the average manager type $\overline{x} = 1$.

This begs the question why the approximation is working, and why matching on the marginal contribution to profits is effective. In the matching problem without externalities, the ranking of the type and the marginal profit coincide. This is not the case with externalities, and that is why using the type is not a good approximation. The same firm type z with competitors whose types are higher will match with a low x, and with a high x if its competitors have lower types. The type z is therefore a bad predictor of the equilibrium matched type x. Instead, in the first case with high type competitors, firm z's marginal profit will be low, and it will be high if the competitors in the market are low types. In other words, marginal profits coincide well with the ranking of manager types x. This can be seen from the first-order condition (13), which ranks managers (mediated through the ranking in the manager pay schedule) by their contribution in terms of marginal profit. It is still an approximation because we do not know the equilibrium allocation and therefore we evaluate the marginal profit at the average type. It turns out that the loss from doing so is small.

4.2 Specify production technology

In the quantitative exercise, we use the CES specification for the TFP function (5):

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

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 (20) 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 (20) 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.

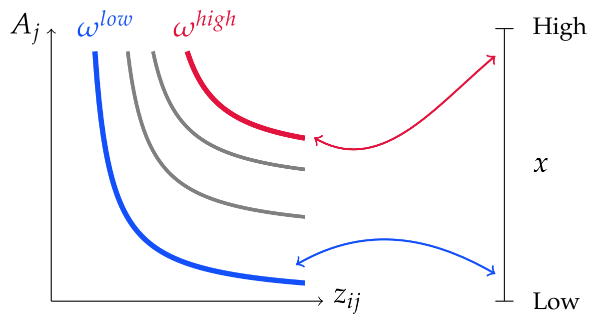


Figure 4: Matching of Managers to firm-market pairs (z_{ij}, A_j) with iso-wage curves

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 4. 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:

$$y_{ij} = A_{ij} \left(l_{ij} + m_{ij}\right)^{\zeta} k_{ij}^{1-\zeta}. \tag{21}$$

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.[33] 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

[33] This is as simplifying assumptions for tractability, but we believe this is not a bad assumption. Estimates for the elasticity of substitutability vary, but they start around 2 and go as large as 6. So being larger than 1, materials and labor are substitutes rather than complements, and they tend to more substitutability for larger elasticities. The elasticity of substitution affects the labor share of production labor (see Ruzic (2023); Mertens and Schoefer (2024)), though the effect on manager productivity and wages is unclear.

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 (21) 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:

$$\omega(x_{ij}) = \omega_0 + \frac{1}{\psi\zeta}\int_{\underline{x}}^{x_{ij}} \left[\underbrace{\frac{\partial \mu_{i'j'}}{\partial \widehat{A}_{i'j'}} W l_{i'j'}}_{\textit{Markup channel}} + \underbrace{\left(\mu_{i'j'} - 1\right) W \frac{\partial l_{i'j'}}{\partial \widehat{A}_{i'j'}}}_{\textit{Firm size channel}}\right] \times \left[\frac{\partial \widehat{A}_{i'j'}}{\partial x_{i'j'}}\right] dx_{i'j'}. \tag{22}$$

Proof. See Appendix B.6. ■

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 (22) 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 (21) 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 distributional assumption is motivated empirically by the fact that manager and firm fixed effects are distributed approximately log-normal, see Figure 2 from the AKM regression. This rules out any negative realizations and has been shown to be consistent with the productivity distribution in the data.[34] Furthermore, as we endogenously estimate α and γ, we are unable to identify $F(x_{ij})$ and $G(z_{ij})$. We assume that the distribution of manager ability is relatively stable over time, and 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.[35, 36] Moreover, we assume that the mean of z_{ij}

[34]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.

[35]We assume, as in Gabaix and Landier (2008), that the distribution of managerial ability is time-invariant. This assumption is consistent with the motivating observation in Figure 2 panel (c) that the time fixed effects are close to zero compared to the manager fixed effects.

[36] We elaborate on the identification challenge in Appendix C.4, where we show that the means of managerial ability and firm-type distributions are not separately identifiable from the parameters α, A_j. Technological change, as captured by α, could equivalently be interpreted as a shift in the distribution of x, without affecting our results or their interpretation: in either case, 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. We also show that separating their variances is possible but relies on

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	Market structure $I_j \sim \mathcal{N}\left(m_I, \sigma_I^2\right)$, $I_j \in \mathbb{N}_+ \cap [1, 10]$
	σ_I	
III. Firm	σ_z	Standard deviation of firm type z_{ij}
	m_A	Mean of market-level productivity A_j
	σ_A	Standard deviation of market-level productivity A_j

is also normalized to 1. Its standard deviation σ_z will determine the lognormal distribution of z_{ij}. The market component A_j therefore captures the TFP level of firms, whose distribution is determined by its mean and standard deviation, m_A and σ_A. To mimic the continuum of markets in the simulation, we set the number of markets equal to $J = 10,000$.[37] 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 $[1, 10]$.[38][39] 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.[40] 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 (9) and average employment and wage from the Compustat data. Given the Cobb-Douglas specification (21), 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 5.

functional-form assumptions and the positive sorting pattern. In Appendix D.1, we estimate a version of the model with an endogenously determined variance for $\log x_{ij}$, and all estimates and results remain robust.

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

[38]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.

[39]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.

[40]In section 5.5 and Appendix D.4, 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 $\eta \in [5, 10]$ 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 5.

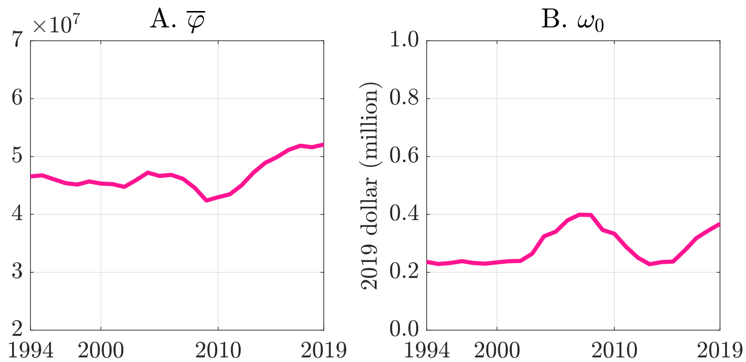


Figure 5: Calibrated parameters

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:

$$\min_{\boldsymbol{\vartheta}} \mathcal{G}(\boldsymbol{\vartheta}) := \left(\widehat{\boldsymbol{M}} - \boldsymbol{M}(\boldsymbol{\vartheta})\right)' \boldsymbol{W}^{-1} \left(\widehat{\boldsymbol{M}} - \boldsymbol{M}(\boldsymbol{\vartheta})\right) \quad , \quad \boldsymbol{\vartheta} := \{\alpha, \gamma, m_I, \sigma_I, \sigma_z, m_A, \sigma_A\}, \tag{23}$$

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.[41]

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 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.

[41] 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)	$\mathbb{V}(\log \mu_{ij} \mid j)$	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.

I. Match. We motivate our choice of moments on the matching side by showing how manager pay is 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 (20), 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 6. 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 6 reiterates the logic of our choice of parameters by plotting the relationship between $\log \chi_{ij}$ and $\log r_{ij}$ when each of the parameters $\{\alpha, \gamma\}$ change.

II. Market. Equation (11) 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 7a shows that markups will increase monotonically as I_j decreases, which helps us identify the average number of firms m_I.[42] Furthermore, because the number of firms differs in different markets, this monotonicity also

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

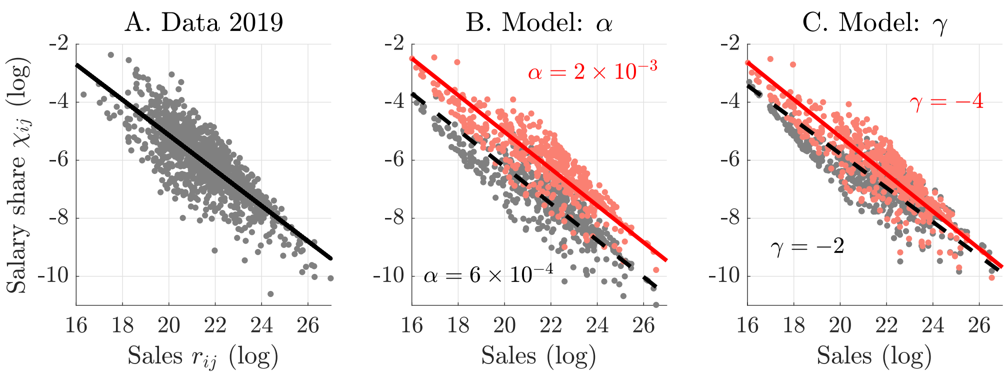
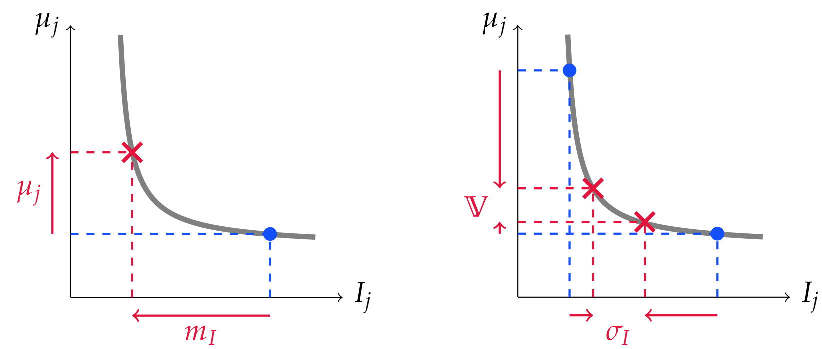


Figure 6: Identification of parameters in category "I. Match"

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

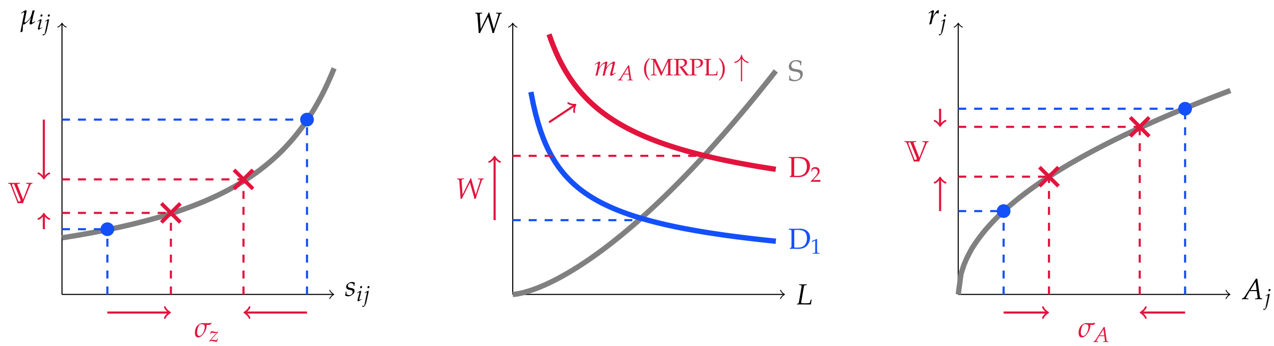
Figure 7: Identification of parameters in category "II. Market"

Notes: This figure shows the determinant of markups in a representative economy where firms have the same TFP. From Equation (11), 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.

makes the distribution of markups *across* markets informative on σ_I. Figure 7b 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.

III. Firm. The variance of markups *within* each market μ_{ij} is in turn determined by the variance in firm type σ_z.[43] As Figure 8a shows, a smaller σ_z will reduce the difference in s_{ij}, which eventually reduces the within-market variance of markups according to Equation (11). 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 8c.

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



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

Figure 8: Identification of parameters in category "III. Firm"

4.5 Estimation

We estimate the seven endogenous parameters jointly, in a separate estimation each year.[44] Figure 9 shows the estimated parameters and how they evolve over time, while Figure 10 reports the close fit of the model moments to those in the data. To further validate our estimation, in Figure 13 and 14 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 9. 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.[45] The estimated elasticity of substitution γ is negative, which confirms the complementarity between firms and managers that is commonly assumed in the literature. Furthermore, γ was relatively stable, 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 10 after 2014. Therefore, managers have recently become more complementary to firms.

II. Market. The second column in Figure 9 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

[44] One concern is the sample selection due to the use of publicly traded firms from the Compustat/ExecuComp sample. To address this issue, we construct the targeted moments based on statistics that are not sensitive to sample selection (e.g., markups rather than HHI). To further ease such concern, in Appendix D.5 we reestimate the model by picking only the largest 50% of firms, which suggests that our results are indeed qualitatively robust, even as we make the sample selection more severe.

[45] 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.

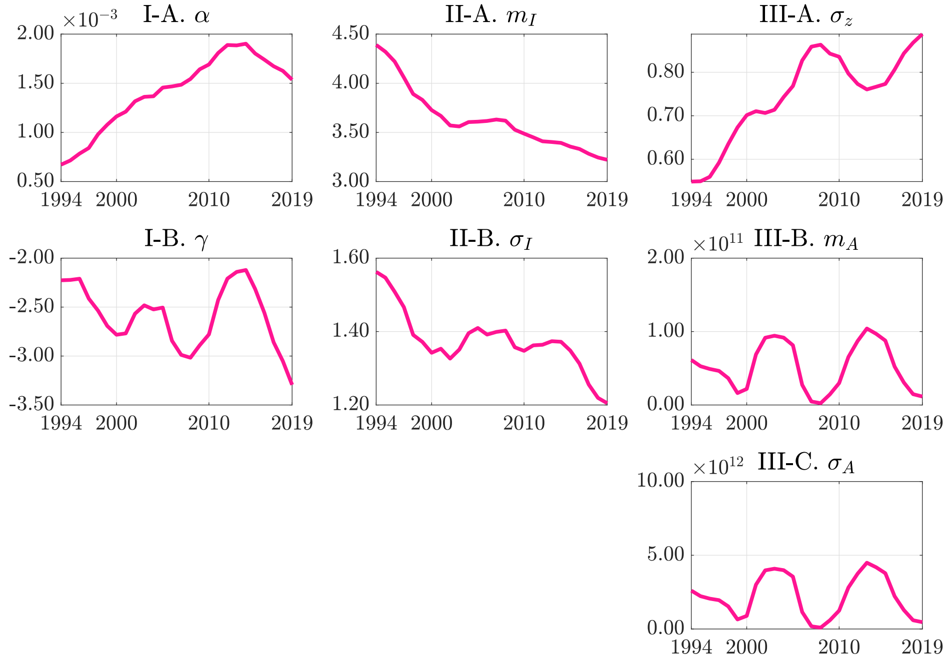


Figure 9: Parameters: I. Match (production technology: level α, and elasticity of substitution γ), II. Market mean m_I and standard deviation σ_I of the number of firms in each market, and III. Firm standard deviation σ_z of the within-market productivity shock, mean μ_A and standard deviation σ_A of the between-market productivity shock (in logs)

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

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, 2019; 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 9 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.

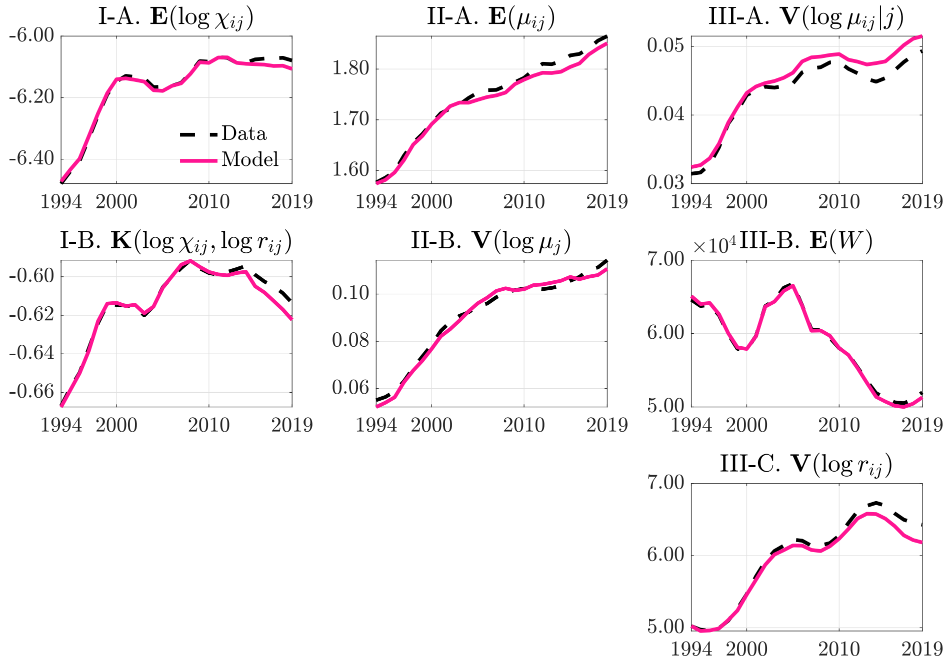


Figure 10: Targeted moments: I. Match, II. Market, and III. Firm

Notes: See Table 5. 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.

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 manager pay. All results are robust in different years, so we will take the year 2019 as the baseline in presenting the crosssectional results.

Figure 11 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 4. 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, 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.[46] 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 12 shows that the

[46]See Appendix C.5 for a time-series plot of these rank correlation coefficients.

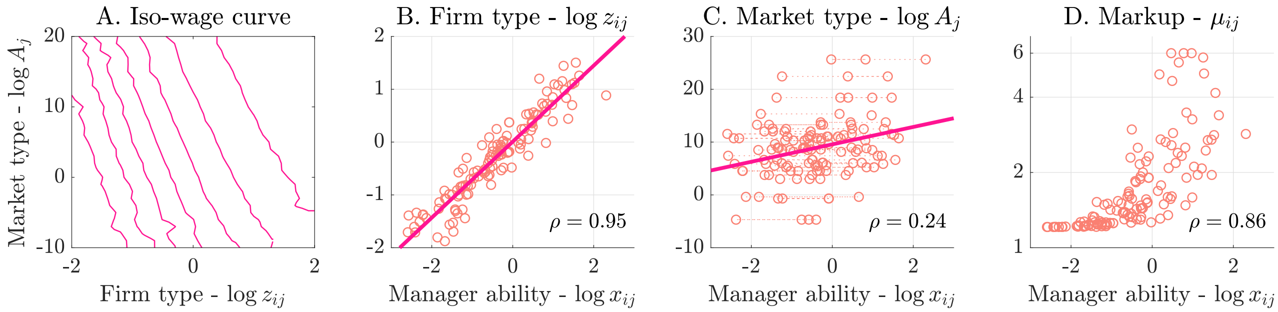


Figure 11: Matching: managers and firms in 2019

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 (imputed from the model) 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.

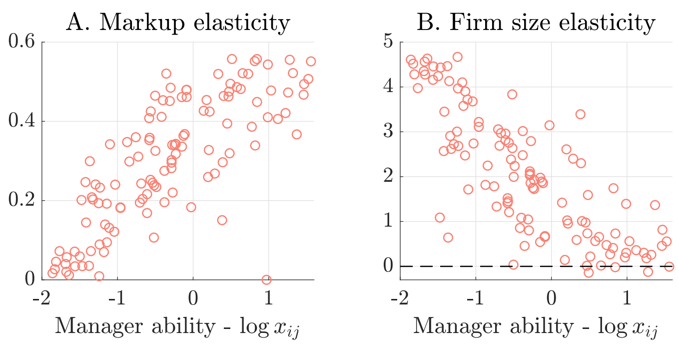


Figure 12: Matching: managers and elasticities in 2019

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

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.[47] 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 Validation

Distribution of manager pay. 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.

In Figure 13 panels A and B, we compare both the level of manager pay and its growth since 1994

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

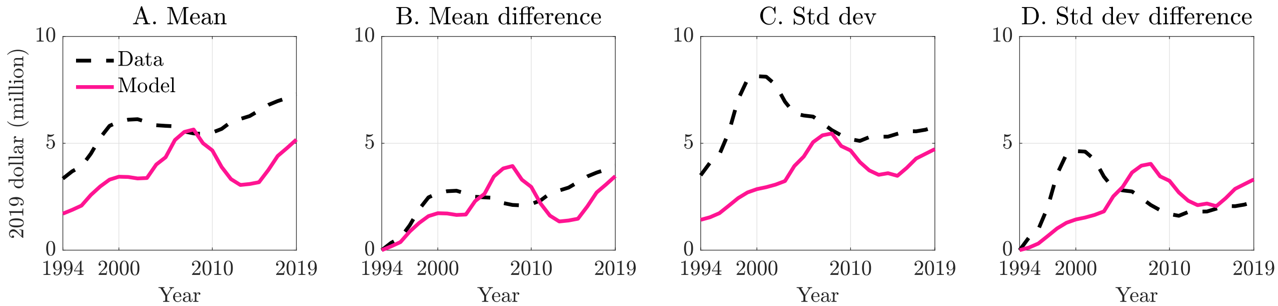


Figure 13: Mean and standard deviation of manager pay distribution: data and model prediction

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

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.[48]

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 13 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 14. 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 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.

Manager pay ranking and markup. In Figure 15, we compare the correlation between the manager pay ranking and markups in the data and the model for the year 2019 (for further details, see Appendix C.8). Our model reproduces the positive correlation observed in the data. Moreover, our model predicts a

[48]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.

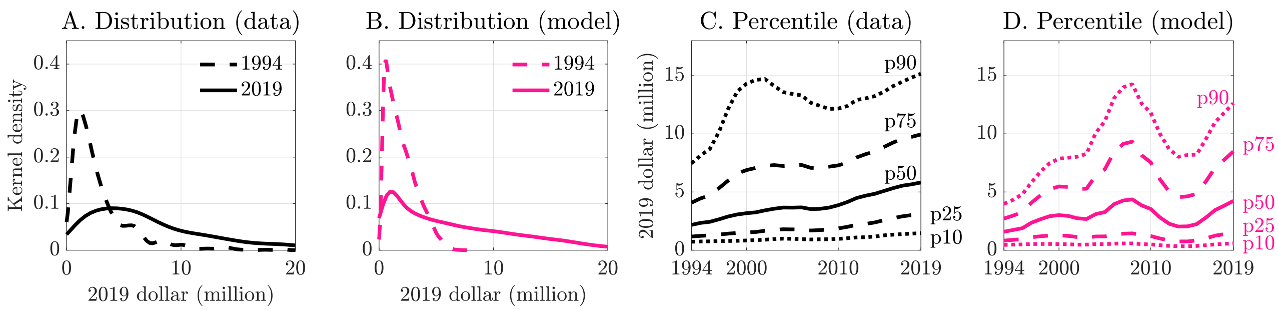


Figure 14: Distribution of manager pay: data and model prediction

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.

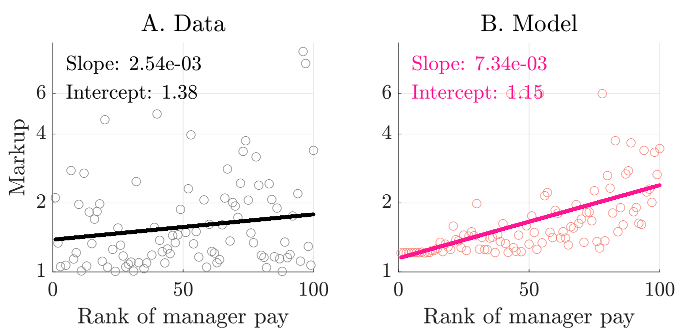


Figure 15: Manager pay ranking and markup

Notes: We make the scatter plot readable by randomly selecting 100 manager-firm pairs in both data and model for year 2019. The x-axis represents for the rank of manager pay, while the y-axis is the markup of the associated firm on a log scale. The solid line in both figures are the linear fit. See Appendix C.8 for further details on the procedure.

reasonable range of markups. The data is more noisy, resulting in a slightly lower correlation coefficient, but we find that higher income managers work in firms with higher markups. This comparison provides extra validation for the estimated model that is able to reproduce the positive correlation between manager ability and markups.

Substitutability of managers. The substitutability of managers is a central aspect of our analysis. As does Gabaix and Landier (2008), we assume managers differ in their one-dimension ability, through which different managers are not perfectly substitutable. Based on our estimation, if we replace the median CEO by the number one CEO, the profit of his firm will on average increase by only 0.19%, which is larger than Gabaix and Landier (2008) where the same exercise yields an increment of 0.016%. We conclude that managers in our estimated model are less substitutable than Gabaix and Landier (2008). The reason is double. First, other than the conventional firm size effect, we have an additional channel of market power, which further distinguishes managers across their ability. Second, we estimate a CES technology that exhibits substantially larger complementarity than Cobb-Douglas.

Distribution of markup and sale 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.[49] The results are shown in Appendix C.7, 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.

Stylized facts. We also validate our model by replicating the stylized facts in Figure 1. The results are reported in Appendix C.6. They confirm that our estimated model is capable of predicting the rise of manager pay in conjunction with changing markups, the rising manager pay inequality, and the correlation between manager pay inequality and markup heterogeneity. Additionally, we compare other measures of market power, such as the model-predicted HHI and the profit share, with the data counterparts to further validate our model estimation.

Motivating regression with simulated data. Finally, we provide further validation by replicating the motivating regressions using simulated data. By making additional assumptions on dynamic firm and manager identifiers, we manage to simulate a year-by-year panel data set from our static model, which allows us to reproduce the motivating regression on this simulated data. The details and results are reported in Appendix C.8.

Replicating our main specification (Table 1, column (6)), the model-generated data produces coefficients of 0.187 and 0.247 for firm size and market power on manager pay, respectively. The signs align with the empirical estimates, and the difference in magnitudes is not statistically significant. This exercise further demonstrates the close connection between the model and the data.

5 Main Results

With the model estimates in hand, we now analyze the different determinants of manager pay, which are summarized in Figure 16. 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 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

[49] 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.

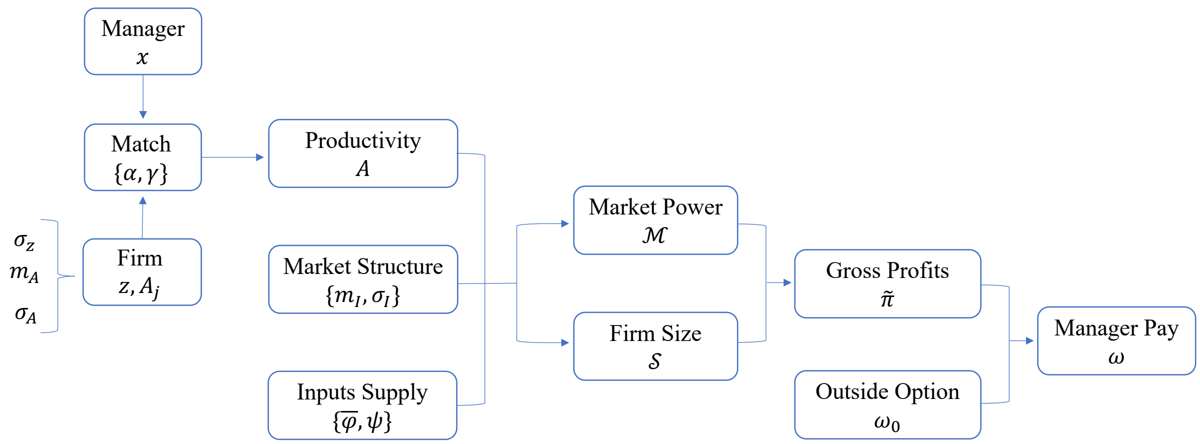


Figure 16: Determinants of Manager Salaries

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 17 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 17, 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 from the market power channel.[50] 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 18, 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 18.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 \$1.71 million to \$5.17 million, where the market power effect increases from \$0.64 million to \$2.51 million and the firm size effect increases from \$1.07 million to \$2.66 million. Panel 18.B further shows that market power and

[50] 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%.

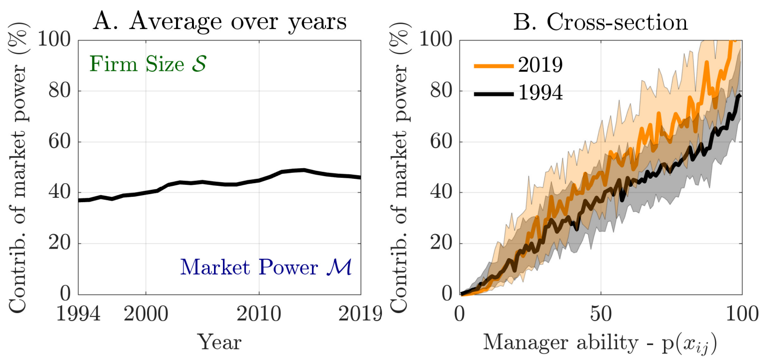


Figure 17: The marginal contribution of market power on manager pay

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 (manager ability is imputed from the model) 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.

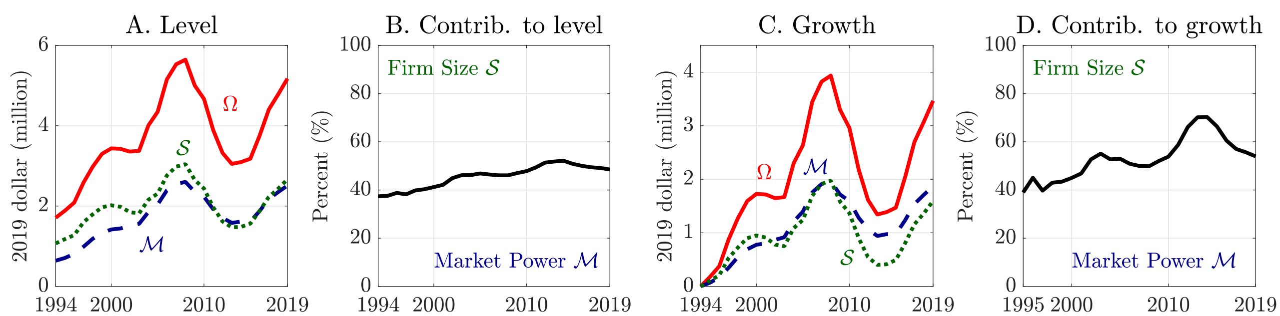


Figure 18: Manager pay decomposition into market power and firm size, by year

KNotes: 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.

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 18.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 \$3.46 million, of which \$1.87 million is due to the increase in market power and \$1.60 million due to the firm size effect. Panel 18.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 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.

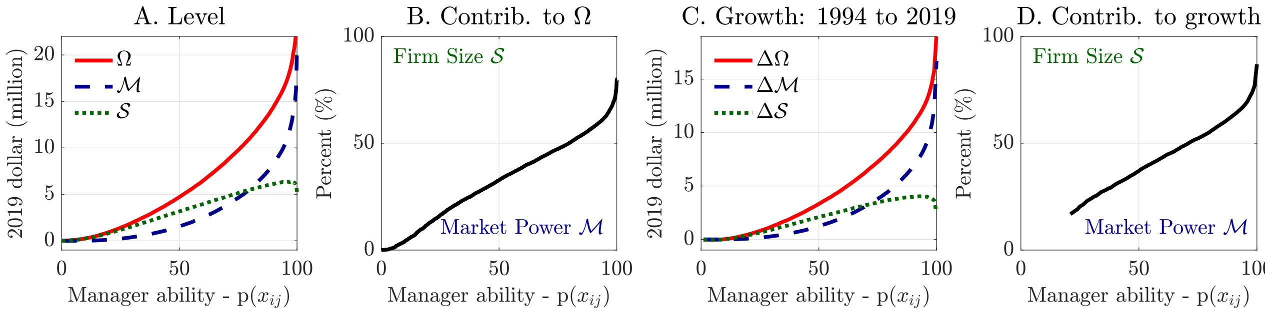


Figure 19: Cross-sectional distribution of manager pay and its decomposition

Notes: The capital letters Ω, $\mathcal{S}$ and $\mathcal{M}$ represents for manager pay, firm size channel, and market power channel, respectively. Manager ability is imputed from the model. 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.

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 19, 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 19.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.[51] 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 19.C,

[51]Observe also a peculiar feature of the largest firms in our model. There is a sharp decrease in the firm size effect among the very top managers. This is because the best managers are matched with superstar, but not monopolistic, firms whose employment elasticity of TFP (equation (17)) is negative. This insight is also confirmed by Figure 12 that the employment elasticity is negative for some high-ability managers.

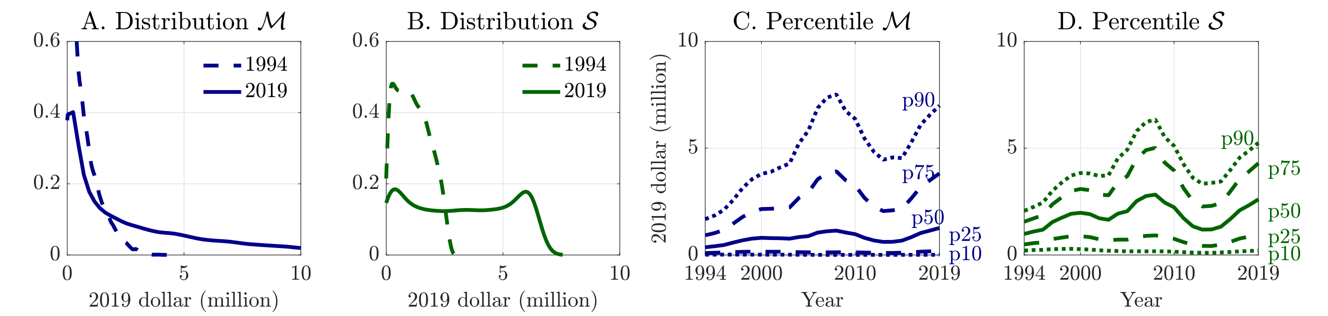


Figure 20: Distribution of manager pay growth from 1994 and 2019

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.

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 14. 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 19 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 20. 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 20 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.

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 21. 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.

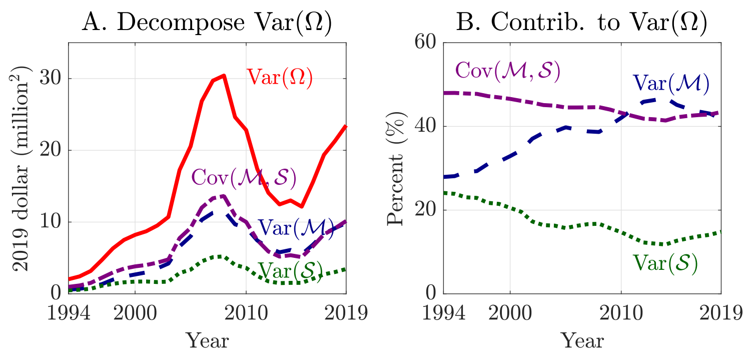


Figure 21: Time series of manager pay inequality and its decomposition

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.

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 inequality. 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 22. 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 22, 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

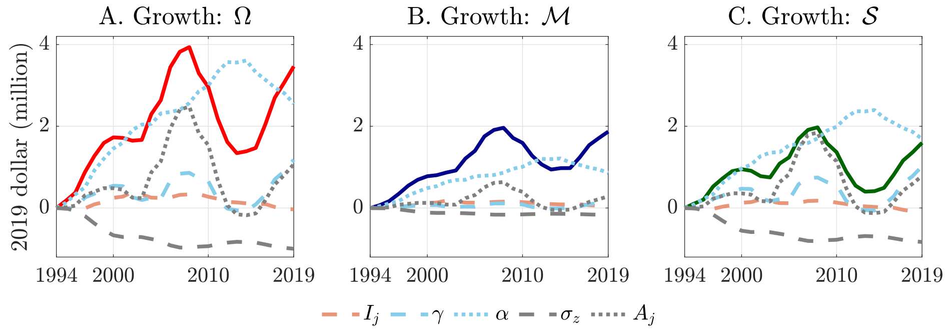


Figure 22: Factor decomposition: The rise of manager pay

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.

other parameters mainly function through the firm size one.

Manager inequality. We perform the same decomposition on the inequality of manager pay in Figure 23. 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 50.0% of the gross rise in the variance of manager pay, which can be attributed into 26.5% in the variance of market power component, 107.8% in the variance of firm size component, and 56.8% 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 contribution of manager skill to output in the production function, 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 24, 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

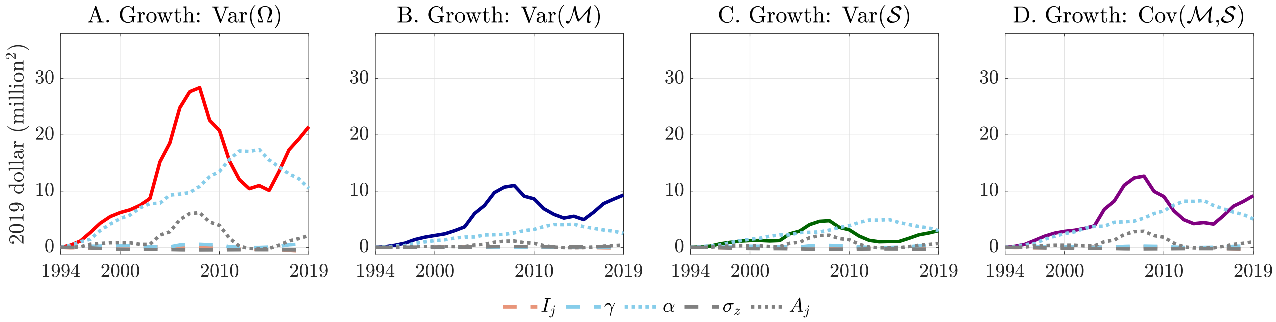


Figure 23: Factor decomposition: The rise of inequality

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.

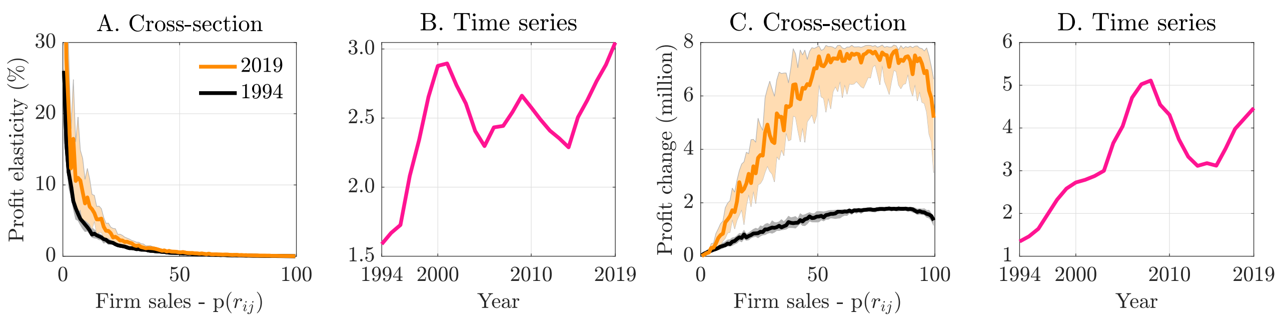


Figure 24: Effects of one-percent manager ability increase on firm profits

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 24. 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 \$4.47 million in 2019.

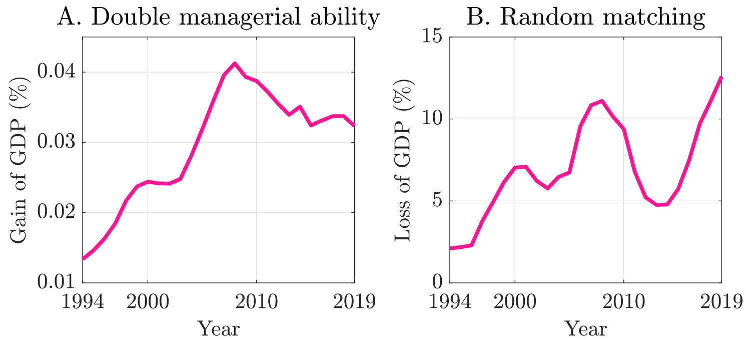


Figure 25: Counterfactual: Importance of managers to the economy

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.

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 25.

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 24.B for two reasons. First, our partial equilibrium analysis on individual firm level rules out the negative externality from competition. Firms 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 elasticity when studying this aggregate effect.

We also demonstrate the increasing importance of managers by examining the output loss due to mismatch. In Figure 25 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.[52] 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

[52] 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,...

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.2, 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).[53] 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 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.3, 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.4, 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.

Kimball Demand. Even though our model and results hold for a general demand system and market structure (see Appendix B.4), quantitatively the findings may depend on the specifics. Most notably, we ask how our quantitative results change under a demand system with monopolistic competition and Kimball demand. Unlike monopolistic competition with Dixit-Stiglitz preferences where the markup is constant, here there is a marginal effect from market power on the profits since firms with lower elasticities of substitution have higher profits. As a result, a firm will bid for a higher-ability manager because the manager marginally reduces demand elasticity and increases the markup. Therefore, under Kimball demand, manager pay will reflect market power. The mechanism under Kimball (higher pay due to a lower demand elasticity) is different from the mechanism in our model (higher pay due to strategic interaction with competitors). In Appendix D.6 we report the setup and calibration under the Kimball demand system and find results that are consistent with our main conclusions.

[53] The detailed decomposition expression is documented in Appendix D.2 as well.

Shortage of Managers. Manager pay may also be determined by the relative supply of managers and firms. A shortage of skilled managers, for example, drives up manager pay. In our setting, we assume that the number (measure in the continuous case) of firms and managers is identical is for data reasons. If we want to analyze the extensive margin, we need data on the universe of managers. Unfortunately, our sample is only for publicly traded firms, and even for those, we do not have observations on manager pay for all firms. Therefore, we do not have the data to quantitatively investigate the role of limited supply of managers. Instead we 'calibrate' the outside option by assuming that the wage of the lowest paid manager is equal to the wage of the lowest paid manager, and that the lowest ranked firm receives the remainder of the surplus as profits.

Theoretically, if the number (measure) of managers M_m is lower than the number (measure) of firms M_f, then $M_f - M_m$ firms at the bottom of the distribution will not find a match. Due to the strong complementarity ($\gamma < 0$), these bottom firms will have zero productivity and exit the markets. The lowest ranked manager will therefore be able to extract all the surplus of the firm with rank $M_f - M_m$ under the threat of not finding a manager. This increases the pay of the lowest ranked manager. In addition, manager shortage will also impact pay via strategic interaction, where the exit of unmatched firms increase the marginal product of matched firms and contributes to manager pay.

Overall, we believe it is best to think of manager shortage as reflected in a changing distribution of manager types. The fact that the time fixed effect is small relative to the manager fixed effect (see Section 2.2 above) suggests that there is limited variation in the supply of managers over time.

6 Conclusion

Market power in the goods market affects the efficient allocation of resources. In this paper, we show that market power also determines manager pay, as a manager's productivity not only influences a firm's size, but also its market power. High-ability managers increase firms' efficiency – reflected in their pay because the market for managerial talent is competitive. However, they also help firms widen their productivity lead over competitors, raising profits from market power by restricting how much efficiency is passed on to customers. Consequently, managers are compensated for their contribution to productivity, which partly boosts efficiency and partly reinforces a firm's market power.

The central insight of this paper is to separate the share of manager pay attributable to market power from the share attributable to firm size and efficiency. We estimate our model using data on manager pay and show that, even without directly using the manager pay distribution, our quantitative model explains most of the observed level of manager pay and nearly all of its growth. According to our model, on average 45.2% of manager pay is due to market power, increasing from 36.7% in 1994 to 48.9% in 2019, and accounting for 55.6% of the total growth in compensation over this period.

Our analysis further reveals that market power drives the rise in wage inequality among managers. For lower-ranked managers, nearly all their compensation is determined by firm size. In contrast, for top-ranked managers, market power accounts for 80.3% of their pay. The most talented managers tend to join large, high-markup firms, making them more efficient and generating substantial profits for shareholders. However, not all the efficiency gains accrue to customers because of incomplete pass-through. Moreover, the market power-related compensation has grown over time, leading to a longer and thicker right tail in the manager pay distribution and thus increasing manager pay inequality.

This reward structure crucially depends on competitive conditions in each market. Under perfect competition, better managers make firms more efficient. Under imperfect competition, the most productive firms earn higher rents than their less productive peers. Thanks to the complementarity between managerial ability and firm productivity, these leading firms can widen their advantage further by hiring highly skilled managers, which boosts their markups. Meanwhile, less productive firms see relatively small gains from hiring superstar managers. Because firms compete for top managerial talent, those that benefit most from hiring a top manager bid up wages accordingly, and managers at leading firms are rewarded for extending the gap with direct competitors.

Finally, this link between market power and compensation is not limited to managers only. A superstar coder who enhances an algorithm for a dominant tech firm, for example, can command a superstar salary, as her work helps that firm outcompete its rivals. Similarly, professional sports leagues exhibit strategic interaction reminiscent of oligopoly: teams that sign top athletes are more likely to win and thus bid up salaries for the best talent.

Data Availability Statement

The data and code underlying this article are available on Zenodo at https://doi.org/10.5281/zenodo.18224629.

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