ESSAYS ON UPPER ECHELONS

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ABSTRACT

Understanding how much influence managers have over firm performance has been one of the central questions in strategic management during the last five decades. Despite sustained scholarly interest in this question, the results of the empirical studies have been inconsistent and increasingly divergent. In this dissertation, I suggest that the current theorizing on this question has failed to consider the role of complementarities – or fit – between managers and firms in determining firm performance. To illuminate the role of complementarities as a source of variation in firm performance, I combine a proprietary dataset containing information on top management teams for every company in the Compustat sample with a novel Group Fixed Effect estimator based on machine learning. My findings provide new insights into the factors that affect firm performance and have implications for the Upper Echelons and agency theories.

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INTRODUCTION

A critical area of strategic management research concerns the study of how managers – and CEOs in particular – influence organizational performance (Hambrick & Quigley, 2014; McGahan & Porter, 1997; Misangyi et al., 2006). While the influence of managers on shaping an organization's fortunes is the central focus of the study of the Upper Echelons (UE) theory, understanding their role is of critical importance for advancing research in the selection and compensation of new managers, top management team dynamics, the resource-based view (RBV) and other important topics in strategic management (Finkelstein et al., 2009).

Researchers have extensively studied the factors that affect organizational performance using Variance Partitioning Methodology (VPM) studies (Bertrand & Schoar, 2003; Hambrick & Quigley, 2014; Lieberson & O'Connor, 1972). These studies have become increasingly sophisticated over time, identifying both firm and manager effects on organizational performance. However, the estimates of manager effects have varied widely, with recent studies suggesting that the impact of CEOs on firm performance can range from insignificant to extremely important (Fitza, 2014; Quigley & Hambrick, 2015). This lack of consensus highlights the need for a better understanding of the relative importance of firm-specific and manager-specific factors, which are the basis of two critical theories in strategic management: Resource-Based View (RBV) and Upper Echelon (UE) theory (Barney, 1991; Hambrick & Mason, 1984). While VPM studies have used various statistical techniques, they rely on several strong assumptions. Prior studies assumed additivity in manager and firm-specific effects and exogenous manager mobility (Hambrick & Quigley, 2014) . These assumptions suggest a random allocation of managers to firms. Thus, they ignore the potential contribution of complementarities – or "fit" (also referred to as synergies) – between managers and the firm in performance outcomes. The critical problem with these assumptions is that they have been frequently criticized as unrealistic and have been refuted in various contexts (Bagger & Lentz, 2019a; Gibbons et al., 2005; Hagedorn et al., 2017; Woodcock, 2008). Violating these assumptions can lead to a significant bias in the estimates of manager and firm-specific contributions to performance while ignoring the role of complementarities in explaining performance outcomes (Abowd et al., 2019; Bagger & Lentz, 2019).

In this dissertation, I build on previous VPM studies of manager effects by incorporating the notion of complementarities between managers and firms driven by endogenous manager-firm matching in the manager labor market. Previous studies have highlighted the economic value that matching managers with firms can create, but the idea of complementarity has been excluded from previous research (Gibbons & Roberts, 2013). I aim to understand how complementarity impacts firm performance by analyzing the information gathered from the matching process. To evaluate the significance of manager effects, firm-specific effects, and complementarities for organizational performance and manager compensation, I employ a methodological framework based on a Group Fixed Effects approach proposed by (Bonhomme et al., 2019) (henceforth, BLM). To further illuminate the role of complementarities and endogenous matching, I study the role of complementarities in manager compensation, where performance complementarities should be directly mirrored (Eeckhout & Kircher, 2011; Shimer, 2005). Manager compensation is central to agency theory and the strategic leadership research (Finkelstein et al., 2009). However, the compensation literature has frequently produced ambiguous findings across various studied variables, including pay-for-performance and the very determinants of manager compensation (Aguinis, Martin, Gomez-Mejia, O'Boyle, & Joo, 2018). Previous studies of manager compensation relied on various fixed-effects specifications while noting that endogenous manager-firm matching may substantially influence the inference from the results (Graham et al., 2012; Li & Perez, 2021). Incorporating complementarities and endogenous matching allows for a more nuanced view of manager compensation and what factors drive compensation beyond the usually theorized role of manager ability.

Many employee-firm matching models rely on complementarities in compensation (Shimer, 2005). This means that when a manager and a firm are well-matched, their compensation is higher due to positive performance complementarities. However, I argue that previous firm compensation also plays a role in determining manager compensation, in addition to complementarities and time-invariant effects of both firms and managers. Endogenous matching models incorporate search and bargaining processes between managers and firms, leading to path dependence in manager compensation. This means that a manager's current compensation may be influenced by their compensation at their previous employer for two reasons. Firstly, if a manager works in a high-wage firm, they may be more likely to move to another high-wage firm based on their ability. This is known as the "network effect" (Bonhomme et al., 2019). Secondly, the previous firm may directly impact current compensation by establishing a reference point of acceptable compensation for the agent. This direct effect is referred to as "state dependence" (Bagger & Lentz, 2019a; Postel-Vinay & Robin, 2002).

While previous research has found correlations in terms of the current and past compensation (Fee & Hadlock, 2003), theoretical work has yet to establish the role of state dependence in agency theory. The network effect and state dependence subsume the path dependence in compensation with the previous firm (Bagger & Lentz, 2019a; Postel-Vinay & Robin, 2002). These models contrast with previous agency research, which suggested that the socio-political dimension of managerial entrenchment happens gradually over time as managers – and CEOs specifically – build influence over the board (Bebchuk & Fried, 2006; Westphal &

Zajac, 1995). As such, incorporating endogenous mobility allows for a more fine-grained overview of compensation determinants at managers' entry to firms instead of the subsequent changes related to performance or other reasons. As such, my model diverges from standard agency models concerning the determinants of compensation by also considering the endogenous matching process that occurs in the labor market instead of treating the labor market as a source of purely implicit incentives (i.e., (Fama, 1980)).

I utilize a unique dataset with information on the top four managers in the entire Compustat sample of over 22,000 distinct firms from 1990 to 2018 compared to the usually used Execucomp sample that provides data on the 1,500 largest US firms by market capitalization for each year. Estimating the model on a sample with much greater firm size dispersion enhances the estimates' external validity while sharpening the analysis due to a much higher number of turnover events between different firms, which is the primary source of identification in the model we use. I find that complementarities are an important predictor of firm performance. The current estimates of manager effects are likely biased due to the incidental parameter problem caused by the network spareness of manager labor markets and the failure to consider endogenous manager mobility in the empirical frameworks.

This dissertation makes several contributions to the literature on the effects of managers on organizational performance. First, I build on previous studies, such as the seminal work by Lieberson and O'Connor (1972), by introducing new methods to more accurately estimate the impact of managers and firm-specific factors. Understanding these contextual causes of firm performance is crucial to guide future research in strategic management.

Second, I address key criticisms of previous VPM studies by introducing an alternative approach to estimating VPM that was recently developed in labor economics. VPM studies have been criticized as providing associative, rather than causal, interpretations of manager and firm effects on organizational performance (Hambrick & Quigley, 2014; Quigley & Hambrick, 2015). While some studies have used exogenous changes in the composition of managers to provide a more causal interpretation, they are usually limited by their sample size or the external generalizability of the institutional setting (Bennedsen et al., 2020; Fee et al., 2013; Quigley et al., 2017). Other studies that examine stock market reactions to sudden manager departures are also limited in their ability to account for differences between firms' replacement pools (Cziraki & Jenter, 2020; Fee et al., 2013; Yonker, 2017). This methodology introduced here addresses these limitations and enables a causal interpretation of the findings.

Third, my dissertation contributes to understanding the importance of contextual factors throughout time. Previous VPM studies have suggested the "CEO effect" has increased over time, often citing the celebrity status of CEOs as evidence (Quigley & Hambrick, 2015). However, recent evidence points to structural shifts in the manager labor market in the last three decades (Graham et al., 2020; Murphy & Zabojnik, 2007). I thus consider the role of changing labor markets and how changes in the sorting and manager-firm complementarities, rather than firm and manager-specific factors, influenced their contribution to organizational performance.

Fourth, the empirical results that highlight complementarities as an economically significant source of performance variation suggest that further studies in UE research should consider the joint impact of manager-firm matches instead of considering various CEO psychological facets and demographic attributes in isolation from the wider firm context. As such, I contribute to the UE literature by providing novel findings concerning the effects of managers on organizational performance by underscoring the role of fit between managers and firms rather than viewing both in isolation.

By integrating complementarities and endogenous manager mobility into the econometric model, we gain a new understanding of the factors that drive manager compensation and optimal contracting. This approach adds significant nuance to existing models of manager compensation design, particularly through the insight that state dependence plays a role in determining compensation. Specifically, a portion of a manager's compensation may be influenced by their previous employment history and compensation negotiations during their move, regardless of their underlying ability or the firm's pay practices.

Overall, my dissertation extends UE theory and executive compensation research by offering a more detailed and precise understanding of how managers select firms to work for and how this sorting process affects their performance and compensation through matching mechanisms and complementarities.

THEORY & HYPOTHESES

UE theory has been one of the most cited and influential theories in strategic management (Hambrick, 2007; Hambrick & Mason, 1984). Essentially, this theory examines how managers, with their unique characteristics, experiences, and biases, impact their firms' decision-making processes and overall outcomes. Since its inception in 1984 by Hambrick and Mason, UE theory has undergone further development through various studies that aim to provide a more comprehensive understanding of how executive biases and experiences affect decision-making (Hambrick, 2007).

The central element of UE theory is the notion from the behavioral theory of the firm (BTOF) that human rationality is bounded by the ability to process information (Cyert & March, 1963; March & Simon, 1958). When faced with too much information, decision-makers use heuristics to simplify their decision-making process. This means that different individuals may interpret the same situation differently, depending on their personal traits, past experiences, or previous work areas, which are often used as indicators of underlying cognitive processes that are hard to observe and measure (Finkelstein et al., 2009).

Since its inception, UE theory has been refined in numerous ways (Hambrick, 2007). The first key innovation was the idea that the effect of managers on firm decision-making is moderated by managerial discretion, as managers in highly regulated industries such as utilities have less freedom to "imprint" their traits on firm outcomes (Finkelstein & Hambrick, 1990). The second advancement was acknowledging the crucial role of executive job demands. In high-velocity industries, for example, the effect of innate traits on the company's outcomes is more pronounced as executives tend to rely more on the imprecise heuristics (Hambrick et al., 2005). However, despite strong evidence that the CEO’s decision-making is contingent on the environmental context, the current theorizing does not consider the configurational effect of CEO-firm fit nor the resulting performance and manager style ramifications.

Previous CEO effect findings

Researchers have focused on understanding the key factors that drive firm performance by conducting VPM studies. These studies vary in their modeling choices, time frames, levels, and objects of analysis. Some focus solely on firm and industry effects, while others include manager and other types of effects. Significant variation exists in the decomposition of manager and firm effects across these studies, and this variance does not seem to decrease over time. However, more recent decomposition studies have shown a greater emphasis on the importance of the manager effects (Keller et al., 2023; Quigley & Hambrick, 2015).

The original study by Lieberson and O'Connor (1972) found that around 14% of firm performance is attributable to managers. A follow-up replication by Weiner (1978) found that the manager effect was around 9%. Due to the influence of industrial economics and the structure of the US economy in the 1980s, VPM studies shifted into analyzing the role of the industry and the corporate parent effect (e.g., Brush & Bromiley, 1997; McGahan & Porter, 1997; Rumelt, 1991). In one of the studies evaluating the relative importance of firm and industry factors, Misangyi and colleagues (2006) found that firm-specific factors are the most important in explaining performance. This conclusion was supported by a recent study by Sharapov and colleagues (2021) found similar results.

In the early 2000s, VPM studies again started to incorporate manager effects. Bertrand & Schoar (2003) attributed around 3% of the variance in ROA to the CEO and around 5% for the entire TMT. Using a similar approach, Mackey (2008) found that CEOs explain over 23% of the variance in firm performance. However, both of these studies relied on the mover dummy variable (MDV) approach of following managers who move across firms, where the estimation is confounded by other changes that happen around the turnover. Crossland and Hambrick (2007) found that CEOs explain between 30% and 35% of firm performance, depending on the dependent variable.

The most recent set of studies, coinciding with the growing media importance of CEOs, similarly offer contradictory findings. Crossland and Hambrick (2011) found the CEO effect in the US to be between 15% and 35% depending on the firm performance variable. The findings from both studies by Crossland and Hambrick underscored how the CEO effect differs based on manager discretion. These two studies suggested that the CEO effect is more pronounced in industries with higher management discretion, consistent with prior empirical work in this area (Finkelstein & Hambrick, 1990). In a follow-up study, Hambrick & Quigley (2014) found that CEOs explain over 38% of the variance in firm performance, the highest identified CEO effect across previous studies. In another study, the same authors also suggest that the importance of CEOs has grown over time and that in recent periods, CEOs exert a dominating influence on firm performance compared with other factors (Quigley & Hambrick, 2015). A recent replication and extension study largely supported this finding (Keller et al., 2023). However, using a different econometric approach, Fitza (2014, 2017) argued that the CEO effect is statistically indistinguishable from zero. Using plausibly exogenous changes in CEOs, Fee and colleagues (2013) also suggested that CEOs do not affect firm-level performance nor key strategic choices. The conflicting studies raise concerns about how the CEO effect findings are affected by modeling choices and the context of the studies.

Taken together, the existing VPM studies have used a variety of modeling approaches, historical samples, and different types of empirical designs. These studies have analyzed the effects of managers across different time periods, in different countries and used accounting-based and market-based performance measures. While it is natural to expect a degree of variability in findings, the sheer extremeness in results – with the most recent findings on the CEO effect being statistically indistinguishable from zero (e.g., Fitza, 2014, 2017) to over 35% of overall firm performance (e.g., Hambrick & Quigley, 2014; Quigley & Hambrick, 2015) – suggests a need for methodological reconciliation. In other words, after half a century of research into factors determining firm performance, there is still a puzzling lack of consensus concerning key factors determining firm performance.

Although research has focused on CEOs as the most influential decision-makers in a firm, UE scholars have also extensively studied top management teams. This dissertation examines the top management team, not just the CEO, for three key reasons. Firstly, evidence suggests that TMT members other than CEOs can significantly shape firm-level policies and contribute to performance (Bertrand & Schoar, 2003; Finkelstein et al., 2009; Hambrick et al., 2015; Malmendier et al., 2022). Secondly, each TMT manager has different roles that vary significantly between firms, indicating that the CEO's control domain is not as monolithic as previously assumed. Lastly, CEOs tend to be replaced alongside the restructuring of the entire TMT, so ignoring other TMT executives in the empirical design could lead to incorrect attribution of performance changes to the CEO (Dewar et al., 2022).

In sum, I extend UE theory by recognizing that the CEO effect on performance may rest not only on the contribution of the CEO to firm performance but also on the degree to which the CEO complements the nature and needs of the firm. Thus, I provide an additional refinement to the question: how much do CEOs matter? In addition, I look beyond prior research that has focused almost exclusively on the CEO to consider the influence of the entire TMT on firm performance. Given the shared purpose of the members of the TMT to enhance firm performance, it seems reasonable to examine their role in addition to that of the CEO in understanding contributions to firm performance.

SORTING AND COMPLEMENTARITIES

The sorting effect has long been a focal point of research in the labor economics literature (Dess, 1987). The sorting effect has also been studied in other contexts with two-sided matching, such as the venture capital (Sørensen, 2007) and alliance portfolios (Mitsuhashi & Greve, 2009). The critical prediction from the competitive assignment models is that higher-ability managers match with large or highly valuable firms in the manager labor market because they would be more likely to earn higher compensation as their marginal product of human capital would be more valuable in these firms (Gabaix & Landier, 2008; Terviö, 2008). However, various labor market frictions influence the dynamics of the employee-firm sorting (Carnahan et al., 2022; Combes et al., 2008). For example, Edmans and Gabaix (2011) show that moral hazard can distort the allocation of the most talented managers to the largest firms. Additionally, CEOs may derive utility from the prestige associated with working for the largest firms, potentially distorting the labor market allocation (Focke et al., 2017; Malmendier & Tate, 2009).

Sorting plays a crucial role in matching, but whether the outcome is positive or negative depends on the context (Milgrom & Roberts, 1995). The effect of sorting on performance is then determined by whether the overall performance or output is greater or less than simply the sum of the abilities of the firm and manager. Previous labor economics and compensation studies have yielded varied results due to differences in empirical settings and methodologies (Abowd et al., 2019). The impact of complementarities on performance can be influenced by strong sorting patterns, but this alone is not sufficient. High-ability managers may be matched with larger firms for reasons other than complementarities, such as job attributes (Bonhomme et al., 2019; Sorkin, 2018).

In the context of a firm, the production function relies on complementary inputs that work together to generate even higher outputs. This is known as "fit" or "synergy" in strategy, and a production function where the value of one variable increases with the value of others is called supermodular (Milgrom & Roberts, 1995; Porter, 1996). This concept suggests that combining complementary assets can amplify the final result, particularly in relation to human capital and its impact on firm performance (Gibbons & Roberts, 2013). Many studies have identified the complementarity between employees and the firm as a crucial source of competitive advantage (Hayes et al., 2005; Hitt et al., 2001; Jovanovic, 1979; Lepak & Snell, 1999).

Although the organizational economics literature provides a formal model of complementarities, the HRM literature on selection and fit offers more detailed insights into their importance. Person-environment (PE) fit is defined as the compatibility between an individual's characteristics and their work environment, and it has been a significant concept in HRM for over a century (Kristof-Brown et al., 2005, p. 281). The emphasis on PE fit is evident from the fact that its underlying theories precede those of complementarities and supermodularity in economics. (Dawis, 1992; Parsons, 1909)

PE fit can take several forms. These include the matching of personal interests and job characteristics, congruence of personal values and organizational culture, or the match between knowledge, skills, and abilities (KSAs) and job requirements (Kristof-Brown & Guay, 2011). Considering the scholarly interest in PE fit, numerous meta-analyses have studied the overall findings from the literature. These findings have broadly confirmed the importance of PE fit in predicting various performance measures, suggesting that PE fit – and the complementarities – matters on all hierarchical levels of an organization (Kristof-Brown et al., 2005). Unsurprisingly, the HRM literature has found that the value of selection practices (as a screening tool used to assess PE fit in the recruitment stage) is greatest in dynamic industries, consistent with the notion that the value of matches can rapidly fluctuate in a dynamic environment (Kim & Ployhart, 2018). Taken together, PE fit theories suggest that PE fit should be an essential predictor of CEO and TMT performance.

In support of the HRM theories, the baseline prediction from agency theory is that the boards, contingent on not being coopted (Westphal & Zajac, 2001; Zajac & Westphal, 1996), should be efficient at replacing poorly performing CEOs. CEOs can underperform due to a lack of ability, effort, or a mismatch with the company's evolving industry and job demands. As industries mature, companies shift their focus from growth to profit, which brings about changes in management style and job requirements. Existing research suggests that boards are, on average, efficient in replacing CEOs who no longer fit the company's needs (Fee et al., 2018; Jenter & Kanaan, 2015). These results indicate that boards fire mismatched CEOs while retaining CEOs who match job requirements well. The empirical evidence on CEO turnover in changing industries, PE fit theories, and normative models on manager assignment would suggest that complementarities between managers and firms should positively impact firm performance.

Combining the literature in organizational economics and human resource management, I expect to find a statistically significant influence of managers and complementarities on firm performance. Said formally, the interaction between manager effects and firm effects on firm performance will result in a significant increase in the model’s adjusted R^2.

Influence of size and asset growth

The importance of complementarities can significantly vary across specific sub-samples due to their relative importance in different contexts and periods (Eeckhout & Kircher, 2011; Lindenlaub, 2017). For example, complementarities in performance tend to be more critical for less prestigious law firms (Oyer & Schaefer, 2016). Large firms tend to be more structurally complex in the broader corporate context and have higher information-processing requirements (Lawrence & Lorsch, 1967; Marcel et al., 2011). These types of firms usually have a higher degree of human capital specialization, and they tend to feature a higher degree of vertical integration, which is an especially prominent feature of modern platform-based firms with a high level of asset intangibility (Campbell et al., 2012, 2012; Hatch & Dyer, 2004). In addition, large firms tend to experience inertia due to established norms and conventions (DiMaggio & Powell, 1983; Kraatz & Zajac, 1996).

Furthermore, legitimacy constraints can limit the available repertoire of strategies meaningfully shaping a firm's direction (Benner & Ranganathan, 2012; Pfeffer & Salancik, 1977). Legitimacy requirements and isomorphic pressures are especially salient in large and publicly known firms (Suchman, 1995). The combination of inertia and decision-making limitations imposed by legitimacy requirements can reduce managers' discretion in shaping a firm's policies and performance (Finkelstein & Hambrick, 1990). Environmental inertia, in particular, tends to influence large firms more (Hannan & Freeman, 1977). Low discretion in large firms suggests that potential mismatches between managers and firms would likely lead to an attenuated effect of complementarities. More discretion would be needed to facilitate the effect of complementarities on overall performance. Based on this, I expect that the positive contribution of complementarities to firm performance will be stronger in smaller firms.

While it may seem logical to sort companies based on their size, as larger firms are likely to have higher-performing managers, it's important to consider other factors that may impact a company's success, such as growth opportunities. In particular, companies experiencing high levels of growth are often found in rapidly expanding industries that are still in their early stages of development. Executive job demands tend to be exceptionally high in these industries (Bourgeois & Eisenhardt, 1988; Eisenhardt, 1989). High executive job demands usually lead to a stronger association between a manager's characteristics and firm policy choices, as managers rely on decision-making heuristics that reflect their accumulated personal experience (Ganster, 2005; Hambrick et al., 2005). When it comes to high-growth firms, relying on decision-making heuristics indicates that complementarities are crucial. If managers and firms match up properly, it can lead to better strategic decision-making and help the firm's performance. As a result, I predict that the benefits of having complementarities in place for a firm's success will be more significant for firms experiencing substantial asset growth.

Exploring the performance mechanism

While the contribution to performance is arguably the most critical component of assessing the importance of TMTs, UE researchers have devoted significant attention to understanding more proximal outcomes of heterogeneity in managerial ability. These researchers have examined various outcomes, such as the firm's strategy, level of diversification, and innovative efficiency (Custódio et al., 2019; Finkelstein et al., 2009; Hambrick, 2007). For example, prior research has identified a strong link between manager traits, experience, and innovation (Balkin et al., 2000; Barker & Mueller, 2002). Finally, TMT composition can also influence operating profitability (Waldman et al., 2001). Understanding where and how complementarities manifest in the value chain can help inform the nature of the exact mechanism through which manager-firm complementarities manifest. Based on this, I propose considering two intervening factors linking manager-firm complementarities and firm performance: operational and innovative efficiency.

Manager effects over time

As noted previously, the VPM literature has suggested that the manager effect has grown over time, implying that managers – and CEOs, especially – have a more significant role in shaping firm performance than in previous periods (Quigley & Hambrick, 2015). While the media superstar status CEOs have achieved is well-documented (Malmendier & Tate, 2009), the exact mechanism explaining why CEOs matter more in recent decades than in prior years is unclear.

One explanation for the changes in contextual factors influencing firm performance is the changes observed in the manager labor market. The manager labor market has significantly changed in the previous three decades. The 1990s were a decade with higher manager turnover compared to prior eras, a trend that continued into the 2000s and 2010s (Cziraki & Jenter, 2020; Murphy & Zabojnik, 2007). In addition, managers become more likely to move across industries instead of being constrained by the industry in which they are specialized, and firms became more likely to hire managers outside of the firm rather than promoting internally (Graham et al., 2020). These trends were potentially underpinned by the gradual switch to more general manager skills, where managers are no longer highly specialized in one industry or functional area (Custódio et al., 2013, 2019). One reason why general management skills are becoming more important is because there has been an increase in knowledge about how public firms work. This is supported by the fact that more managers now hold MBA degrees focusing on general management. (Murphy & Zabojnik, 2007).[1] Similar patterns, however, are also documented in the broader labor market, which has increasingly emphasized social skills compared with more technical skills in the past (Deming, 2017).

Labor markets are becoming more efficient as a result of a shift towards generalist human capital and higher turnover rates. Generalist managers can transfer their skills between firms more easily than those with firm-specific expertise, making them more valuable. This increased mobility and emphasis on generalist skills should lead to better firm performance due to increased matching efficiency. Overall, I predict that complementarities will play a larger role in firm performance in more recent times.

[1] Growing proportion of MBA degrees is society-wide phenomenon and not confined to CEOs (Acemoglu et al., 2022; Graham et al., 2020). This further motivates extending the proposition to all managers instead of the CEOs only.

COMPLEMENTARITIES AND COMPENSATION

Complementarities between employees and firms in compensation are central predictions in the labor sorting models of how employees match with firms (Bender et al., 2018; Card et al., 2013). Prior research on the role of human capital in manager compensation has primarily relied on Becker's (1962) human capital model, where compensation is reflective of the manager’s ability – or human capital –, thus abstracting from the potential complementarities resulting from manager-firm matches (Becker, 1973; Graham et al., 2012; Harris & Helfat, 1997). While previous research in the manager compensation literature has explored how time-invariant factors (usually estimated as manager fixed effects) influence manager compensation, these studies, similarly to the VPM studies on manager performance, were plagued by endogeneity issues. These studies found substantial heterogeneity in both firm and manager fixed effects, suggesting a high degree of persistence in compensation between managers and between firms (Coles & Li, 2022; Graham et al., 2012). However, building on the previous theorizing regarding the role of complementarities in performance should also be mirrored in complementarities in compensation, reflecting the sharing of the surplus value created through a high-quality match between a manager and the firm (Becker, 1973). More specifically, the degree of complementarities in performance will be reflected in compensation through rent sharing, as managers will capture part of the value created by the complementarities in the performance (Shimer, 2005). Thus, I predict that complementarities will have a statistically significant effect on explaining variation in executive compensation.

When it comes to compensation, smaller firms and those experiencing high levels of asset growth may be more affected by complementarities. In rapidly growing firms and high-pressure job environments, the importance of finding the right match between managers and the company may be reflected in how they are compensated. In contexts where complementarity has the strongest synergistic effects between managers and firms on performance, we should see a more significant influence of complementarities on executive compensation. Specifically, smaller firms and those with higher levels of asset growth may benefit more from complementarity in performance, leading to an increase in compensation for managers. Smaller firms and firms with higher levels of asset growth have higher executive job demands, in which case the manager would resort more to using heuristics. Since heuristics are more closely related to the match component, the influence of complementarities is more pronounced in these contexts. This suggests that the role of complementarity in executive compensation depends on the context, with complementarities positively impacting manager compensation in certain situations.

The literature on compensation has offered various explanations for the significant size and uneven distribution of manager pay. These generally revolve around the social and political factors that allow managers to influence the board for more favorable pay or the managerial entrenchment hypothesis proposed by (Bebchuk & Fried, 2006; Westphal & Bednar, 2008; Zajac & Westphal, 1994). Additionally, the structural literature on labor markets has identified two other mechanisms contributing to the discrepancy between manager pay and performance.

Endogenous mobility implies that managers consider their current match quality before deciding to move (Abowd et al., 2019; Card et al., 2013). Endogenous mobility suggests that managers will move to a new firm only if the perceived match quality is better. Additionally, managers working at high-wage firms will be more likely to move to another high-wage firm, conditional on their ability, which is also referred to as the network effect (Bonhomme et al., 2019). Additionally, manager compensation may also be influenced by bargaining. Managers who observe low match quality endogenously search for another job and negotiate with the new firm. This bargaining process is similar to an offer-counteroffer process, as described by Bagger

& Lentz (2019) and Postel-Vinay & Robin (2002). The compensation for the new job is influenced by the compensation received in the previous job, due to both the network effect and state dependence. This implies that future compensation is path-dependent on previous compensation, even after controlling for firm and manager-specific effects.

As such, the overall effect of the previous employer on current compensation can be decomposed into the network and state dependence effect (Bonhomme et al., 2019). Market sorting can account for some of the variation in manager compensation, which is unrelated to their ability or the pay practices of their current company. Additionally, there may be a lack of pay-for-performance sensitivity in certain situations due to the persistence of path dependence, as noted by Pisani et al. (2020). Path dependence means that a manager's current compensation may be affected by their previous firm's compensation, regardless of their current performance or ability.

METHODOLOGY

Sample

The data on the firm financial information and the names of the top four executives is from Compustat Research Insight distributed on compact disks (CDs). The sample contains information on the titles of the top four managers from the entire Compustat sample from 1989 to 2018, as reported in the US Security Exchange Commission filings with over 200,000 firm-year and over 808,057 firm-manager-year observations. I remove all observations from the financial services industry (SIC codes between 6000 and 6999), utilities (SIC codes from 4900 to 4999), as well as the public sector and unclassified firms (SIC codes above 9000), as these industries use different metrics for the measurement of corporate policy decisions and firm performance (Hambrick & Quigley, 2014). After removing the financial services utilities, public and unclassified firms, and observations missing the key variables from Compustat, the remaining sample size is 553,619 firm-manager-year observations. The data on executive compensation is from Execucomp. The data on turnovers is captured using Factiva to ensure the correct turnover timing.

I use the Levenshtein distance fuzzy name-matching algorithm to ensure consistency in tracking managers as they move across firms. This machine-learning algorithm identifies similar names by calculating the smallest number of single-character adjustments needed to make them identical (Cohen et al., 2013). When the algorithm produces close but not exact matches, I manually check these “close” matches to confirm whether or not the two names belong to the same individual. Mismatches are removed from the sample.

The estimation method is based on a connected set of firms and managers. I construct a connectedness set of managers who move to or stay in the focal firm from the assembled dataset in the spirit of the AKM estimator, which relies on graph theory to create groups of connected individuals (Abowd et al., 1999). The connectedness set encompasses all the managers who move between firms and those who stay in a firm where at least one other manager previously moved to that firm. This is a sufficient condition for the separate identification of firm and manager fixed effects in the first stage of the model (Abowd et al., 2002). This connected set resembles a social network built around weak ties, where it is only necessary that a manager at one point works for a firm who has a manager who at another point in time worked in another public firm for connectivity to hold. Thus, managers that never move from and who work for firms that no other manager joins during the period of the study fall out of the final sample. For example, this may include smaller firms in states with lower levels of economic activity that primarily rely on geographic labor pools for hiring or have very low manager turnover. Constructing the connected set reduces the final sample to 526,111 observations, representing over 95% of the baseline filtered dataset. This compares highly favorably to the Execucomp sample, where the connected dataset is usually around 50% of the baseline filtered sample (Coles & Li, 2022; Graham et al., 2012). The construction of the connected set is explained in Appendix.

The secondary advantage to using the Compustat Research Insight CDs (CRI) to collect data on managers is that CRI covers the entire Compustat sample, which Execucomp does not. Execucomp data coverage is limited due to turnover events in which managers enter and leave the 1500 firms listed in Execucomp (e.g., firms in lower size quantiles of Russell 3000) (Cziraki & Jenter, 2020). Incorporating the full sample of managers holding TMT positions increases the number of turnover events. This also increases turnover events using the Execucomp sub-sample because I can capture the employment history of managers entering and leaving the largest 1500 firms included in Execucomp. This is crucial for the empirical design since the estimation model is based on manager movement between firms. More observed turnover events reduce network sparsity, which addresses the incidental parameter problem (Jochmans & Weidner, 2019).

To test the effects of complementarities over time, I split the sample into sub-samples corresponding to historical US business cycles (Kiley, 2023). These include 1990-1999, 2000-2008, and 2009-2018 sub-samples, as our data ends in 2018. The variables are deflated from nominal dollar values to their 1990 inflation-adjusted equivalent using Consumer Price Index (CPI) data from the Bureau of Labor Statistics (BLS).

Variables

Dependent variables. The literature on performance implications of managers delineates between accounting and market-based measures of performance (Hambrick & Quigley, 2014; Quigley & Hambrick, 2015). For consistency with the previous studies, I use Return on Assets (ROA) as the accounting-based measure of performance and Tobin's Q as the market-based performance measure. Using these measures allows me to compare my results to prior findings. These measures are widely used in the strategic management literature and reflect the backward-looking nature of performance (ROA) and the forward-looking market-based measure (Tobin's Q). As such, they capture both how managers influence operational efficiency via ROA and how the market perceives the firm's future value (Tobin's Q). I calculate ROA as the ratio of earnings before interest and taxes (EBIT) to total assets as it is more proximal to CEOs' ability to influence operational effectiveness compared to using net income in the denominator, which also contains changes in capital structure. I calculate Tobin's Q as the firm's market value divided by its assets' replacement cost.

While the choice of the dependent variables is motivated by the consistency with the literature (e.g., Fitza, 2014; Hambrick & Quigley, 2014; Mackey, 2008), a potential concern is that other exogenous factors may influence performance around the turnover events. As such, I regressed each performance measure on a set of year × industry interaction dummies. I used the residual from the equation as the dependent variables in my models estimating manager and complementarity effects (Bonhomme, 2021). This ensures that the dependent variables are purged of exogenous shocks around turnover events as it sweeps out any shocks in the focal firm's industry during the year when the turnover happens. The industry definitions are based on the Fama – French 49 Industry Portfolios.

For the executive compensation tests, I use the total compensation (tdc1 in Execucomp) (Coles & Li, 2020; Graham et al., 2012). Total compensation includes salary, bonus, the total value of granted restricted stock, the total value of granted stock options (valued using the Black-Scholes model), and other forms of payments to the manager. Given that my concern is with the compensation provided to the managers when they join a firm, as opposed to their compensation in later years when performance and other factors may influence compensation, this measure provides a good proxy for capturing the manager's initial compensation package.

Subsample grouping variables. I calculate firm size as the log of total assets. Asset growth is calculated as the yearly growth rate of total assets.

Mediating variables. There is a variety of methods to operationalize firm-level efficiency in the literature. I focus on two facets of efficiency: operational efficiency and innovative efficiency. Operational efficiency should capture how a firm can produce outputs using a given set of inputs. To capture the degree of a firm's operating efficiency, I calculate two variables widely used in the literature as proxies that capture a firm's ability to produce outputs efficiently.

I calculate *operational efficiency* using total factor productivity *(*TFP*)* to capture a firm's ability to efficiently generate revenue using key tangible inputs (Levinsohn & Petrin, 2003). I use the production function estimator proposed by Ackerberg and colleagues (2015) to account for endogenous input choices. I define the production function output as gross output (equal to the difference between sales and material, as defined in Compustat). I use the book value of the capital stock and the number of employers as the inputs and firm investments as the intermediary input. The residual from the TFP production function indicates whether a firm is more or less efficient than expected, given the tangible inputs used in the production. I estimate the TFP model separately for every industry.

The *innovative efficiency* variable should capture a firm's ability to convert R&D spending into firm value successfully. I follow the recent innovation literature (Cohen et al., 2013) and define *innovative efficiency* by first running a rolling firm-by-firm regression of firm-level (logged) sales growth on the log of lagged R&D scaled by total sales. I run separate regressions for five different lags of R&D (i.e., R&D from years $t-1$, $t-2$, $t-3$, $t-4$, and $t-5$) and then take the average for all five regression coefficients (betas from the firm-level regression) as my measure of innovative efficiency. The essential advantage of using an innovative efficiency measure based on the relationship between sales growth and R&D spending compared to measures based on patents and citations is that there is no sample attrition due to a lack of information on patents and cites. In estimating a firm's ability, I use the preceding eight years for the time-series regressions for every firm-year observation. I require that R&D expenditures are reported in at least 75% of observations to be included in the sample. The final measure captures the firm's ability to convert innovation inputs (R&D spending) into output (sales).

Estimation method

Estimation of the variance decomposition is based on the BLM estimator (Bonhomme et al., 2019). BLM is conceptually based on the Abowd, Kramarz, & Margolis estimator (referred to here as the "AKM" estimator). AKM estimator has been used to understand the determinants of inequality (Card et al., 2013), whether venture capital performance is driven by firms or partners (Ewens & Rhodes-Kropf, 2015), as well as to decompose the variance in innovation output between innovators and firms (Bhaskarabhatla et al., 2021).[2] While AKM has been extensively used in various contexts, the model is static because it does not consider the choice of the manager to dissolve the match and leave the firm based on match quality. More specifically, the decision by those who choose to move is endogenous to their current performance and performance in their previous positions (Bhaskarabhatla et al., 2021; Card et al., 2013; Ewens & Rhodes-Kropf, 2015). Furthermore, standard AKM cannot accommodate the role of complementarities nor the search intensity and bargaining processes that underpin much of labor market theory.

The inability of AKM to estimate complementarities and nuanced micro processes that underpin labor markets is a significant limitation considering the theorized importance of these processes (i.e., Bagger & Lentz, 2019; Postel-Vinay & Robin, 2002). However, recent advancements in econometrics have tackled this issue. BLM is a novel framework that estimates variance components while allowing for two-sided manager-firm unobserved heterogeneity and endogenous mobility (Bonhomme et al., 2019). BLM allows for estimating endogenous mobility, defined as the process through which managers and firms simultaneously search for the best match, through a dynamic Markovian process. The identification in BLM depends on manager

[2] AKM is a two-way fixed effects (TWFE) estimator usually used to decompose the variance in the dependent variable into firm-specific and variable of interest factors, such as manager-specific effects.

movement between firms or between classes of firms. To ensure sufficient manager movement, the model requires that managers be grouped into distinct types and firms be grouped into distinct classes. This additional requirement then models how managers of different types move between different classes. Comparing changes in performance around turnover events when managers of different types move to different firm classes provides estimates on the role of firm-specific and manager-specific factors in explaining variance in performance and compensation. In other words, BLM attributes part of the overall variance in firm performance to firm-specific factors and another part to manager-specific factors (representing manager human capital). The critical assumption of the BLM model is that the probability that a manager moves to another firm depends on the manager's current performance, in addition to the manager's ability and firm class. In addition, the probability of moving from one firm class to another also depends on current performance. Thus, BLM overcomes the endogeneity issue that plagues AKM estimators used in prior VPM research.

The estimation method has two steps. In the first step, a dimensional reduction technique using *k-means* machine-learning clustering algorithm is used to classify firms into a specified number of clusters according to the distribution of a specified variable. *K-means* clustering is a form of unsupervised machine learning which sorts firms into clusters based on the Euclidean distance (Hartigan, 1975). *K-means* clustering allows for grouping firm heterogeneity into clusters, which is the critical aspect of the Group Fixed Effects estimator on which BLM is based (Bonhomme & Manresa, 2015). There is currently no widely accepted approach in econometrics or computer science to selecting an optimal number of clusters, given the unsupervised nature of the machine learning algorithm used. As such, I use a battery of robustness checks to make sure the results are not overly sensitive to the specification of the number of clusters and latent manager types.

The crucial motivation behind clustering firms is to alleviate the incidental parameter problem (also called the limited mobility bias) (Neyman & Scott, 1948). The incidental parameter problem typically arises with panel data models when allowances are made for individual-specific intercepts or parameters. Incidental parameter problem leads to an estimation bias of manager and firm effects when there is a low number of managers who move between firms (Andrews et al., 2008; Kline et al., 2020). The incidental parameter problem is a result of the fact that standard asymptotic theory does not hold in the AKM context (Bonhomme, Holzheu, et al., 2022). Under a standard OLS estimator, increasing the sample size by increasing the sample cross-section (in this case, the number of firms in the sample) reduces the estimation bias of the beta coefficients, as $N \rightarrow \infty$. The AKM estimator is based on estimating the fixed effects from a model rather than the beta coefficients, as the fixed effects are necessary to understand the contribution of firms and managers to the outcome variable of interest. As the sample size grows by increasing the number of firms in the sample, so does the number of the parameters (firm and manager fixed effects) that have to be estimated. In this sense, the bias cannot be alleviated by increasing the sample size through increases in the cross-section by adding more firms in the sample. In the context of networks, this issue is also called the limited mobility bias (Andrews et al., 2008). In essence, under a network structure (such as one created by the connections between firms via manager movements), firms and managers have to be strongly connected for fixed effects to be separately identified, which is necessary for an unbiased variance decomposition. However, most labor markets – including the one for managers in top management teams – have low connectivity as managers are not sufficiently mobile (Graham et al., 2020). Under these conditions, there is an insufficient amount of information to separately identify manager and firm fixed effects, leading to estimation bias known as the limited mobility bias (Kline et al., 2020). Recent estimates suggest that the BLM estimator performs favorably among a similar class of estimators which resolves the limited mobility bias in various ways and has negligible bias even with a low number of movers (Bonhomme et al., 2022).

After clustering the firms into classes, the model estimates the transition probabilities of managers between classes and assigns managers to latent "ability" types. The process considers the manager’s employer performance in allocating managers to types. The assignment of firms to a specified number of classes (in this case, ten) reduces the number of parameters that need to be estimated and, thus, the bias from the incidental parameter problem. Assigning managers to latent types solves the same issue on the manager side. It repeats this process hundreds of times and selects the version that best reflects the data. I estimate ten firm classes and five manager types as a baseline, with a robustness check of five and fifteen firm classes.[3] I use the dependent variables (Tobin’s Q, ROA, and log of total compensation) for clustering. I also weight measurements by firm size using total assets as the weighting variable (Bonhomme et al., 2019).

In the second step, the model is estimated using the Expectations-Maximization estimation algorithm that yields the parameters of interest, conditional on the estimated firm classes (Dempster et al., 1977). The identification of firm and manager effects is based on separately estimating the changes in the performance of managers who move between firms and the proportions of latent manager types of both those who move and those that stay with their

[3] Reducing the number of classes allows for a more precise estimate because of a greater number of job movers between classes but having too few classes introduces unnecessary noise since firms are grouped using an overly coarse specification.

firm (Bonhomme et al., 2019; Bonhomme & Manresa, 2015). The estimator first estimates performance densities using only those that move between firms and then estimates manager-type proportions in the first period using job movers and stayers. This step then estimates the relative contributions of firm, manager, and interactive effects. I estimate all performance decompositions using bootstrapping with 1,000 replications. After the firm and manager effects are estimated, I then add an interaction term that interacts firm with manager effects, which represents the influence of complementarities (or fit) in explaining the firm performance (Bonhomme et al., 2019). The resulting change in R^2 captures the portion of performance variance attributed to the complementarity between managers and firms.

Finally, I perform a counterfactual exercise to calculate the heterogeneous effect of complementarities across different firm classes. I use the BLM estimator to estimate the manager and firm effects and their covariance structure. To do this, I run 10,000 simulations, in which I randomly shuffle managers between different firms. This random sorting of managers to firms artificially "breaks" the matches and sets the covariance between manager and firm effects to zero. The difference in the expected performance between results where managers are randomly allocated to firms and results where managers seek strong matches with firms is the *net* contribution of complementarities to firm performance. The net contribution shows the discrepancy between the actual model and the simulated counterfactual and how some firms gain from improved complementarity while others may lose due to poor complementarity. To illuminate the effects of complementarities at the tails of the performance distribution, I estimate the contribution of complementarities to firm performance for 10%-Quantile and 90%-Quantile of the performance distribution. This allows me to distinguish between situations of strong and weak complementarity.

For the sub-sample tests of the net effects of complementarities on large and small firms and firms with high and low asset growth rates, I sort firms into percentiles based on size and asset growth. Since I have fewer firms in each sub-sample, I cluster around eight firm clusters and keep the standard five manager types. I then re-run the analyses on each sub-sample and compare effect sizes using a standard *t*-test. This allows me to examine how the importance of complementarity to firm performance might vary with firm size and firm growth.

RESULTS: PERFORMANCE VARIATION

Table I displays the summary statistics of the connected sample. For comparison with other datasets, I also show the values for R&D intensity (R&D expenditures divided by total assets), capital intensity (capital expenditures divided by total assets), leverage (sum of long-term and short-term debt divided by total assets), and total assets (logged).

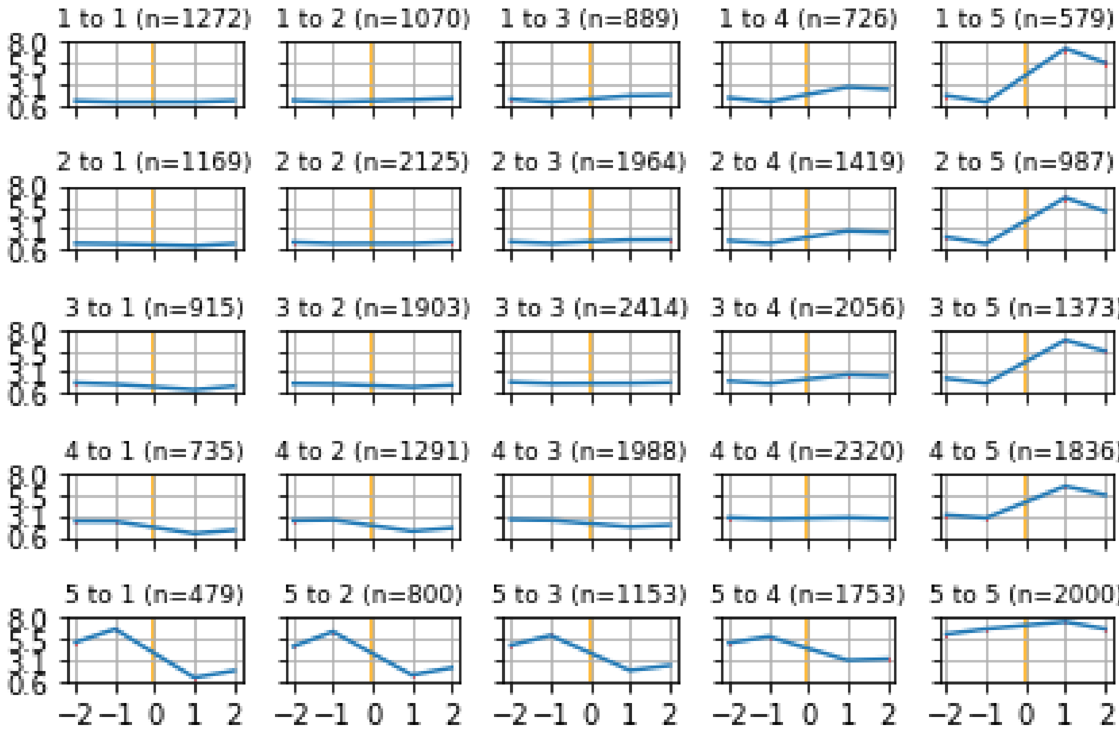
Table 1
Summary Statistics

Variable	Mean	Standard Deviation
Tobin's Q	2.679	3.391
ROA	0.049	0.495
R&D Intensity	0.067	0.138
Capital Intensity	0.057	0.065
Total Assets (logged)	5.138	2.400
Leverage	0.255	0.294

N = 526,111

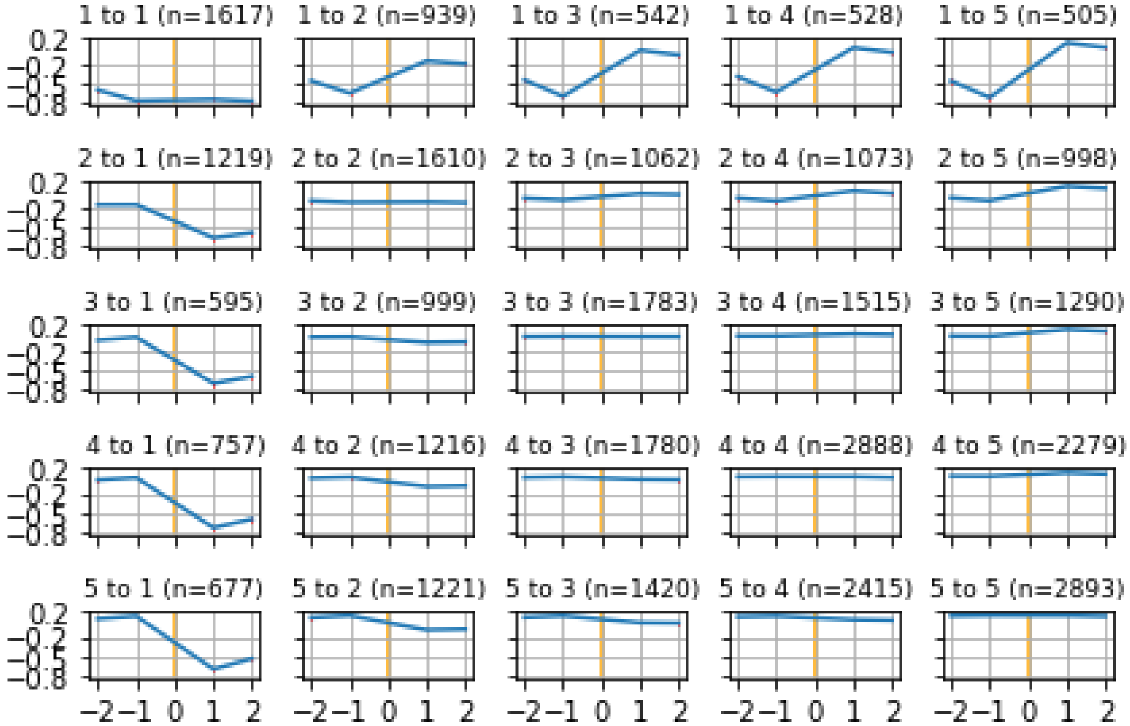
Since the identification strategy is based on the movement of different manager types between different firm classes, as a preliminary diagnostic test, I construct an event study to check performance variation around turnover events and to show whether there is sufficient between-class mobility. The event study is a transparent way to assess whether the movements of executives lead to performance variation around the turnover year. The Card-Heining-Kline (CHK) event studies displayed in Figure 1 (for Tobin's Q) and Figure 2 (for ROA) show performance variation at the event year (t = 0) and two years before and after the turnover (Card et al., 2013). For ease of interpretation, I cluster the firms into five classes to capture the movement across the five × five firm cluster cells. As shown in Figures 1 and 2, while there is somewhat higher mobility between the same or adjacent classes, there is still sufficient mobility across distant classes (one to five and five to one). This alleviates the concerns that there is poor mobility across the manager-firm network while providing prima facie evidence of the importance of managers in determining firm performance.

Figure 1
Event Study – Tobin's Q



The figure shows movers between firm classes. *N* shows the number of movers between specified classes. Y-axis shows performance changes.

Figure 2
Event Study – ROA



The figure shows movers between firm classes. *N* shows the number of movers between specified classes. Y-axis shows performance changes.

Baseline results: performance variation

As the initial model, I set the number of firm clusters to ten and the number of latent manager types to five. The results are shown in Table 2 (Tobin's Q) and Table 3 (ROA). The overall variance in firm performance can be decomposed into manager effects α, firm effects ψ, twice the covariance between manager and firm effects (which represents sorting), and the variance of residuals ε. As shown in Tables 2 and 3, managers explain around 5.12% of the variation in firm performance when firm performance is measured as Tobin's Q and around 2.13% when firm performance is measured as ROA. In contrast, the firm-specific effect is around 44.21% for Tobin's Q and 31.92% for ROA. Compared to the higher estimates in the existing literature (Hambrick & Quigley, 2014; Quigley & Hambrick, 2015), these results indicate a smaller influence of managers and a more substantial influence of firm-specific factors. I explore the robustness of these results in the section below. Thus, by controlling for endogeneity and instrumental parameter biases, I find that complementarity explains substantially more variance in firm performance than manager effects alone.

Table 2
Variance Decomposition and Reallocation Exercise – Tobin's Q

Variance decomposition (× 100)				
$\frac{Var(\alpha)}{Var(y)}$	$\frac{Var(\psi)}{Var(y)}$	$\frac{2\,Cov(\alpha,\psi)}{Var(y)}$	$\frac{Var(\alpha \times \psi)}{Var(y)}$	$\frac{Var(\varepsilon)}{Var(y)}$
5.12	44.21	1.51	9.11	40.05

Relocation Exercise (× 100)			
Mean	Median	10% - Quantile	90% - Quantile
10.31	7.89	12.11	-13.20

In the upper part of the table, α refers to manager effects, ψ refers to firm effects, covariance between α and ψ refers to sorting, α × ψ refers to complementarities, and ε refers to the residual. The variance decomposition is performed through bootstrapping with 1,000 replications. In the lower part of the table, I report differences in mean, median, 10%, and 90%-quantile of Tobin's Q between two samples: a counterfactual sample where managers are reallocated to firms randomly and the original sample. The results are obtained using 10,000 simulations. The relocation exercise is performed by non-residualized (raw) variables for interpretability.

Table 3
Variance Decomposition and Reallocation Exercise – ROA

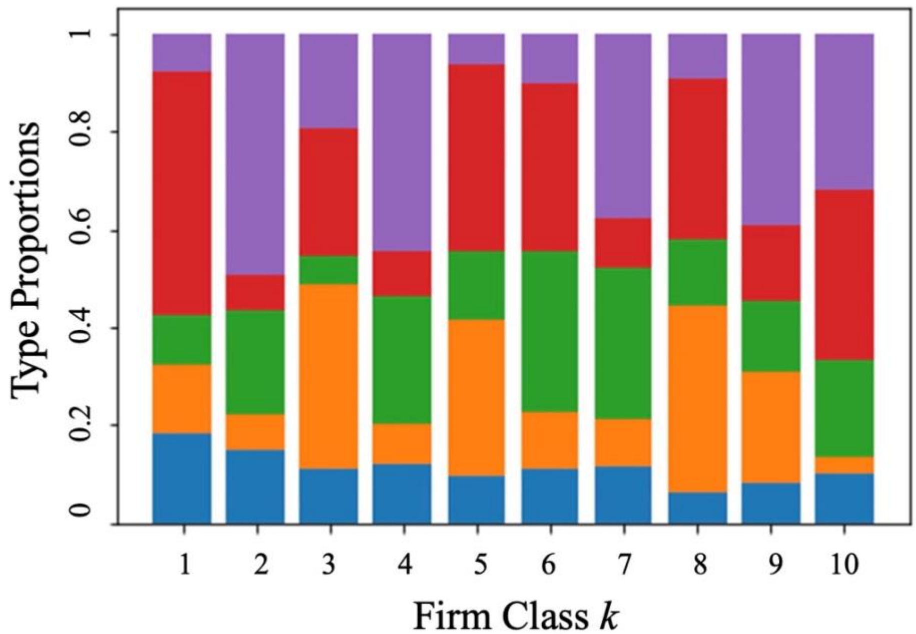
Variance decomposition (× 100)				
$\frac{Var(\alpha)}{Var(y)}$	$\frac{Var(\psi)}{Var(y)}$	$\frac{2\,Cov(\alpha,\psi)}{Var(y)}$	$\frac{Var(\alpha \times \psi)}{Var(y)}$	$\frac{Var(\varepsilon)}{Var(y)}$
2.13	31.92	0.64	10.87	54.44

Relocation Exercise (× 100)			
Mean	Median	10% - Quantile	90% - Quantile
9.24	6.39	12.26	-10.31

In the upper part of the table, α refers to manager effects, ψ refers to firm effects, covariance between α and ψ refers to sorting, α × ψ refers to complementarities, and ε refers to the residual. The variance decomposition is performed through bootstrapping with 1,000 replications. In the lower part of the table, I report differences in mean, median, 10%, and 90%-quantile of Tobin's Q between two samples: a counterfactual sample where managers are reallocated to firms randomly and the original sample. The results are obtained using 10,000 simulations. The relocation exercise is performed by non-residualized (raw) variables for interpretability.

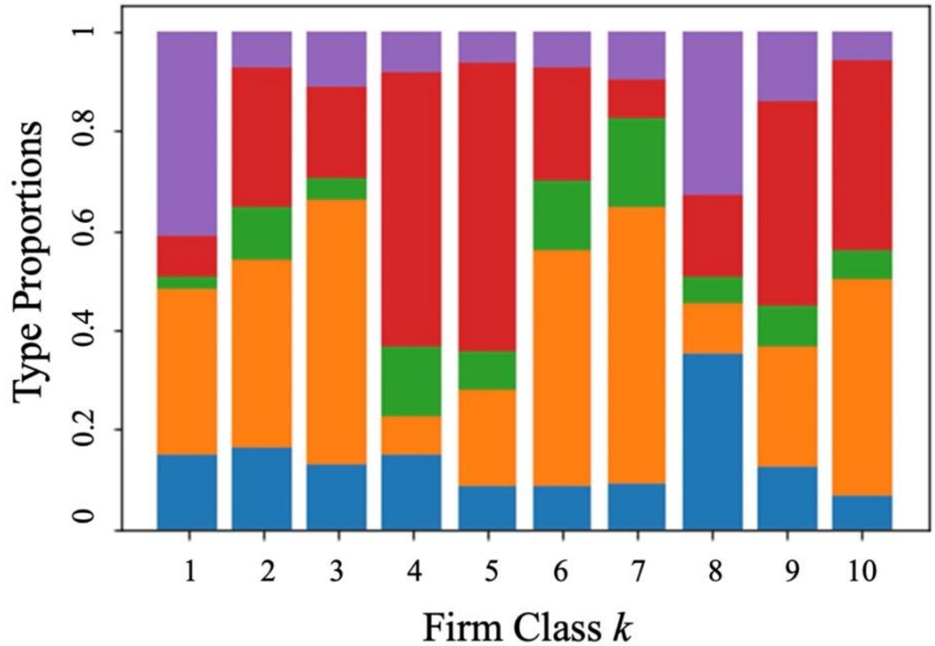
In Figures 3 and 4, I report the estimated proportions of manager types across firm classes. The results show how the composition of manager types differs noticeably across firm classes. However, the figures do not show strong sorting patterns where the most capable managers (in terms of realized firm performance) would sort into highest performing firms, as predicted by the competitive assignment models that predict that highest ability managers should work for the highest performing firms (e.g., Gabaix & Landier, 2008; Terviö, 2008). Overall, Figures 3 and 4 suggest that the between-variation in Tobin's Q and ROA among firm classes is partly due to firms employing different types of managers, as it shows that classes employ different types of managers.

Figure 3
The Proportion of Manager Types – Tobin's Q



The figure shows the proportion of latent manager types across *k* firm classes in different colors. Firm classes are ordered from one (lowest performance) to ten (highest performance). Blue refers to latent type I (lowest in terms of ability), orange refers to type II, green to type III, red to type IV, and purple to type V (highest ability).

Figure 4
The Proportion of Manager Types – ROA



The figure shows the proportion of latent manager types across *k* firm classes in different colors. Firm classes are ordered from one (lowest performance) to ten (highest performance). Blue refers to latent type I (lowest in terms of ability), orange refers to type II, green to type III, red to type IV, and purple to type V (highest ability)

To quantify the importance of complementarities, I add the interactions between manager latent type indicators and firm classes into the regression with latent manager types and firm classes (Bonhomme et al., 2019). The R^2 for the benchmark model for Tobin's Q is 50.85% for the linear regression and 59.96% when worker types and firm classes enter the regression interactively (representing the contribution of complementarities). As such, complementarities add around 9.11% incremental R^2, a much higher number compared with baseline manager estimates. For ROA, the baseline model R^2 is 34.70%. Adding interaction between worker types and firm classes increases R^2 by 10.87%. As such, complementarities relative to pure manager effects are an economically important source of variation in firm performance.

Counterfactual model. The estimated covariances between manager and firm effects are positive, suggesting the presence of some degree of sorting on the labor market. To assess the effects of sorting on the distribution of performance across firms, I generate a counterfactual scenario where I randomly shuffle managers across firms and check for changes in expected performance. I then compare the results from the counterfactual estimation with my baseline findings. The counterfactual scenario should be similar to the baseline estimate if the economy is additive in manager and firm performance (i.e., no complementarities between managers and firms). In other words, if complementarity between managers and firms does not explain variance in firm performance there should be no difference in results between those produced by the counterfactual and the baseline results. Said another way, the difference between the two estimations is the net contribution of complementarities to average firm performance.

As shown in the lower parts of Tables 2 and 3, I find a positive and statistically significant effect of complementarities on firm performance. I additionally estimate the entire performance distribution to evaluate the effects of complementarities on firm performance at the tails of the performance distribution. I find that the bottom of the distribution would be hurt the most from a random allocation, while complementarities do not contribute to performance in the upper quintiles. Indeed, where managers are not matched to firms endogenously, performance on average appears to benefit across both Tobin's Q and ROA models. I estimate bootstrapped standard errors and find that these differences are statistically significant across all quintiles of the performance distribution ($p < 0.01$). In other words, firms that are performing poorly would exhibit even lower performance if they didn't benefit from the complementarities. In contrast, firms that are highly performing would perform even better if they were matched with managers who are complements.

The finding that the lower quintiles of the performance distribution benefit from complementarities, while the higher quintiles do not benefit from complementarities, is surprising. I revisit this finding in the discussion section, where I offer a theoretical rationale for this finding.

Mediating mechanisms

I estimate the same models using operational and innovation efficiency variables to better understand how managers influence performance variation. The results are displayed in Tables 4 and 5.

Table 4
Variance Decomposition – Total Factor Productivity

Variance decomposition (× 100)				
$\frac{Var(\alpha)}{Var(y)}$	$\frac{Var(\psi)}{Var(y)}$	$\frac{2\,Cov(\alpha,\psi)}{Var(y)}$	$\frac{Var(\alpha\times\psi)}{Var(y)}$	$\frac{Var(\varepsilon)}{Var(y)}$
4.02	35.48	1.92	9.13	49.45

In the upper part of the table, α refers to manager effects, ψ refers to firm effects, covariance between α and ψ refers to sorting, α × ψ refers to complementarities, and ε refers to the residual. The specification is estimated with *K* = 10 firm classes and *L* = 5 manager types.

Table 5
Variance Decomposition – Innovation Efficiency

Variance decomposition (× 100)				
$\frac{Var(\alpha)}{Var(y)}$	$\frac{Var(\psi)}{Var(y)}$	$\frac{2\ Cov(\alpha,\psi)}{Var(y)}$	$\frac{Var(\alpha\ \times\ \psi)}{Var(y)}$	$\frac{Var(\varepsilon)}{Var(y)}$
4.48	37.91	2.13	8.46	47.02

In the upper part of the table, α refers to manager effects, ψ refers to firm effects, covariance between α and ψ refers to sorting, α × ψ refers to complementarities, and ε refers to the residual. The specification is estimated with K = 10 firm classes and L = 5 manager types.

The variance decomposition for TFP and innovation efficiency are largely in line with ROA and Tobin's Q results, with the manager factors explaining between 4 % and 5% of the variance in TFP and innovation, respectively, and firm-specific factors explaining most of the explained variance in each model. Adding interacted manager-type × firm class explains an additional 9.13% of the variance for TFP and an additional 8.46% for innovation efficiency, suggesting a sizable role of complementarities in understanding the cross-sectional variation in firm-level efficiency across firms. That is, complementarity between managers and firms explains a greater portion of innovative and operational efficiency than the effect of managers on firm efficiency. This again supports my main contention that complementarity between managers and firms represents an under-examined though important factor in explaining firm outcomes.

Influence of size and asset growth

Table 6 displays the reallocation exercise I used to assess the effects of complementarities on sub-samples sorted across firm size and asset growth divided across our dependent variables. The results indicate that smaller firms and firms with higher asset growth benefit more from complementarities. The differences in means, medians, and at the 10% and

90% tails are statistically significant at $p < 0.01$ (computed using bootstrapping, with a relatively stable pattern of results across the distribution's tails. The sub-sample tests confirm heterogeneity in how complementarities affect firm performance.

Table 6
Influence of Firm Size and Asset Growth on Complementarities

	Relocation Exercise ($\times$ 100)			
	Mean	Median	10% - Quantile	90% - Quantile
	Tobin's Q			
$\leq$ 50th Size Percentile	11.48%	9.03%	13.32%	-14.31%
> 50th Size Percentile	9.46%	6.51%	9.15%	-9.91%
Sub-sample difference significance (*p*-value)	0.01	0.01	0.01	0.01
	ROA			
$\leq$ 50th Size Percentile	10.47%	7.11%	13.1%	-11.24%
> 50th Size Percentile	8.87%	5.59%	11.07%	-9.11%
Sub-sample difference significance (*p*-value)	0.01	0.01	0.01	0.01
	Tobin's Q			
> 50th Growth Percentile	13.07%	8.87%	14.04%	-13.78%
$\leq$ 50th Growth Percentile	7.78%	6.58%	10.47%	-12.01%
Sub-sample difference significance (*p*-value)	0.01	0.01	0.01	0.05
	ROA			
> 50th Growth Percentile	10.59%	7.11%	13.42%	-11.58%
$\leq$ 50th Growth Percentile	8.76%	5.76%	11.47%	-8.69%
Sub-sample difference significance (*p*-value)	0.01	0.01	0.01	0.01

In this table, I report differences in mean, median, 10%, and 90%-quantile of Tobin's Q and ROA between two samples: a counterfactual sample where managers are reallocated to firms randomly and the original sample. The results are obtained using 10,000 simulations. I split each full sample into sub-samples using firm size and asset growth as criteria. The relocation exercise is performed by non-residualized (raw) variables for interpretability.

Effects over time

To examine how the effects of complementarities change over time, I split the sample into three sub-samples according to the US historical business cycles. The sample sizes corresponding to the business cycles are 175,180 for the 1990-1999 cycle, 134,578 for the 2000-2008 cycle, and 117,710 for the 2009-2018 cycle. Due to the reduced number of firms in each period sub-sample, I estimate the models using five manager types and eight firm classes using the same *k-means* clustering algorithm. The results of the estimates are shown in Table 7.

Table 7
Variance Decomposition Over Time

	$\frac{Var(\alpha)}{Var(y)}$	$\frac{Var(\psi)}{Var(y)}$	$\frac{2\,Cov(\alpha,\psi)}{Var(y)}$	$\frac{Var(\alpha \times \psi)}{Var(y)}$	$\frac{Var(\varepsilon)}{Var(y)}$
	1989-1999 Business Cycle				
Tobin's Q	3.49	47.21	2.01	7.58	39.71
ROA	1.95	36.48	2.19	8.61	50.77
	2000-2008 Business Cycle				
Tobin's Q	5.53	43.17	3.01	10.31	37.98
ROA	3.12	30.05	1.03	12.62	53.18
	2000-2008 Business Cycle				
Tobin's Q	6.12	40.18	2.59	11.77	39.34
ROA	4.08	26.77	0.02	13.22	44.09

In the upper part of the table, α refers to manager effects, ψ refers to firm effects, covariance between α and ψ refers to sorting, α × ψ refers to complementarities, and ε refers to the residual. The variance decomposition is performed through bootstrapping with 1,000 replications.

As it can be seen, there is a general trend in increasing manager effects over time, both for Tobin's Q and ROA. I find that this is also consistent with complementarities. For Tobin's Q, adding complementarities to the variance decomposition increases R^2 by 7.58% in the 1990-1999 cycle, 10.31% in the 2000-2008 cycle, and 11.77% in the 2009-2018 cycle. The numbers are relatively similar for ROA, with increases of 8.61%, 12.62%, and 13.22%, respectively. As such, the importance of complementarities for firm performance appears to increase over time. Importantly, these results indicate that complementarity between managers and firms has consistently contributed a sizable explanation for firm performance across time, suggesting that the sample-wide findings are not driven by a specific business cycle or a historical trend.

Robustness analysis

Modeling choices. One explanation for the discrepancy between our results and the previous literature is that our results may be an artifact of our modeling choices or the choice of the estimator. To alleviate these concerns, I run robustness checks by varying the number of firm classes used for clustering and the number of manager types. As shown in Tables 8 (Tobin's Q) and 9 (ROA), the results are not very sensitive to modeling choice. The only exception arises when I restrict the number of firm clusters to five in the ROA case resulting in an increase in the manager contribution and a decline in the firm-level contribution. In all other cases, the results do not drift away from the benchmark estimate meaningfully.

Table 8
Variance Decomposition – Tobin's Q – Robustness Check

	$\frac{Var(\alpha)}{Var(y)}$	$\frac{Var(\psi)}{Var(y)}$	$\frac{2\,Cov(\alpha,\psi)}{Var(y)}$	$\frac{Var(\alpha\times\psi)}{Var(y)}$	$\frac{Var(\varepsilon)}{Var(y)}$
	Baseline Model				
K = 10, L = 5	5.12	44.21	1.51	9.11	40.05
	Different Number of Firm Clustering Classes				
$K = 5$	2.32	40.97	1.44	9.57	45.7
$K = 15$	1.06	46.50	1.06	9.62	41.76
	Different Number of Manager Types				
$L = 3$	2.60	41.48	4.37	9.43	42.12
$L = 7$	3.14	44.18	1.29	9.75	41.64

In the upper part of the table, α refers to manager effects, ψ refers to firm effects, covariance between α and ψ refers to sorting, α × ψ refers to complementarities, and ε refers to the residual. The variance decomposition is performed through bootstrapping with 1,000 replications.

Table 9
Variance Decomposition – ROA – Robustness Check

	$\frac{Var(\alpha)}{Var(y)}$	$\frac{Var(\psi)}{Var(y)}$	$\frac{2\,Cov(\alpha,\psi)}{Var(y)}$	$\frac{Var(\alpha \times \psi)}{Var(y)}$	$\frac{Var(\varepsilon)}{Var(y)}$
	Baseline Model				
K = 10, *L* = 5	2.13	31.92	0.64	10.87	54.44
	Different Number of Firm Clustering Classes				
K = 5	9.64	24.99	1.80	8.68	54.89
K = 15	2.28	35.30	2.00	10.53	49.89
	Different Number of Manager Types				
L = 3	3.71	31.42	0.81	10.12	53.94
L = 7	1.77	32.65	1.16	11.51	52.91

In the upper part of the table, α refers to manager effects, ψ refers to firm effects, covariance between α and ψ refers to sorting, α × ψ refers to complementarities, and ε refers to the residual. *K* refers to the number of clustered firm classes and *L* refers to the number of manager types.

Estimators. The second concern is that the findings may result from the specific estimator we used (in this case, the BLM) and its ability to deal with relatively sparse network structures (when comparing the manager labor markets with the rank-and-file labor markets). Tables 10 and 11 display the results from this robustness check for Tobin's Q and ROA. I start with the standard AKM two-way fixed effects model, which is the workhorse of the literature. Consistent with the current literature, I find that AKM produces estimates somewhat in line with other findings, with a higher estimate of manager effects (36.69% for Tobin's Q and 36.30% for ROA) and lower estimates of firm-specific effects 43.27% for Tobin's Q and 34.21% for ROA).

To further explore this issue, I estimated the results using other recent estimators that aim to resolve the incidental parameter problem using different econometric approaches. These estimators include the homoscedastic fixed effects bias-correction (FE-HO) (Andrews et al., 2008), heteroskedastic fixed-effects bias-correction method (FE-HE) (Kline et al., 2020), Static BLM (Bonhomme et al., 2019), Correlated Random Effects estimator (CRE), and the Posterior

CRE (CRE-P) (Bonhomme et al., 2022).[4] Note that static BLM abstracts from endogenous mobility, while CRE relaxes the assumption that there is no variation in performance within a firm class. If the incidental parameter problem is biasing the AKM estimates of manager effects we should see a consistent decrease in the estimates of manager effects regardless of which alternative estimator I use. Because the findings from all the alternative estimators converge, the limited mobility of managers between firms most likely drove the high estimates of manager effects in the previous literature. The results for the alternative estimators are displayed in Table 10 (Tobin's Q) and Table 11 (ROA).

Table 10
Robustness check – Tobin's Q – Alternative Estimators

	$\frac{Var(\alpha)}{Var(y)}$	$\frac{Var(\psi)}{Var(y)}$
FE (AKM)	36.69	43.27
FE - HO	17.05	44.26
FE - HE	5.04	47.28
CRE	4.15	45.04
CRE - P	4.11	45.03
BLM (Static)	3.91	46.03
BLM (Dynamic; Without endogenous mobility)	4.09	45.79
BLM (Dynamic, With endogenous mobility)	5.12	44.21

Note: FE (AKM) refers to the Two-Way Fixed Effects Model (Abowd et al., 1999). FE-HO refers to the homoscedastic bias reduction of the AKM proposed by Andrews et al. (2008). FE-HE refers to the leave-one-out approach to debiasing AKM proposed by Kline et al. (2020). CRE and CRE-P are based on the Correlated Random Effects estimator (without and with Posterior estimates) proposed by Bonhomme et al. (2022). Dynamic BLM without endogenous mobility is estimated in the same way as the baseline Dynamic BLM, but with the endogeneity parameter set to zero. Static and Dynamic BLM models, along with CRE and CRE-P, are estimated with ten firm classes and five manager types, equivalent to the benchmark specification used in the baseline analyses. α refers to manager effects, and ψ refers to firm effects.

[4] For a review of various methods to solve the incidental parameter problem in labor markets, see Bonhomme et al. (2022).

Table 11
Robustness check – ROA – Alternative Estimators

	$\frac{Var(\alpha)}{Var(y)}$	$\frac{Var(\psi)}{Var(y)}$
FE (AKM)	36.30	34.21
FE - HO	2.39	36.73
FE - HE	4.29	38.84
CRE	1.87	35.60
CRE - P	1.85	35.61
BLM (Static)	1.70	34.01
BLM (Dynamic; Without endogenous mobility)	1.74	33.05
BLM (Dynamic, With endogenous mobility)	2.13	31.92

Note: FE (AKM) refers to the Two-Way Fixed Effects Model (Abowd et al., 1999). FE-HO refers to the homoscedastic bias reduction of the AKM proposed by Andrews et al. (2008). FE-HE refers to the leave-one-out approach to debiasing AKM proposed by Kline et al. (2020). CRE and CRE-P are based on the Correlated Random Effects estimator (without and with Posterior estimates) proposed by Bonhomme et al. (2022). Dynamic BLM without endogenous mobility is estimated in the same way as the baseline Dynamic BLM, but with the endogeneity parameter set to zero. Static and Dynamic BLM models, along with CRE and CRE-P, are estimated with ten firm classes and five manager types, equivalent to the benchmark specification used in the baseline analyses. α refers to manager effects, and ψ refers to firm effects.

The results displayed in Tables 10 and 11 correspond to results presented earlier. All the alternative estimators produce estimates of manager effects lower than AKM, with some cases (like FE-HE) generating results fully in line with the BLM estimator.[5] Due to the inherent limitation of all variations of the AKM estimator, estimating the contribution of complementarities would cause an extreme level of bias (as the number of estimated parameters would increase exponentially), which is why I must abstract from estimating them in this robustness check.

While these results showcase that the AKM results are likely biased due to the network sparsity (Jochmans & Weidner, 2019), the second potential explanation is that endogenous mobility may also influence the results. Aside from BLM, no other estimator directly deals with

[5] I interpret FE-HE results with some caution, as it relies on using the sub-dataset of the connected set where connectivity is relatively strong (leave-one-out set) (Kline et al., 2020). As such, FE-HE uses a smaller dataset compared to other methods.

the network sparsity issue, considering that other alternative estimators cannot nest structural models within the estimation framework. I also separately estimate BLM with and without endogenous mobility structural components. BLM without endogenous mobility produces estimates close to other alternative estimators. Switching on the structural component that governs endogenous mobility slightly increases the magnitude of manager effects, depending on the modeling choices. As such, I conclude that the incidental parameter problem has inflated the estimates of manager effects and by not considering endogenous mobility, manager effects are decreased. However, the effect of the incidental parameter problem appears to exhibit a much more prominent influence leading to the overstatement of manager effects in the prior research.

DISCUSSION: PERFORMANCE VARIATION

Despite fifty years of research on the impact of managers on firm-level outcomes, there is ongoing debate regarding whether they are the primary factor influencing performance variation (Hambrick & Quigley, 2014; Quigley & Hambrick, 2015) or whether are they interchangeable and unable to make a significant impact (Fitza, 2014; Simon, 1947). In this study, I introduce significant refinement to the empirical approach to estimating firm and manager effects while reframing the theoretical question to examine the importance of complementarities between managers and firms rather than treating them in an additive manner. After introducing complementarities as a novel source of performance variation, I find that while the managers have a statistically significant effect on firm performance, a significant share of the cross-sectional firm performance variation is explained by firm-manager complementarities rather than manager human capital alone. Additionally, I find that complementarities are more pronounced in smaller firms and firms with high asset growth. The importance of complementarities has grown over time, consistent with the changes in the manager labor market. Overall, managers play a crucial role in firm performance, but their role is primarily defined through their match with the firm.

Theoretical analysis

The theoretical rationale for sorting & matching results. The results section presents two key findings that diverge from prior research. First, the estimates of the sorting coefficient – the extent to which the best managers work for the best firms – are very low. This occurs across both dependent variables (Tobin's Q and ROA) and various robustness specifications, indicating that the results are not an artifact of modeling choices. The second surprising finding is that a random allocation of managers would harm low-performing firms – the lack of endogenous matching driven by complementarities – while high-performing firms would benefit from a random allocation. These findings are difficult to reconcile with standard competitive assignment models where the highest-performing managers work in the highest-performing firms, which assign the greatest value to their marginal product of the human capital (Gabaix & Landier, 2008; Terviö, 2008). In this section, I theorize about potential reasons why my results challenge the predictions of competitive assignment models and propose a mechanism to explain the observed matching process.

The reason why the highest-ability managers do not work in the highest-performing firms may be due to various factors. One possible explanation is that the labor market is inefficient, and different issues can cause this inefficiency. For instance, there may be silos within the market (i.e., mobility barriers), which can restrict the options of managers seeking to improve the match between their ability and the firm. This is evident in how manager and director hiring is often influenced by geographic labor pools (Bernile et al., 2018; Knyazeva et al., 2013; Yonker, 2017). Moreover, hiring is typically facilitated by common work experience and happens within similar industries (Cziraki & Jenter, 2020; Graham et al., 2020). All of these factors contribute to a fragmented and less efficient labor market, resulting in difficulties in improving manager-firm matching.

The key assumption underlying the competitive assignment models is that manager ability is unidimensional, or some “talent” that is directly transferable from one firm to the other (Gabaix & Landier, 2008; Rosen, 1982; Terviö, 2008). Simply put, certain managers possess skills that can directly affect a company's performance. Therefore, it is beneficial for these managers to work for larger firms, as they tend to benefit the most from employing such high-skill managers. However, the idea of a uni-dimensional ability contradicts the extensive research that has identified a manager's "style" as a unique and consistent element of their decision-making process (Bertrand & Schoar, 2003; Hambrick, 2007), where style captures a variety of individual characteristics including experience, temperament, and education to name a few. This means that companies are more inclined to hire managers whose decision-making style aligns with the current strategy and environment, ensuring a better fit for the chosen strategy (Custódio et al., 2013; Fee et al., 2013; Pan, 2017).

Hiring managers based on style substantially complicates the hiring process. Indeed, both the demand side (the firms) and the supply side (managers) have asymmetric information regarding the quality of the match, which itself is revealed only after the hiring occurs (Holmström, 1979; Jovanovic, 1979). As such, there are substantial risks involved with making a hiring decision. Foremost is the problem of adverse selection in which managers (or even firms) misrepresent themselves such that the selection process results in a mismatch. Firms risk sub-par performance if the match is of low quality and the additional costs of hiring a new manager, while managers risk their reputation if the match is of low quality.

The second complication of matching is a result of the implicit incentives of the directors. The members of the board of directors are evaluated on the director labor market by the performance of the firms they govern (Cowen & Marcel, 2011; Zajac & Westphal, 1996). The reputational concerns extend to directors' approach to evaluating CEOs. Indeed, an extensive literature has documented that boards are relatively efficient in dissolving poor matches (the relative performance evaluation hypothesis) (Aggarwal & Samwick, 1999; Garvey & Milbourn, 2003). According to this hypothesis, directors judge CEOs based on the actual success of the firm rather than the perceived value of their unique skills. This is because it can be challenging for directors to accurately assess the value of a CEO's unique skills, especially when considering the firm's overall performance and the CEO's abilities. Even if directors can use soft signals to evaluate the CEO's value to the firm, external stakeholders may be unable to do so as they do not have access to the same information as the board (Jenter & Kanaan, 2015). This then raises the issue of how external stakeholders would perceive the firing of an outperforming CEO, based on the board's assessment that someone else may be a better match at the given moment. That is, boards are unlikely to fire a well-performing CEO solely for reasons of potential opportunity costs created by a less-than-optimal match.

The theorized model, thus, has two key ingredients. First, there is uncertainty when it comes to the outcomes of firm-manager matches. The match quality can be assessed, but the outcome is only observable after some time post-hire. This is consistent with the models incorporating learning about CEO ability (Hermalin & Weisbach, 1998; Pan et al., 2015). In simple terms, the board only learns about the manager's ability over time as the idiosyncrasies are slowly revealed. The second ingredient is the directors' career concerns. The rational board follows a relative performance evaluation algorithm under which a manager is fired after the performance falls below an endogenous threshold when the board can hire a higher-ability manager, net of replacement costs. However, the key issue is that the board cannot credibly signal that the focal manager is no longer the best fit based on soft signals alone. This distinction is crucial. Because of this, the board follows relative performance evaluation logic, where the likelihood that the board will fire a manager increases as the firm's performance falls below its (industry) peers (Custódio et al., 2013, 2019; Hatch & Dyer, 2004). Thus, weak matches may be sustained—managers less fitted to the firm than others remain in office—until performance fails to meet board expectations.

The second part of the theoretical model concerns the issue of matching when the performance is low or high. The board can try to predict a manager's performance by considering the manager's permanent skill component along with their unique match component. However, the board can only learn about this unique match component after hiring the manager. The primary issue concerns the *variance* of the idiosyncratic component. In other words, boards have difficulty assessing the match component of a manager's performance. This substantially complicates hiring new managers, as the value of the match cannot be determined before the manager is hired.

Despite the impediments to assessing manager-firm complementarity, some firms may have difficulty finding an adequate match. For example, firms with low levels of technological complexity in stable, low-discretion industries may have an easier time finding a good match. In other words, the performance of these firms would not be adversely impacted by a poor match. However, firms with complex technologies and tacit knowledge – typically at the top of the performance spectrum– may require a more specialized skillset. These firms often rely on unique resources and asset combinations that necessitate specialized knowledge to use effectively, making it harder to find a good match (Teece, 2007; Zollo & Winter, 2002). As such, these firms may require specific managers with unique skills to maximize their performance. In simplified terms, when it comes to more complex firms that require specialized skills in their managers, predicting how well a manager will fit in can be more difficult. This leads to a higher variance in individual matches compared to less complex firms that don't require such specific skills. In other words, the overall ability of a manager to perform well is not the sole determining factor in their success within these more complex firms.

The lack of perfect sorting is, indeed, entirely rationalized by the multi-dimensional skill bundles of managers who match with firms with heterogenous task requirements (or job demands) (Lindenlaub & Postel-Vinay, 2023; Lise & Postel-Vinay, 2020). In this framework, the manager would not match with the firm that is of a similar "*ability*" level (high or low performance). Rather, the manager would match with the firm that can best use the skill bundle endowed in the manager.

As such, my proposed framework crystalizes down to several dimensions. First, the boards make decisions based on the relative performance evaluation. As such, boards are less likely to fire an outperforming manager relative to the firm's peers. This creates relative stability in terms of firm-manager matches at the top of the performance distribution, as it is difficult to justify replacing a CEO when a firm is performing highly. This is mirrored by findings that the performance-induced turnover is relatively love at the top of the firm performance distribution (Jenter & Lewellen, 2021). Indeed, even under a poor match, the board is unlikely to fire the manager, as firing a manager of an outperforming firm could have negative ramifications for directors' careers. In this sense, the managers in high-performing firms are "shielded" by the high performance of the firm itself. Second, the skill bundles required for managers working in low-performing firms are simpler and, thus, easier to find in the manager labor market. This implies that the expected variance of the match-specific component for low-performing firms is lower than for high-performing firms. This means that boards in low-performing firms may have an easier time assessing how well a replacement manager would perform prior to the hiring. Under this rationale, with both more frequent firing and a better ability to assess match quality, low-performing firms would do better in terms of matching with adequate managers.

In contrast, highly successful firms that tend to be more tacit and internally complex may struggle to evaluate prospective managers before hiring them. However, even if they end up hiring a poor match, the firm's overall strong performance often prevents the manager from being replaced. This framework predicts the range of net effects of complementarities, as described in this essay's counterfactual model. On the other hand, less complex, low-performing firms are better equipped to identify suitable matches beforehand. Furthermore, boards can easily justify replacing CEOs in these firms by using peer performance as a benchmark. Higher-performing companies, which are more implicit and intricate, assess the match's unique qualities more carefully than low-performing firms. After the match quality becomes known, it is more challenging to replace CEOs in these firms, as they can argue that the company is outperforming its peers.

Taken together, in a multi-dimensional sorting model, there would not be a strong sorting purely on ability alone, and the firms in the lower parts of the performance distribution would benefit from complementarities, while higher-performing firms would have a net loss from complementarities, consistent with my findings.

Theoretical contribution

The primary theoretical contribution of this essay is to introduce the notion of complementarities – or fit – into the UE literature, thus advancing the understanding of how managers can influence firm-level outcomes. Previous research on UE has analyzed the demographics and personality traits of CEOs and top management teams but without considering the importance of fit between managers and the company. By considering the role of fit, new theories can be developed to explain how managers with certain traits and demographics can impact firm-level outcomes through the matching mechanism.

The secondary theoretical contribution is a theoretical model that rationalizes the unexpected results in terms of firms that gain and lose from complementarities. My model combines insights from corporate governance and the literature on human capital to demonstrate why low-performing firms can benefit more from complementarities. It emphasizes the role of corporate governance in the two-sided search process and highlights the significance of studying how boards make hiring decisions instead of only firing decisions, which was the focus of prior governance research (Jenter & Lewellen, 2021; Parrino, 1997).

On a broader level, the findings in this essay show that the influence of managers on the performance of firms is more complex than the one painted by UE or the Romance of Leadership (RoL) views. The findings in this essay show that the causal attribution of performance – both good and bad – to corporate leaders fundamentally ignores what seems to be the primary mechanism through which managers influence performance – complementarities. As complementarities seem more important to explaining variations in firm performance, future theorizing in Upper Echelons should much more closely consider the intricacies of complementarities and how they drive performance. Similarly, the RoL approach to managers ignores the fact that the reason some managers perform well and some do not is contextual. The context in which they operate – and how well it matches their skills – determines the performance outcomes. As such, understanding the role of managers in determining the fortunes of corporations is arguably much more complex than the one painted by current key theoretical paradigms in the field of strategy, as it requires a careful examination not only of manager traits but also how they fit the context in which they operate.

Methodological contribution

This dissertation directly contributes to a stream of research that has lasted over five decades that attempts to identify critical sources of firm performance heterogeneity (Lieberson & O'Connor, 1972; Mackey, 2008; Quigley & Hambrick, 2015). Over the past 50 years, the methods used in econometrics have changed, but recent advancements have highlighted problems with standard two-way fixed effects models that have dominated prior variance decomposition research. These issues include estimation bias caused by the incidental parameter problem and endogenous mobility in sparse network structures, particularly in the manager labor markets that have historically had low mobility rates (Abowd et al., 2019; Andrews et al., 2008; Bonhomme et al., 2022). Indeed, the results shown here indicate that prior results indicating an overwhelming dominance of manager human capital as an explaining factor of cross-sectional variation in firm performance was overstated due to the incidental parameter problem.

My dissertation contributes a new method of identifying the effects of individual firms and managers. Previous studies that used variance decomposition had limitations due to their associative nature (as highlighted by Hambrick & Quigley (2014)). I use a unique approach that produces precise estimates of manager and firm effects, even when the mobility of managers between firms is low. The low mobility of managers was previously shown to have a detrimental effect on the estimation of manager and firm effects in a variety of contexts. I provide additional support to the results presented in this essay by comparing the results between the baseline results and the results of several other novel estimators. The consistency of findings between these models suggests that the low mobility of managers has inflated prior estimates of the manager effects. The econometric framework introduced in this study yields different results compared to previous cross-sectional studies. I also provide evidence that my estimates are reliable and not an artifact of modeling choices. Based on my approach, recent estimates of the CEO effect in the range of 30% to 45% are likely due to the limited mobility bias caused by incidental parameter problem, consistent with recent econometric theorizing on estimation in sparse network structures (Jochmans & Weidner, 2019).

The second methodological contribution concerns the application of an econometric framework that can directly assess the significance of complementarities in variance decomposition models. Regardless of the lack of theorizing, the previous approaches used in the literature cannot, under any conditions, consider the importance of complementarities due to the inherent statistical and computational limitation imposed by prior models of estimation. Specifically, the number of parameters that would need to be estimated to identify complementarity would exceed the computational limits of current statistical and computer processing abilities. As such, the econometric framework laid out in this essay allows for a more nuanced econometric estimation of variance decomposition models in the manager context, as it can also consider the role of complementarities.

The third methodological contribution of the dissertation is the novel usage of structural models in strategy research. Structural models enable counterfactual simulations, which help to reveal intricate relationships and mechanisms that drive these relationships by comparing baseline estimations with simulated scenarios. By using counterfactuals, this dissertation provides a detailed understanding of the varying importance of complementarities across different levels of firm performance and their overall impact on the distribution of performance, rather than just their contribution to explaining the between-firms distribution of performance (the model implied R^2).

Specifically, I break the relationship between managers and their employers by randomly assigning managers to firms where it is less likely that there will be a match between the manager's human capital and the firm. The degree of complementary resulting from situations in which managers and firms actively seek to find the best match can then be compared to this counterfactual condition where match is unlikely to determine the existence and importance of complementary in firm performance variance.

Practical implications

The findings of this dissertation have important implications for boards making decisions about hiring and firing CEOs and other members of the TMT. Unlike simple agency theory models where boards regularly replace under-performing CEOs with someone with greater human capital or higher motivation, this research highlights the added complexity of considering complementarities between managers and the firm. Boards must assess not only a potential replacement's general human capital and their willingness to commit effort on behalf of the firm but also how their human capital complements those of the existing team and how this fit might evolve in the future. Therefore, boards should prioritize finding managers who fit well with the firm over hiring the 'best athlete" based on the individual's prior performance.

In this dissertation, I do not directly examine the rent-sharing of complementarities between firms and managers. However, it is important to consider this factor when designing contracts to ensure both sides benefit from the value created in a two-sided match. This helps prevent one side from capturing all the value created.

Future directions and limitations

This essay is the first to estimate the importance of firm-manager complementarities, but it doesn't directly reveal the positive or negative fit mechanisms. Future studies in UE and Strategic Leadership literature should focus on modeling the determinants of fit and misfit and how the fit between managers and firms evolves. With the recent availability of CEO personality measures and measures related to tacit elements of organizations, such as corporate culture, future research could utilize textual analysis and machine learning to model fit and the antecedents and consequences of manager-firm matching (Harrison et al., 2019, 2020; Hill et al., 2019). In parallel, researchers in agency theory could study optimal contracting in the presence of fit and the structuring of incentive plans to act as sorting devices to attract the best-fitting managers (Lazear, 2000) or how the incentive structure should evolve over the manager tenure (Finkelstein et al., 2009; Miller, 1991). The concept of fit and match quality raises concerns about how boards can determine if potential successors for TMT members are a good fit and whether there are any biases involved in hiring based on perceived fit (Park & Westphal, 2013; Westphal & Zajac, 1995).

While this essay focuses on complementarities in performance, the empirical approach utilized here could be used for other contexts in which endogenous matching influences outcomes. Future research could consider rent-sharing due to the complementarities (Coles & Li, 2020; Graham et al., 2012), optimal contracting under search-and-bargaining processes and endogenous matching (Ackerberg & Botticini, 2002), complementarities between VC funds and partners (Ewens & Rhodes-Kropf, 2015) or inventors and firms (Bhaskarabhatla et al., 2021).

RESULTS: COMPENSATION VARIATION

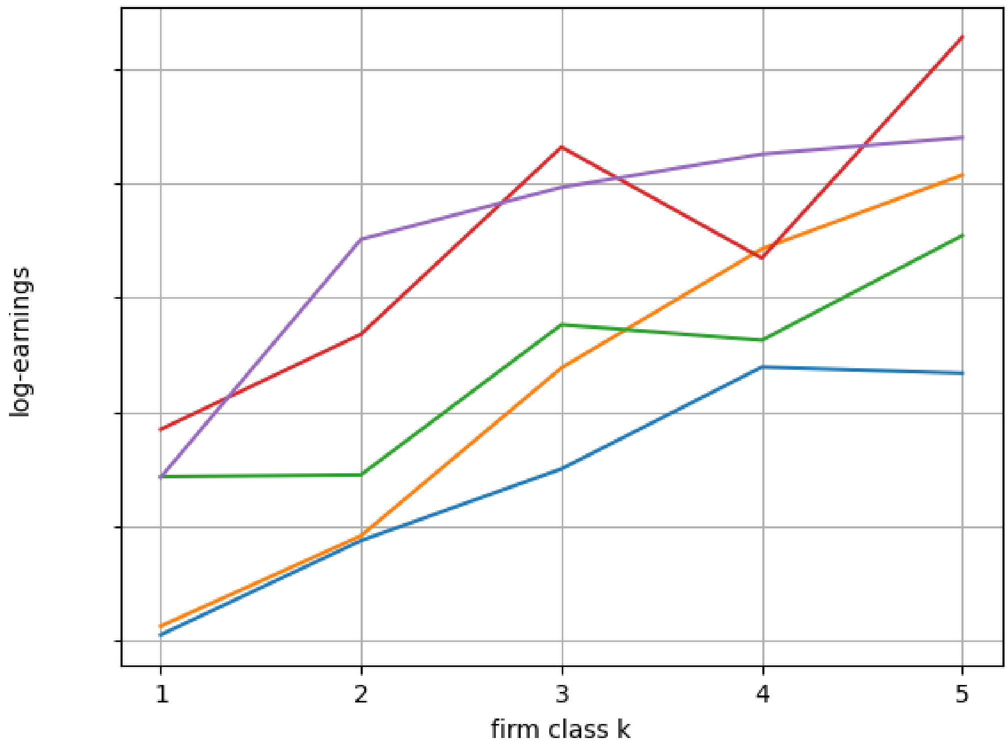
As explained in the theory development section, there are several models of compensation determination explored in labor economics based on the influence of labor markets on compensation determination that has been absent from agency theory. The first model involves endogenous mobility. Under endogenous mobility, the current compensation affects a manager's decision to move to another firm, as the manager is more likely to accept a new job offer if the current match is poor (Bagger & Lentz, 2019a). The second model is state dependence. Under state dependence, the compensation of the prior employer directly influences the compensation in the current job, controlling for manager ability and firm pay practices (Bonhomme et al., 2019).

Considering the theorized role of endogenous mobility and state dependence, I present four model specifications to better understand the role of endogenous mobility and state dependence in compensation. Since the Execucomp sample contains around 20% of the number of unique firms compared to the full Compustat sample, I set the number of firm clusters to five and the number of latent manager types to five, as this improves the numerical stability of the estimator as the Silhouette approach indicates better fit of five clusters compared to ten. The Silhouette approach is a statistical technique that seeks to find an "optimal" number of clusters using the k-means machine learning algorithm (Hartigan, 1975). The central aspect of the BLM empirical approach is to "compress" a large number of different firms into clusters for estimation. Since the Execucomp sample has around 1,500 firms per year, compared to the 7,500 used in CRI in the first essay, it is expected that a smaller number of clusters would fit the data better.

Figures 5 and 6 shows the distribution of latent manager types across firm classes, suggesting that the distribution of manager ability across firms is one the drivers of cross-sectional heterogeneity in compensation.

Figure 5

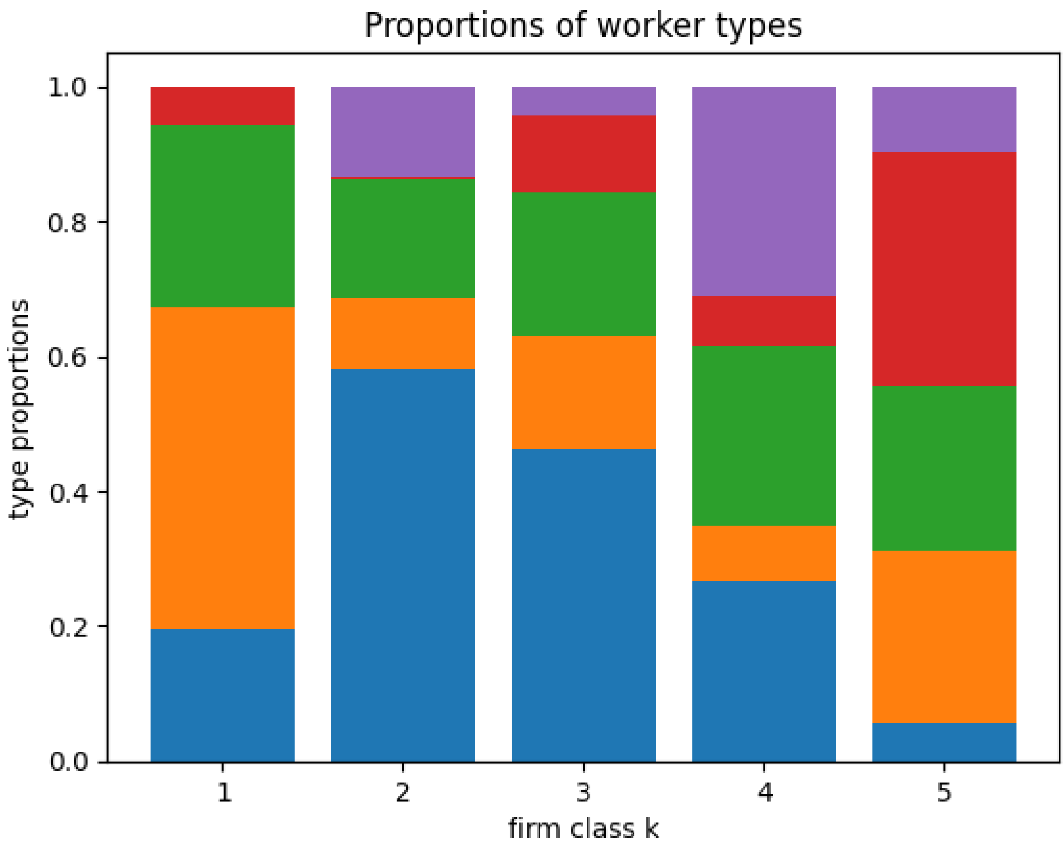
Estimates of means of log-earnings, by worker type and firm class



X-axis shows $K = 5$ firm classes by mean log-earnings. Y-axis displays estimates of mean log-earnings for the $L = 5$ manager latent types. Firm classes are ordered from one (lowest performance) to ten (highest performance). The blue line refers to latent type I (lowest in terms of ability), orange refers to type II, green to type III, red to type IV, and purple to type V (highest ability).

Figure 6

Estimates of the proportions of manager types across firm classes



The figure shows the proportion of latent manager types across *k* firm classes in different colors. Firm classes are ordered from one (lowest performance) to ten (highest performance). Blue refers to latent type I (lowest in terms of ability), orange refers to type II, green to type III, red to type IV, and purple to type V (highest ability).

Tables 12 and 13 present the baseline model, abstracting from state dependence. Table 12 presents results where the structural component of the model assumes that mobility is exogenous, meaning that the decision of a manager to leave a firm and join another is not driven by performance in the current firm. Conversely, Table 13 presents the result where the structural component directly models the probability of turnover based on the compensation realization where mobility is assumed to be endogenous. Thus, mobility in this model is assumed to be endogenous or determined by the current firm's performance.

Table 12
Variance Decomposition – Total Compensation
Exogenous Mobility & No State Dependance

Variance decomposition ($\times$ 100)				
$\frac{Var(\alpha)}{Var(y)}$	$\frac{Var(\psi)}{Var(y)}$	$\frac{2\,Cov(\alpha,\psi)}{Var(y)}$	$\frac{Var(\alpha \times \psi)}{Var(y)}$	$\frac{Var(\varepsilon)}{Var(y)}$
28.63	12.42	17.22	7.53	34.2

In the upper part of the table, α refers to manager effects, ψ refers to firm effects, covariance between α and ψ refers to sorting, α × ψ refers to complementarities, and ε refers to the residual.

Table 13
Variance Decomposition – Total Compensation
Endogenous Mobility & No State Dependance

Variance decomposition ($\times$ 100)				
$\frac{Var(\alpha)}{Var(y)}$	$\frac{Var(\psi)}{Var(y)}$	$\frac{2\,Cov(\alpha,\psi)}{Var(y)}$	$\frac{Var(\alpha \times \psi)}{Var(y)}$	$\frac{Var(\varepsilon)}{Var(y)}$
25.65	13.71	19.06	5.27	36.31

In the upper part of the table, α refers to manager effects, ψ refers to firm effects, covariance between α and ψ refers to sorting, α × ψ refers to complementarities, and ε refers to the residual.

The model without state dependence and assuming exogenous mobility shows that manager effects explain 28.63% of the cross-sectional firm variation in compensation, while firm-specific factors explain around 12%. Consistent with the estimates of firm performance variation, the covariance between firm and manager effects is positive but relatively small. This suggests that while there is a degree of positive assortative matching in the labor market, its magnitude is less than expected under the competitive assignment models. In competitive assignment models, we would expect that the highest-performing managers would work for highest performing firms (Gabaix & Landier, 2008; Terviö, 2008). I next add interacted manager-type × firm-class effects to understand the effects of complementarities. In this model, complementarities between managers and firms explain around 7.53% additional variance in compensation, broadly mirroring the findings in the first part of the dissertation.

The model with endogenous mobility is presented in Table 13. Compared with the results with assumed exogenous mobility, the estimates are similar, with a slightly lower estimate of manager-specific effects (25.65%) and slightly high estimates of firm-specific effects (13.71%). This suggests that endogenous mobility does not appear to drive differences in compensations between firms and managers. Adding the interacted manager-type × firm-class effects explains an incremental 5.27% of the variation, indicating a somewhat lower effect of complementarities compared to the exogenous mobility model. This indicates that the managers appear to consider the current performance when deciding to move as they likely assess whether the current firm may be a bad match.

Tables 14 and 15 present the results of the models which assume state dependence in compensation design. That is, a manager's compensation from their new employer upon being hired is assumed to be influenced by the compensation they received at their prior employer. Table 14 assumes full exogeneity in executive turnover, while Table 15 shows the fully specified structural model results with endogenous mobility and state-dependence structural components. In addition, the lower part of Table 15 presents the results of the counterfactual simulation in which there should be no complementarity between the manager and the firm.

Table 14
Variance Decomposition – Total Compensation
Exogenous Mobility & State Dependance

Variance decomposition (× 100)				
$\frac{Var(\alpha)}{Var(y)}$	$\frac{Var(\psi)}{Var(y)}$	$\frac{2\,Cov(\alpha,\psi)}{Var(y)}$	$\frac{Var(\alpha\,\times\,\psi)}{Var(y)}$	$\frac{Var(\varepsilon)}{Var(y)}$
25.65	13.71	7.96	11.62	41.06

In the upper part of the table, α refers to manager effects, ψ refers to firm effects, covariance between α and ψ refers to sorting, α × ψ refers to complementarities, and ε refers to the residual.

Table 15
Variance Decomposition and Reallocation Exercise – Total Compensation
Fully Specified Structural Model (Endogenous Mobility & State Dependence)

Variance decomposition (× 100)				
$\frac{Var(\alpha)}{Var(y)}$	$\frac{Var(\psi)}{Var(y)}$	$\frac{2\,Cov(\alpha,\psi)}{Var(y)}$	$\frac{Var(\alpha\,\times\,\psi)}{Var(y)}$	$\frac{Var(\varepsilon)}{Var(y)}$
18.84	21.57	15.02	7.12	37.45

Relocation Exercise (× 100)			
Mean	Median	10% - Quantile	90% - Quantile
0.52	0.45	6.52	-2.92

In the upper part of the table, α refers to manager effects, ψ refers to firm effects, covariance between α and ψ refers to sorting, α × ψ refers to complementarities, and ε refers to the residual. In the lower part of the table, I report differences in mean, median, 10%, and 90%-quantile of log-compensation between two samples: a counterfactual sample where managers are reallocated to firms randomly and the original sample. The results are obtained using 10,000 simulations. The relocation exercise is performed by non-residualized (raw) variables for interpretability.

Table 14 presents the model with assumed exogenous mobility and state dependence. Manager effects explain around 13.67% of cross-sectional variation in compensation, while firm effects explain around 32.07%. Adding complementarities explains another 11.62% of initial compensation. Consistent with other estimated models, the effects of sorting are positive but relatively small and smaller than in the models where prior compensation is not factored in, i.e., without state dependence.

Finally, Table 15 presents the results from the fully specified structural model with both endogenous mobility and state dependence influencing the initial compensation contract. As shown in the table, manager effects explain around 18.84% of cross-sectional variation in compensation, firm-specific effects explain an additional 21.57%, while the contribution of sorting is 15.02%. Adding interacted manager-type × firm-class explains another 7.12%. Thus, on average, 37.45% of a CEO's initial compensation contract remains unexplained by these factors.

These findings indicate that state dependence substantially impacts the distribution of compensation and that the absence of the consideration of state dependence has biased previous results, likely even more than the issue of endogenous mobility. This finding shows that previous findings in this literature resulted from ignoring state dependence, which was subsumed into the manager effect. This finding gives strong credence to the labor market as a supplier of implicit incentives. In other words, managers who work in firms with high levels of compensation subsequently receive even higher compensation, controlling for other factors in the model.

The lower part of Table 15 shows the results of the counterfactual exercise. In the counterfactual exercise, I simulate a reshuffling of latent manager types across firms to assess the role of sorting in the distribution of earnings. The tables show the result of the difference in average earnings between two samples: a counterfactual simulation and the baseline estimated sample. In an economy with no manager–firm complementarities, we expect the counterfactual and the baseline to show the identical distribution of earnings. However, the results show that complementarities have a small but statistically significant average effect on earnings (0.52%). The median estimate (0.45%) is similarly in line. In other words, the presence of complementarities contributes to increasing average compensation paid to managers at their new firm.

However, constructing the entire performance distribution reveals a heterogenous impact on the tails of the distribution. The findings suggest that the lower quantile of the distribution would be hurt by a random allocation (as complementarities have a positive mean effect on the earnings in this quantile (6.52%)). At the same time, compensation within the highest quantile would benefit as complementarities have a negative effect on earnings in this quantile (-2.92%). This suggests that complementarities have a more substantial effect on compensation in the lower deciles of the distribution.

Robustness check

To assess the robustness of results by varying the number of firm clusters and latent manager types. The results are displayed in Table 16.

Table 16
Variance Decomposition– Total Compensation
Robustness Check

	$\frac{Var(\alpha)}{Var(y)}$	$\frac{Var(\psi)}{Var(y)}$	$\frac{2\ Cov(\alpha,\psi)}{Var(y)}$	$\frac{Var(\alpha \times \psi)}{Var(y)}$	$\frac{Var(\varepsilon)}{Var(y)}$
	Baseline Model				
K = 5, *L* = 5	18.84	21.57	15.02	7.12	37.45
	Different Number of Firm Clustering Classes				
K = 10, L = 5	16.04	27.57	11.94	3.96	45.7
	Different Number of Manager Types				
L = 3, K = 5	16.21	26.57	11.21	3.59	42.42
L = 7, K = 5	16.67	24.88	13.50	9.32	35.63

K refers to the number of firm classes, while *L* refers to the number of latent manager types. α refers to manager effects, ψ refers to firm effects, covariance between α and ψ refers to sorting, α × ψ refers to complementarities, and ε refers to the residual. The variance decomposition is performed through bootstrapping with 1,000 replications. All models are estimated with endogenous mobility and state dependence structural components. The relocation exercise is performed by non-residualized (raw) variables for interpretability.

As shown, and as the Silhouette method indicates, five clusters best fit the cross-sectional distribution of firms sorted by performance. The robustness check indicates that the results are not very sensitive to variations in the key model parameters. All models produce similar results for the manager and firm effects as the baseline model.

For comparison, the most cited paper in the manager compensation literature (Graham et al., 2012) that used AKM with the same Execucomp dataset, although with a shorter panel, found that manager effects explain around 54%, while firm fixed effects explain around 5%. The more recent paper by Coles & Li (2022) using the same AKM approach and the same period as used in the analysis presented here found that manager fixed effects explain around 35% of the variation in compensation, while firm fixed effects explain around 7%. Considering the findings presented here, the inflated estimates of manager effects reported in prior studies can be attributed to using AKM in a limited mobility setting that causes high network sparseness and the lack of consideration of state dependence (Jochmans & Weidner, 2019). As such, the AKM estimation bias and the resulting overinflation of manager contribution to the cross-sectional variation in both firm performance and compensation widely reported in the literature appears to be a direct result of the incidental parameter problem, which has been ignored in prior research as well as the failure to consider state dependence (which AKM-type of models cannot directly accommodate). Thus, by controlling for endogenous mobility and state dependence, I find that manager effects are much lower and firm effects are much higher than found in prior research. Further, I am also able to identify the potential role of complementarities in compensation that is not accounted for in prior research.

DISCUSSION: COMPENSATION VARIATION

The pattern of results shown here presents a picture where firm-specific heterogeneity – largely ignored by the prior literature – appears to be an important feature of the data and an economically important determinant of cross-sectional variation in compensation. Indeed, firm-specific heterogeneity is economically more important than manager-specific heterogeneity across all tested specifications and modeling approaches. This finding largely echoes the broader literature in labor economics that has persistently found differences in pay practices across firms – even when hiring employees of similar skill levels. The exact mechanism through which this process occurs is unexplored in this dissertation, but it remains a potentially important avenue for future research.

The second finding concerns the role of managers. Consistent with prior literature, the results show that manager-specific heterogeneity is an important predictor of cross-sectional heterogeneity in compensation. However, the findings of this study indicate a lower significance of manager effects compared to prior literature. Consistent with the findings on the role of managers in firm performance, prior literature has largely overemphasized the role of manager effects in the cross-sectional variation in compensation due to the inability to control for the incidental parameter problem.

The third finding concerns the role of complementarities, as it appears that complementarities shape the distribution of compensation across firms in an economically meaningful manner, consistent with the findings that complementarity also explains a portion of firm performance identified in the first study of this dissertation. Indeed, the influence of complementarities is displayed both in terms of the model R^2 explained and also in terms of the net effects on the compensation distribution among firms. The elevated role of complementarities in the lower quintile of performance distribution may be caused by more attentive boards actively seeking better matches to engineer a mean reversal in firm performance. This would explain why higher-performing firms – which should have a much deeper labor pool to draw replacements from - may not find complementarities of the essence, as high-performing CEOs are less likely to be replaced regardless of the degradation in match quality. As the results in terms of compensation broadly reflect the results in the distribution of performance, the hypothesized model I presented in essay one can be used to rationalize the findings regarding the compensation distribution.

The fourth finding is the surprisingly low level of sorting identified in the data. This finding reiterates the low estimates of sorting when it comes to manager-firm matching on performance outcomes. This finding goes against the logic that the assignment of managers to firms should follow positive assortative matching (PAM), where the best managers work for the best firms. Potential explanations for this finding include the role of peer effects and the non-monetary component of the compensation. Peer effects suggest that some managers may enjoy working with similar managers in terms of ability (Bhaskarabhatla et al., 2021). Under this explanation, the matching is influenced by the complementarities between firms and managers and how well managers match with other managers in the firm. The explanation around matching centered on the non-monetary component of compensation, such as amenities, suggest that managers evaluate multiple aspects of the job when deciding on whether to move from one firm to another, rather than solely focusing on the compensation aspect of the contract (Adda & Dustmann, 2023; Hall & Mueller, 2018).

The fifth finding indicates a substantial role of state dependence in terms of how it affects the estimation of variance components. This finding indicates that manager contracts are influenced by prior contracts of the same managers, which is difficult to reconcile with current agency theoretical models of optimal contracting, which suggest that manager compensation should be tied primarily to ability. However, the findings in this essay suggest that controlling for manager ability, compensation in a prior firm directly influences compensation in the poaching firm. This may be because working in higher productivity firms, which tend to pay higher compensation, allows the manager to extract a higher share of the surplus from the poaching firm (Bonhomme et al., 2019).

Taking all the pieces of evidence together, the low levels of sorting along with moderate effects of complementarities are in striking contradiction with competitive assignment models (Gabaix & Landier, 2008; Terviö, 2008) and indicate that managers may match with firms based on reasons not entirely related to performance (or the subsequent passthrough rents). There is an opportunity for future research to understand the causes of friction in the executive labor market and how this affects how managers match with firms. This matching process may also shed light on the lack of mobility in the manager labor market and the changes in executive compensation that have been happening over the last 40 years.

CONCLUSION

My dissertation introduces a new theoretical model that builds upon the UE theory and extends both UE and agency theories. This model recognizes the significance of complementarities, which refers to the compatibility between managers and firms. By examining how complementarities impact the variation in firm performance and contracting design, the dissertation reveals that they play a crucial role in driving persistent differences in firm-level performance. Moreover, the dissertation highlights how complementarities shape the executive labor market's manager-firm contracting.

The methodological approach used here has also illuminated several issues with the current approaches to understanding how unobserved manager and firm-level heterogeneity influences various outcomes. The approach taken here to alleviate the incidental parameter problem shows that the estimates of the effects of managers – net of complementarities – have been overstated to varying degrees in the prior literature. Using a variety of triangulation approaches, this dissertation's results indicate that managers' overall effects on firm performance consistently reported in the literature mainly resulted from the limited mobility bias in the executive labor market, as managers rarely move between firms. Similarly, the effect of manager-specific heterogeneity on cross-sectional differences in compensation has also been overstated, although somewhat less. The key discrepancy between the findings presented in essay two and those in previous research is primarily driven by the lack of consideration of state dependence in prior literature. That is, prior research has been unable to control for manager compensation history, which this research has done. By controlling for past compensation history (i.e., state dependence), I find a lower manager effect on compensation than found in prior research.

Most importantly, the results displayed here show the need to more closely study the role of matching between managers and firms in terms of the antecedents to matching and consequences of (mis)matches. The importance of complementarities is reflected in their contribution to the variation of firm performance and in how they shape contracting design. While the approach taken here seeks to identify their direct effect and fine-grained heterogeneity, future research could also elucidate how it influences rent-sharing and performance pass-through to contract design while also considering other elements of contract design (such as delta and vega). Additionally, the puzzling lack of expected levels of sorting presents an interesting research opportunity, as both the UE and agency theories have largely ignored the role of team formation and team production models when studying the antecedents and consequences of top management team matching.

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APPENDIX

The connectedness sample is constructed as follows: I start with a random manager and include all the firms in which that manager has ever worked. After that, I add all other managers who have worked in any of the firms where the random manager worked. Then, I continue adding all other firms for which these managers ever worked for and additional managers who have worked in those firms until no other manager can be added to the group. This procedure is repeated for other managers until the sample is entirely exhausted. At the final point, all managers belong to one group, and within each group, every manager is somehow connected to all other managers and firms. In contrast, there is no connectedness between the groups. The technical details of the procedure are explained in Abowd et al. (2002). The largest of these groups is used for the model estimation (Bonhomme et al., 2019).