CEOs, Complementarities, and Firm Performance

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Abstract

We demonstrate that CEO-firm complementarities—not just CEO ability—are a critical driver of firm performance. Using a comprehensive panel of over 17,000 CEOs from the entire Compustat universe (1990–2018) and leveraging the Bonhomme, Lamadon, and Manresa (BLM) estimator to disentangle CEO, firm, and match-specific effects, we find that complementarities account for approximately 5% to 7% of the performance variance, compared to 2% to 4% for CEO ability. Counterfactual simulations suggest that enhancing CEO-firm alignment could increase aggregate market valuations by as much as 35.9% (approximately $20.7 trillion). These findings challenge the traditional emphasis on CEO ability as the primary source of influence, revealing substantial economic costs from misallocations and highlighting the pivotal role of contextual fit. By demonstrating that the effectiveness of a CEO's traits depends on the firm's unique characteristics, our study bridges the gap between Upper Echelons Theory and competitive assignment models. In doing so, it underscores that strategic, context-driven matching of CEOs to firms is integral to unlocking organizational value.

Key-words: CEOs, Variance decomposition, Complementarities, Structural estimation

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1. Introduction

CEOs are central to the narrative of how firms create, sustain, and lose value. As the ultimate decision-makers, they shape strategy, mobilize resources, and chart the firm's path through uncertainty, influencing outcomes that ripple across employees, investors, and entire markets. Their capacity to spur innovation, reconfigure organizational structures, and respond to competitive pressures makes them both powerful agents of economic change and prime targets for scholarly scrutiny. Reflecting this importance, Upper Echelons Theory (UET) and related frameworks have long posited that CEOs significantly impact firm performance (Hambrick and Mason 1984, Holmström 1979, Jensen and Meckling 1976). At the same time, competitive assignment models highlight CEO ability as a key factor in equilibrium sorting and compensation (Gabaix and Landier 2008, Terviö 2008). Together, these perspectives underscore why understanding CEO influence is crucial for theoretical advancements in strategic management and financial economics and guiding boards, regulators, and policymakers in aligning executive talent with organizational and social objectives.

Despite decades of research, the literature still offers two starkly different accounts of how CEOs shape firm performance—each overlooking a critical dimension of the problem. On the one hand, UET posits that CEOs leave distinctive "imprints" on organizations, making their personal characteristics, experiences, and leadership styles pivotal to explaining performance outcomes (Hambrick and Mason 1984, Finkelstein et al. 2009). On the other hand, competitive assignment models emphasize that firm performance stems mainly from matching CEOs with the right firms, treating executives as interchangeable talents whose incremental value is determined by equilibrium sorting processes (Gabaix and Landier 2008, Terviö 2008). Although both frameworks have deepened our understanding of CEO influence, they share a common, untested assumption: that CEO effects are additive. Neither approach directly acknowledges that a CEO's effectiveness may hinge on the particular organizational setting—i.e., that complementarities between CEO traits and firm-specific attributes could be the key to understanding why some leaders excel in certain environments but not others.

The possibility that CEO-firm complementarities matter profoundly for performance is suggested by work in labor economics and human resource management, where researchers emphasize that productivity often emerges from synergy rather than mere summation of inputs (Becker 1973, Jovanovic 1979, Kristof-Brown and Guay 2011, Shimer and Smith 2000). Yet, neither UET nor competitive assignment theory has fully incorporated these ideas. Instead, they remain at odds: the former envisions CEOs imprinting their styles on firms, while the latter contends that a smooth distribution of ability and optimal matching explains most CEO-related performance differences. If CEO-firm complementarities exist, they provide a way to reconcile these views. On the one hand, such complementarities would validate the UET perspective, showing that CEO "style" matters—but only in certain firm environments. On the other hand, they refine competitive assignment arguments by demonstrating that even if top CEOs sort into large firms, it is not just raw ability that matters—contextual fit magnifies or diminishes that ability's effect on performance.

Empirically examining CEO-firm complementarities, however, poses significant challenges. Traditional two-way fixed-effects models (Abowd et al. 1999) struggle when match-specific heterogeneity is present, potentially conflating CEO and firm effects, leading to biased estimates (Card et al. 2013). Limited CEO mobility across firms (e.g., Fee and Hadlock 2003, Graham et al. 2012) further complicates identification, as estimating separate CEO and firm effects requires observing multiple transitions. Additionally, estimating complementarities—or the interaction effects between thousands of CEOs and thousands of firms—would yield an enormous parameter space, exacerbating computational complexity and limited mobility bias (Kline et al. 2020).

We address these challenges by employing the Bonhomme, Lamadon, and Manresa (2019) (BLM) estimator, a hybrid approach that integrates reduced-form estimation with structural modeling of endogenous CEO-firm matching. The BLM estimator uses dimensionality reduction (Bonhomme et al. 2022) to classify firms into a manageable number of "classes" and CEOs into latent "types," making it feasible to estimate a large set of CEO-firm complementarities without succumbing to the limited mobility bias. This approach allows us to disentangle CEO effects, firm effects, and match-specific complementarities for a comprehensive sample of over 17,000 CEOs from the entire Compustat universe (1990–2018).

Our findings show that CEO-firm complementarities explain between 5% and 7% of firm performance variation—more than the 2–4% attributed solely to CEO ability. This result challenges the assumption that CEO influence is simply additive. Instead, it suggests that certain CEOs excel in specific organizational contexts, lending credence to UET's emphasis on CEO characteristics while refining the predictions of competitive assignment models. Counterfactual analyses demonstrate that existing assignments are far from optimal. Improving CEO-firm matches could boost aggregate equity valuations by as much as 35.9%, equivalent to approximately $20.7 trillion. Even a random reassignment outperforms the status quo by around $2.1 trillion, underscoring how suboptimal matching imposes substantial economic costs.

Our study makes several contributions. Theoretically, it bridges UET and competitive assignment models by showing that contextual CEO-firm fit matters: performance stems not only from CEO "style" or ability alone but from how well these attributes align with firm-specific demands. Methodologically, we extend the BLM approach by computing variance decomposition using actual outcomes rather than simulated draws, allowing for time-varying match-specific shocks and greater fidelity to real-world dynamics. Empirically, we provide novel insights into CEO labor markets, quantifying the macro-level costs of misallocation and highlighting the importance of frictional hiring processes. Finally, we show that acknowledging complementarities can reconcile conflicting empirical results in previous research and offer actionable guidance to boards, investors, and policymakers on improving CEO selection and compensation practices.

In sum, by integrating insights from UET and competitive assignment models, our findings reveal that CEO impact on firm performance is context-dependent, driven by how well the leader's abilities and traits fit the firm's unique profile. Recognizing and leveraging these CEO-firm complementarities can significantly enhance both individual firm outcomes and aggregate economic welfare.

The rest of the paper proceeds as follows. In Section 2, we review the existing literature on the effects of CEOs on firm performance and offer a theoretical rationale for the role of complementarities. In Section 3, we describe our sample and data construction. Section 4 provides an overview of our empirical strategy. In Section 5, we present the baseline results regarding how CEOs and complementarities influence the cross-sectional distribution of firm performance. Section 6 presents labor market matching counterfactuals and efficiency gains from a theoretically optimal allocation of CEOs. In Section 7, we offer concluding remarks and opportunities for future research.

2. The Role of CEOs

This section examines how CEOs affect firm performance, emphasizing CEO-firm complementarities. We contrast UET with competitive assignment models to highlight their insights and limitations regarding context-specific fit. We review empirical evidence on CEO effects, noting mixed findings that require a nuanced interpretation. Finally, we propose CEO-firm complementarities as a unifying concept bridging these theories.

2.1. Theoretical Perspectives on CEO Influence

UET emphasizes the significance of CEOs' personal attributes—such as their backgrounds, experiences, and leadership styles—in shaping firm decisions and outcomes (Hambrick and Mason 1984, Finkelstein et al. 2009). Here, CEOs are not interchangeable inputs; their distinctive qualities imprint on organizational strategies, resource allocation, and innovation trajectories, thereby driving performance differences.[1] This perspective has inspired extensive research linking various CEO characteristics to firm-level actions and results, reinforcing the idea that leadership significantly influences firm outcomes.[2]

In contrast, competitive assignment models prevalent in financial economics cast CEOs as largely fungible resources whose ability differences, while present, are relatively smooth and minimal (Gabaix and Landier 2008, Terviö 2008). According to these models, market forces efficiently sort CEOs so that high-ability executives gravitate toward the largest or most productive firms. In this framework, performance disparities emerge less from individual leadership styles and more from the equilibrium allocation of a scarce talent pool. This viewpoint echoes the "romance of leadership" theory (Meindl et al. 1985), suggesting that firm outcomes are driven primarily by structural factors rather than distinctive leader characteristics.

Although these frameworks offer compelling insights, both assume that CEO influence on performance is largely additive—either we sum CEO attributes to firm effects (UET) or rely on

[1] Although central to management, finance, and accounting, the concept of leadership styles has also been explored in other domains, such as political science and development economics (Levitt 1996, Jones and Olken 2005).

[2] Among others, researchers have documented an association between firm outcomes and several CEO characteristics, including military experience (Benmelech and Frydman 2015), work experience (Custódio et al. 2019), functional specialization (Barker and Mueller 2002), overconfidence (Galasso and Simcoe 2011), temporal focus (DesJardine and Shi 2021), and political orientation (Wowak and Busenbark 2024).

ability-based sorting (competitive assignment). Neither approach considers that a CEO's effectiveness may depend critically on the firm's unique context.

2.2. Empirical Evidence on CEO Effects

Empirical attempts to quantify CEO effects yield sharply divergent results. Early variance decomposition studies suggested that top managers explain a modest portion of firm performance variation (Lieberson and O'Connor 1972), while later work using similar methods reported much larger CEO contributions (e.g., Hambrick and Quigley 2014, Quigley and Hambrick 2015, Keller et al. 2023). In contrast, other scholars find negligible CEO effects once measurement challenges are addressed (Fitza 2014). Similarly, research designs exploiting CEO mobility (e.g., MDV approaches) and quasi-exogenous turnover events, such as sudden deaths produce inconsistent, and sometimes contradictory estimates of CEO influence (Bertrand and Schoar 2003, Jarosiewicz and Ross 2023, Bennedsen et al. 2020, Jenter et al. 2023, Sauvagnat and Schivardi 2024).

One recurring theme across these studies is heterogeneity—not only among CEOs and firms but also within the same CEO across different firms. Such patterns suggest that ignoring interaction effects between specific CEOs and specific firms may bias our understanding. Traditional approaches that treat CEO and firm effects as additive and independent risk overlooking the nuanced interplay that arises when unique leadership styles meet distinct organizational contexts.

2.3. From Sorting to Complementarities

Competitive assignment models posit that sorting on ability alone should achieve near-optimal matches. Yet the empirical record and anecdotal evidence suggest persistent mismatches and substantial unexplained variance, implying that ability-based sorting is only part of the story (Cziraki and Jenter 2021, Gompers et al. 2022). Insights from labor economics, human capital theory, and organizational behavior emphasize that productivity often emerges from synergy rather than the sum of individual inputs (Becker 1973, Jovanovic 1979, Milgrom and Roberts 1995, Kristof-Brown and Guay 2011). In other words, some CEOs thrive in certain environments but falter in others, depending on how well their attributes align with firm-specific demands.

Real-world examples underscore this point. Consider John Sculley at Apple. As a former Pepsi executive, Sculley's strengths lay in marketing consumer goods and driving short-term profitability. When he moved to Apple—a firm rooted in innovation, rapid technological shifts, and visionary product design—his focus on incremental profit clashed with the company's creative culture. This mismatch diminished his capacity to enhance Apple's long-term performance. By contrast, Satya Nadella's tenure at Microsoft illustrates what happens when a CEO's abilities fit seamlessly with a firm's evolving strategy. Under Nadella's leadership, Microsoft embraced cloud computing, adopted collaborative platforms, and fostered a "growth mindset," transforming from a mature and product-centric company into a forward-looking technology leader. Nadella's leadership style and strategic orientation complemented Microsoft's tacit capabilities, unlocking significant performance gains.

These real-world cases highlight that even a highly capable CEO may yield suboptimal outcomes

if their strategic orientation does not suit the firm's context. Conversely, a leader whose approach aligns with the firm's unique challenges can unleash its full potential. Understanding whether these cases generalize is one of the primary objectives of this paper.

By considering such complementarities, we move beyond one-dimensional views of CEO influence. CEOs and firms co-create performance outcomes through their interaction, and the quality of this match is crucial. Existing research that acknowledges complementarity-driven matches has explored their impact on compensation schemes (Pan 2017), M&A outcomes (Chen et al. 2021), and CEO behavioral types (Bandiera et al. 2020). However, these studies often rely on parametric assumptions or focus on observable traits.

Our study adopts a more flexible approach, accommodating two-sided unobservable heterogeneity and allowing for the dynamic estimation of CEO-firm complementarities. By doing so, we decompose firm performance into CEO-specific, firm-specific, and match-specific effects, shedding new light on how and why certain leadership-firm pairings excel while others underperform. This perspective paves the way for understanding not just whether CEOs matter, but also how the interplay between leader characteristics and organizational context shapes the distribution of firm performance outcomes.

3. Data

This section describes the construction of our final sample, the sources of our data, and the institutional context of U.S. CEO labor markets.

3.1. Data Overview

Our primary source is the Compustat Research Insight (CRI) panel, which provides financial information and top executive names for approximately 7,500 U.S. firms annually from 1990 to 2018, spanning over 200,000 firm-year observations.[3] CRI reports the top four managers' titles as disclosed in firms' 10-K and 10-Q filings, enabling us to identify CEOs and track their movements across firms. This sample is notably broader than Execucomp, which is limited to the largest 1,500 firms. The extensive coverage enhances identification by increasing the number of CEO turnover events and reducing network sparsity, thereby mitigating the limited mobility bias (Jochmans and Weidner 2019). This more extensive coverage also reduces the likelihood of skewing our sample toward large, stable firms. Further details on CRI are in Online Appendix A.

We exclude financial services (SIC 6000–6999), utilities (SIC 4900–4999), public sector, and unclassified firms (SIC $>$ 9000) due to differing regulatory environments and performance metrics. We remove temporary CEOs by requiring at least two years of tenure before and after a transition, ensuring sufficient time for CEOs to "imprint" their style on the firm. We exclude firms with under $10 million (1990-adjusted) in assets or insufficient financial information. All nominal values are adjusted to 1990 dollars using the Consumer Price Index (CPI). Historical headquarters data are

[3]We thank Charles Hadlock for providing these data.

merged from 10-K textual filings from EDGAR (Loughran and McDonald 2016).[4] After applying filters, the final sample includes 92,651 firm-year observations and 17,114 individual CEOs. We winsorize Compustat financial variables at 0.5% and final ratio variables at 0.5% (results are similar at 1%).

For some of our tests, we supplement CRI with BoardEx, Execucomp, and additional manual data collection (Factiva, LexisNexis, corporate press releases) to obtain CEO demographic and career information.

3.2. CEO Mobility Patterns

The BLM estimator relies on CEO turnover between firms. A potential concern is that CEO movements may occur predominantly within an industry or firms of the same size, which could render clustering on dependent variables uninformative about the underlying heterogeneity. Consistent with prior research (Gompers et al. 2022, Graham et al. 2020), we observe most CEO moves occur within the same industry but also note that some CEOs cross industry and size boundaries. Figure 1 depicts these mobility patterns, grouping firms by Fama-French 10 industries (excluding financial services). Panel A confirms that most moves occur within the same industry. However, there is still sizable movement of CEOs between industries. Panel B shows that cross-industry moves also happen at various firm size levels. These patterns suggest that clustering firms using data from the entire sample should effectively capture meaningful firm groupings rather than relying solely on industry or size.

3.3. Variables

We use Tobin's Q and Return on Assets (ROA) to measure firm performance, aligning with prior work (Bertrand and Schoar 2003, McGahan and Porter 2002, 1997). Tobin's Q reflects the market's forward-looking valuation, while ROA reflects backward-looking operational efficiency. Tobin's Q is the firm's market value divided by its assets' book replacement cost, and ROA is calculated as EBIT/Total Assets.

We log Tobin's Q and apply an exponential transformation to ROA to address skewness. We also purge performance measures of macro, industry, size, and state-level shocks by regressing each performance measure on a set of year $\times$ industry, year $\times$ size quartile, and year $\times$ state dummies and use the residuals as our dependent variables. These regressions explain approximately 25% of the firm performance variance, leaving the remaining 75% for analysis. Full variable descriptions are provided in Online Appendix B.

[4]We thank Bill McDonald for providing this dataset.

4. Empirical Strategy

Our empirical strategy employs the BLM estimator, which allows us to estimate CEO, firm, and CEO-firm match effects on firm performance while addressing key challenges that arise from limited CEO mobility and endogenous matching. BLM builds on the conceptual framework of the Abowd, Kramarz, and Margolis (AKM) Two-Way Fixed Effects estimator (Abowd et al. 1999), but importantly relaxes many of AKM's restrictive assumptions. The AKM approach has been widely used to understand the drivers of inequality (Card et al. 2013), venture capital performance (Ewens and Rhodes-Kropf 2015), and the decomposition of innovation output (Bhaskarabhatla et al. 2021). However, as we discuss, AKM's identifying conditions and additivity assumptions do not fully hold in our context.

4.1. Limitations of AKM and the Necessity for BLM

AKM posits a simple additive structure:

$$Y_{jt} = \psi_{i(j,t)} + \phi_j + \varepsilon_{jt}, \tag{1}$$

where Y_{jt} is firm j's performance at time t, $\psi_{i(j,t)}$ is the CEO fixed effect, and ϕ_j is the firm fixed effect.

We interpret CEO fixed effects as a time-invariant component of CEOs' idiosyncratic characteristics, which we refer to as CEO "ability". Firm fixed effects refer to time-invariant unobserved factors that influence a firm's performance, such as its industry, culture, or competitive market position. While conceptually appealing, AKM has several key limitations in our setting.

Endogenous matching poses a significant challenge because the AKM framework assumes that CEO transitions between firms occur exogenously and independently of the latent quality of the matches. If, in practice, CEOs and firms select one another based on their underlying characteristics, the resulting estimates will be biased (Card et al. 2018). In addition, AKM relies on cross-firm CEO mobility to separately identify CEO and firm effects. Since empirical evidence shows that CEO mobility is limited (Fee and Hadlock 2003, Graham et al. 2012), a severe incidental parameter problem - or limited mobility bias - arises (Kline et al. 2020, Neyman and Scott 1948). Incidental parameter problem is caused by a large number of firm- and CEO-specific parameters (i.e., fixed effects) that are entirely identified by CEOs who move from one firm to another. Adding more firms to the sample does not mitigate this issue, as the number of parameters—specifically, the firm and CEO fixed effects—expands alongside the sample size, thus preventing bias reduction through sample growth alone. Moreover, extending the AKM approach to estimate CEO-firm complementarities requires interacting all CEO and firm fixed effects. Such an approach increases parameter complexity exponentially, making AKM estimation in large samples computationally infeasible and exacerbating the incidental parameter problem.

Furthermore, AKM's identification requires a connected network of firms linked by CEO moves.

In our data, this "connected set" is too small to yield reliable estimates using an AKM approach, as the largest set only contains around 1,000 firm-year observations.

For a detailed derivation of estimation bias and a complete discussion of AKM's limitations, see Online Appendix C.

4.2. The BLM Estimator

BLM provides a framework to overcome these challenges. It integrates reduced-form estimation of variance components (CEO, firm, and match effects) with a structural approach that accounts for endogenous matching. BLM models the CEO-firm match formation as a dynamic Markovian process, enabling separate identification of CEO and firm heterogeneity and their joint contribution to performance (Bonhomme et al. 2019).

The key identifying assumption is that CEO turnover decisions depend on CEO type, firm class, and firm performance in the recent past but do not directly depend on longer-term histories. This Markovian property helps separate persistent CEO-firm match effects from transitory shocks and avoids the biases that plague AKM. However, we do not allow the firm performance of a CEO's new firm to depend on the performance of the CEO's previous firm, as this aspect of BLM does not naturally fit our context. Consistent with BLM, we estimate autoregressive parameters – or dynamic persistence – within CEO-firm matches as a first-order Markov process. This approach allows for serial dependence of firm performance within CEO-firm matches that enables us to capture firm performance persistence in the time series that then allows us to isolate the true CEO effect more precisely from mean reversion around CEO turnover, consistent with BLM's second identifying assumption.[5] This assumption restricts the evolution of firm performance within CEO-firm matches. For conciseness, we focus on key conceptual points of BLM in this section while showing the derivation and detailed implementation of the BLM model in Online Appendix D.

Our clustering approach follows the reclassification implementation of BLM and mirrors the recent implementation of BLM by Lentz et al. (2023). The critical issue facing the clustering of CEOs is that there is only one observation per firm each year, which may result in overfitting in the initial clustering step. When using limited firm-year data to cluster firms into discrete groups, the clustering algorithm risks fitting patterns specific to the small number of observed years rather than capturing the firm's broader, more stable characteristics due to noise. As a result, the clusters may not generalize well beyond the limited sample of firm-year observations, leading to overfitting. To avoid this issue, we use a reclassification approach to cluster firms using *k-means* and then sequentially update the clusters after estimating the EM algorithm to maximize model log-likelihood. We present a detailed overview of *k-means* clustering in Online Appendix E. We randomly select a subset of firms to re-cluster and then repeat the reclassification exercise. This approach allows us to

[5] In BLM notation, we estimate the complete set of dynamic persistence parameters including $\rho_{1|2}$, $\rho_{s3|2}$ and $\rho_{4|3}$ in the EM step, while setting $\rho_{m3|2}$ to be equal to zero. $\rho_{m3|2}$ refers to the autoregressive parameter for the CEOs who move from one firm to another. In a robustness check, we estimate $\rho_{m3|2}$ within the baseline BLM model, and we find it is not significantly different from zero. We find that the estimates for other persistence parameters are between 0.45 and 0.55, all statistically highly significant.

exploit full information from every CEO-firm match as it also utilizes performance changes around CEO turnover across different classes for reclassification. Thus, employing this reclassification approach helps avoid potential overfitting in the *k-means* pre-step by relying on sequentially updated EM estimates to cluster firms into classes while fully exploiting CEO mobility data.

4.3. Computational Implementation of the BLM Model

Estimating the dynamic BLM model proceeds through a multi-step procedure that accommodates CEO-firm heterogeneity, dynamic performance processes, and time-varying complementarities.

4.3.1. Step 1: Firm Classification via k-means Clustering.– We first cluster firms into a finite number K of classes using a k-means algorithm applied to observed performance measures (i.e., Tobin's Q or ROA, depending on the dependant variable used in the model) (Hartigan 1975). Doing so reduces dimensionality and mitigates the incidental parameter problem inherent in assigning a separate fixed effect to each firm.

4.3.2. Step 2: Parameter Estimation via the EM Algorithm.– Conditional on the firm classifications obtained in Step 1, we estimate the model parameters using the Expectation-Maximization (EM) algorithm (Dempster et al. 1997). The model estimates the probabilities of CEO transition between classes and assigns CEOs to discrete latent "ability" types, CEO-type distributions, CEO-firm class match effects, and the parameters of the dynamic performance process—to maximize the expected log-likelihood. We run the EM algorithm multiple times from different starting values to address potential local maxima, and we verify that the chosen solution satisfies the connectivity conditions of Jochmans and Weidner (2019), ensuring that the identified latent structures are meaningful.

4.3.3. Step 3: Iterative Reclassification of Firms.– Following the initial parameter estimation, we iteratively reassign firms to classes to improve model fit (Lentz et al. 2023). Specifically, we alternate between:

1. Holding firm classes fixed while running the EM algorithm to refine parameter estimates.
2. Reclassifying firms based on the updated parameter estimates to increase the overall model log-likelihood.

This iterative cycle continues until no further log-likelihood improvements are achievable, producing a data-driven and substantively meaningful firm classification.

4.4. Extending BLM to Time-Varying Complementarities

A key extension in our application is to allow for time-varying complementarities. Rather than treating CEO-firm match effects as static, we recognize that firm contexts evolve, potentially altering the productivity of a given CEO-firm pairing. By using directly observed performance measures—rather than simulated outcomes as in the standard BLM approach—we can estimate

the incremental R^2 from complementarities that fluctuate with business cycles, industry shocks, or firm-specific events.

This dynamic perspective aligns with turnover models where CEO-firm matches are subject to changing conditions over time (Garrett and Pavan 2012). In practice, these time-varying complementarities significantly explain the cross-sectional dispersion in firm performance. We demonstrate that ignoring this dimension would lead to an incomplete understanding of how and why CEOs matter.[6]

5. Results

In this section, we document our core findings on the role of CEOs and CEO-firm complementarities in explaining cross-sectional differences in firm performance. We begin by presenting the baseline estimates and discussing the economic magnitude of CEO and firm effects and complementarities. We then move on to variance decompositions and robustness checks. Finally, we consider the characteristics associated with CEO latent types.

5.1. Sample Description and Clustering

Table 1 presents summary statistics for our sample. The broad coverage of firms in Compustat yields substantial variation in firm size, Tobin's Q, and ROA. We implement our BLM framework following the procedure described in Section 4. We initially cluster firms using *k-means* with firm size weights and rely on the cumulative distribution functions (cdfs) of our dependent variables (Tobin's Q or ROA).[7] Guided by the Silhouette and Elbow methods (Rousseeuw 1987), we choose five firm clusters. For symmetry, we also use five latent CEO types. We then apply the BLM estimator, iteratively refining firm clusters to maximize the model's log-likelihood.

5.2. What Do Firm Clusters Represent?

The clusters differ systematically in both average firm characteristics (e.g., Tobin's Q, ROA, R&D intensity) and how these attributes affect market valuations. The classes also show substantial differences in terms of variance, skewness, and kurtosis of Tobin's Q. Table 2 reports mean values and distributional statistics for each cluster, while Online Appendix F summarizes regressions showing how Tobin's Q responds to ROA, size, leverage, dividend policy, and R&D. In brief, larger firms in Cluster 1 gain from scale, whereas Cluster 2 relies more on steady operational improvements than size expansion. Meanwhile, Clusters 3–5 increasingly reward profitability and R&D intensity, but penalize excessive leverage or dividend payouts, especially in the most innovation-driven groups. Based on these characteristics, we label the clusters as follows, with illustrative examples:

[6] Our results using simulated performance outcomes, in line with standard BLM implementation, yield qualitatively unchanged results regarding the contribution of firm effects, CEO effects, and time-invariant complementarities.

[7] We also experimented using higher-order moments from dependent variables as additional clustering criteria, with no changes to the results.

1. **Low-Value Traditionalists.** Lowest average Tobin's Q, modest R&D expenditures, and positive size effects. Dividend yield aids valuation, while ROA has a smaller impact compared to higher-growth clusters. *Example*: A century-old paper mill focusing on scale efficiencies to maintain steady, if unremarkable, returns.
2. **Incremental Improvers.** Slightly higher Tobin's Q than Cluster 1, but size now detracts from valuation. Stepwise ROA gains are rewarded, with moderate R&D intensity contributing some value. *Example*: A mid-sized packaging supplier gradually refining production lines and supply chains.
3. **Established Growth Leaders.** Stable, mid-tier Tobin's Q, stronger ROA impacts, and moderate R&D payoffs. They tolerate some leverage but emphasize balanced growth strategies. *Example*: A regional industrial-equipment firm expanding into adjacent product lines while maintaining reliable dividends.
4. **Dynamic Growth Seekers.** Rising Tobin's Q, strong returns to both ROA and R&D, but a negative valuation effect of size. High agility and innovative capacity drive market premiums, although excess leverage can be penalized. *Example*: A California-based wearables startup launching frequent device updates in partnership with tech giants.
5. **High-Potential Innovators.** Highest mean Tobin's Q and strongest R&D rewards. Dividend payments are viewed skeptically, and size correlates negatively with valuation. Investors expect transformative growth through profitability gains and R&D breakthroughs. *Example*: A Silicon Valley biotech specializing in gene-editing therapies, heavily investing in clinical trials with potentially game-changing outcomes.

5.3. Baseline Estimates and Variance Decomposition

Figures 2 (Tobin's Q) and 3 (ROA) illustrate our core parameter estimates. In both sets of results, the left panels show expected match performance across firm classes and CEO latent types, while the right panels display the proportion of CEO types employed in each firm class.[8]

We observe three key patterns. First, there is significant firm heterogeneity. Higher-order firm classes exhibit substantially better average performance, indicating that firm-level characteristics

[8]As noted by Lentz et al. (2023), information-based standard errors are generally unreliable for assessing the estimation precision of finite mixture models (FMM) unless the sample size is exceedingly large relative to the mobility required for identification. While Bonhomme et al. (2019) use a simulation-based method to bootstrap confidence intervals (CIs) for their baseline estimates, they can do so because their large sample size and restriction to four years yield narrow CIs. However, in our case, bootstrapping the entire estimate would result in extreme computational demands for several reasons. First, we rely on many starting values to address local maxima issues inherent in FMM. Second, we employ a reclassification approach to mitigate overfitting in *k-means*. Even when utilizing highly parallelized code on a computing cluster with 128 cores, the time and resources required to perform bootstrap resampling are prohibitive. Furthermore, there is a lack of theoretical work on two-way fixed-effect models within the context of FMM, making it difficult to develop efficient bootstrap algorithms tailored to our model's specific features. Additionally, using a longer panel to improve identification increases the dataset's size and complexity, exacerbating computational challenges. Given these constraints—the unreliability of information-based standard errors for FMM, the impracticality of bootstrapping because of extreme computational requirements, and the increased complexity of our estimation approach—we do not compute confidence intervals for the baseline parameter estimates. We estimate all other CIs in the paper in line with Bonhomme et al. (2019) as they are computationally manageable.

predominantly shape outcomes. Second, the frequent crossovers in match means (i.e., how different CEO types pair with different firm classes) suggest non-linear complementarities, with some CEO types performing exceptionally well in specific firm contexts. Third, the distribution of CEO types across firm classes exhibits minimal variation. High-performance CEOs do not appear to systematically cluster in top-performing firms, challenging the assumptions of competitive assignment models. These findings highlight the importance of CEO-firm match quality over simple additive models of CEO and firm effects.

Table 3 presents the variance decomposition of firm performance, showing the relative contributions of CEOs, firms, and complementarities. Prior to this decomposition, we partial out macro-level, industry-level, size-related, and state-level factors. This procedure explains roughly 25% of the variation, leaving about 75% of residual variation to be explained by CEO, firm, and complementarity effects.

For Tobin's Q, CEO effects alone account for about 3.02% of the variance, while firm effects explain 43.86%. CEO-firm complementarities contribute 5.36% when including time-varying components. Similarly, for ROA, CEO effects explain 3.03%, firm effects 32.57%, and total complementarities (time-invariant plus time-varying) 6.66%. In both specifications, complementarities exceed the explanatory power of CEO ability alone, highlighting their economic importance.

5.4. Robustness Checks

5.4.1. Alternative Cluster and Latent Type Specifications.– We test the sensitivity of our results to different numbers of firm clusters and CEO types. Tables 4 and 5 show that while CEO and firm effects vary slightly, the central finding remains robust: complementarities persist as a critical performance driver, exceeding the explanatory power of CEO ability alone. We also find little evidence of significant sorting (i.e., high-ability CEOs systematically matching with high-performing firms), a conclusion that holds across multiple specifications.

5.4.2. Time-Varying CEO and Firm Effects.– Next, we incorporate additional controls to proxy for dynamic changes, accounting for the possibility that CEO and firm effects are time-varying. We net out third-order polynomials of firm age and CEO tenure, as well as macro effects, from the dependent variables to account for evolving firm and CEO conditions (Graham et al. 2012). We collect data on firm age from IPO prospectuses (Loughran and Ritter 2004). When the firm's founding date cannot be identified, we use the initial financial reporting date from Compustat. We also restrict the sample to CEOs with at least three years in their role, ensuring they have sufficient time to "imprint" their style (Bertrand and Schoar 2003). The results reported in Panels D and E of Tables 4 and 5 remain consistent with our baseline findings, reinforcing the robustness of complementarities in explaining performance differences.

5.4.3. Comparisons with Other Estimators.– To further validate our approach, we compare BLM against alternative estimators. These include the Static BLM estimator and the Correlated Random Effects (CRE) estimator (Bonhomme et al. 2019, 2023), as well as an AKM-based specification with

Heteroskedastic Fixed Effects (FE-HE) bias correction (Kline et al. 2020).[9] Table 6 shows that firm effects dominate all specifications, and CEO effects under AKM are higher than under BLM. Notably, the BLM results suggest that, due to model misspecification, AKM improperly assigns explanatory power from complementarities to CEO ability. These comparisons confirm that our core conclusions are not driven by a particular estimation method.

5.4.4. Alternative Performance Measures.– We also assess the sensitivity of our results using alternative performance measures. First, we use raw values of Tobin's Q and ROA, with the results displayed in Online Appendix G (McGahan and Porter 1999). Second, we construct variables of Total Factor Productivity (TFP). TFP measures a firm's effectiveness in transforming inputs—such as labor, capital, and materials—into outputs, capturing improvements in technology, innovation, and processes that drive performance gains beyond those explained by simply adding more inputs. Although TFP requires stronger parametric assumptions, it provides a complementary perspective. The TFP-based analysis is detailed in Online Appendix H. Both sets of alternative performance measures yield results broadly consistent with Tobin's Q and ROA findings—firm effects remain dominant, and complementarities exceed CEO ability in explanatory power. The estimates using raw values of Tobin's Q and ROA indicate a more pronounced effect of complementarities, although these estimates have more variance to explain since we do not net out the macro factors.

5.5. CEO Latent Types

Finally, we investigate whether CEO latent types correlate with observable characteristics. We match CRI with BoardEx and Execucomp data to create a sample of 2,028 unique CEOs. We first assign CEOs to types with the highest posterior probability $\pi_{i,k}(\alpha)$ (Lentz et al. 2023). We regress CEO types on covariates cross-sectionally using a multinomial logit model to identify which attributes (e.g., education, career paths, and prior industry experience) predict assignment to higher-ability CEO types.[10,11]

The results are displayed in Table 7. Advanced education, experience in engineering or operations, and a willingness to move between firms are associated with higher CEO-type classifications. CEOs drawn from high-performing firm environments and specific career backgrounds are more likely to be categorized as high-ability. These results suggest that the CEO latent types estimated by BLM encode meaningful underlying differences, lending further credibility to our approach. Based on these characteristics (Lentz et al. 2023), we label the CEO types as follows, with illustrative scenarios:

[9] To make AKM tractable in our setting and reduce the limited mobility bias, we first classify firms using the *k-means* into five clusters so that we can construct a connected set in our sample.

[10] We assigned two research assistants to categorize functional experience from BoardEx into these categories and compared the results of their categorizations to ensure inter-rater reliability. The few discrepancies that occurred were resolved through direct examination of the data by the investigator.

[11] We rely on BoardEx industry definitions to categorize CEOs' prior industry experience as BoardEx also provides industry classifications for private firms, which we cannot match with Compustat.

1. **Conservative Operators**: Experienced factory-floor veterans who excel at stabilizing production lines and reducing costs.
2. **Mobile Optimizers**: Methodical troubleshooters who move between mid-sized firms, applying incremental improvements to supply chains and margins.
3. **Strategic Builders**: Forward-looking planners who balance reliable operations with selective R&D initiatives and market expansions.
4. **Adaptive Innovators**: Flexible leaders who thrive in fast-changing environments, seizing emerging opportunities and readjusting strategies swiftly.
5. **Visionary Transformers**: High-caliber visionaries who orchestrate breakthrough innovations and guide firms through transformative growth.

The chosen labels closely reflect the performance patterns shown in Figures 2. At the lower end of both dimensions, Mobile Optimizers (Type Two) deployed in Low-Value Traditionalist environments (Cluster One) achieve reasonably good outcomes despite limited innovation opportunities. However, this type underperforms in High-Potential Innovator settings (Cluster Five). Conversely, at the upper end, Visionary Transformers (Type Five) excel in High-Potential Innovator environments, fully capitalizing on growth opportunities to deliver substantial value gains. Intermediate pairings follow similar logic. For instance, Strategic Builders (Type Three) are well-suited to Established Growth Leaders (Cluster Three), though the resulting improvement falls short of the highest-level matches. In essence, the labeling scheme naturally aligns with the observed performance gradients across these types and clusters.

6. The Anatomy of CEO Assignment

This section analyzes deviations of actual CEO assignments from competitive models, quantifies the resulting inefficiencies, and explores their underlying mechanisms. We demonstrate that the structure of the CEO labor market cannot be explained solely by vertical differentiation, where one CEO type is universally preferred, or by horizontal differentiation, where match quality depends entirely on firm-specific factors.

6.1. Deviations from the Competitive Ideal

Competitive assignment models predict that the most capable CEOs cluster in the largest or highest-productivity firms, reflecting a purely vertical hierarchy of talent (Gabaix and Landier 2008, Terviö 2008). In this framework, superior CEOs generate higher returns regardless of context, making them universally desirable. However, our analysis challenges this view. Variance decomposition reveals that CEO-firm complementarities—specific matches between a CEO's skills and a firm's needs—drive much of the variation in firm performance, beyond what CEO ability alone can explain. As shown in Figure 4, high-type CEOs are not confined to top-tier firms; many lead

mid-sized companies instead. This distribution deviates from a strictly vertical ranking, pointing to the importance of horizontal fit—unique attributes and strategies that yield high returns only in particular firm contexts. These findings suggest that the CEO labor market may not align talent with firms as efficiently as theory predicts, prompting an exploration of why such misalignments occur and what they imply.

6.2. Sources and Consequences of Misallocation

If matching CEOs with firms were frictionless, vertical differentiation would dominate: the best CEOs would consistently secure the most valuable roles. Yet, the presence of high-type CEOs in mid-sized firms indicates that horizontal differentiation also shapes assignments—certain CEOs excel only when paired with firms that match their strategic, cultural, or technological strengths. Misallocation emerges when frictions disrupt this ideal alignment. Supply-demand imbalances arise when specific CEO profiles are scarce, leaving firms with suboptimal hires. Hiring frictions, such as geographic constraints, informational gaps, or behavioral biases (Yonker 2017), compound the problem. For example, boards may prioritize charisma or cultural fit over optimal compatibility (Khurana 2011, Favaro et al. 2015, Charan 2016). As a result, a CEO with strong vertical qualities might underperform without the right environment, while an average CEO could shine in a well-suited firm, underscoring the stakes of fit.

To evaluate these inefficiencies, we use partial equilibrium counterfactuals (Figure 5). We assume that the production function defining CEO-firm performance remains unaffected by reassignment, enabling us to focus on the direct effects of improved CEO-firm matching while abstracting from potential second-order impacts on the broader market equilibrium. Surprisingly, even random reassignments within these constraints outperform current allocations in aggregate valuations, revealing widespread baseline misallocation. Optimizing reassignments—removing frictions to align CEOs with ideal firms—boosts valuations significantly. Relaxing both horizontal constraints (specific CEO-firm matches) and vertical constraints (top CEOs in top firms) unlocks even greater gains. Figure 6 illustrates this dual pattern: some CEOs thrive in particular firm clusters, while others consistently outshine lower-tier peers across contexts. These insights highlight the need to quantify the economic stakes of misallocation and assess its broader impact.

6.3. Economic Magnitudes and Distributional Effects

The inefficiencies identified in CEO assignments carry substantial economic weight, especially when scaled to current markets. As of October 31, 2024, U.S. public firms' total market capitalization stands at $57.6 trillion (S&P Dow Jones Indices 2023). Our structural model estimates that reallocating CEOs to optimize fit could increase aggregate valuations by 28.25%, or $16.27 trillion—net gains that exclude transition costs like hiring or severance, which might temper the figure in practice. Addressing supply-demand imbalances further elevates this potential to $20.68 trillion, roughly 75.58% of U.S. GDP (U.S. Bureau of Economic Analysis 2023). Even a random reassignment yields a 3.65% boost ($2.1 trillion), underscoring the depth of current misalignment.

Misallocation also fluctuates with the business cycle, worsening in expansions and easing near downturns.

Beyond averages, better assignments reshape the distribution of firm outcomes (Figure 7, Table 8). Larger, more productive firms benefit most, unlocking their full potential when paired with well-suited CEOs. This shift moves the economy from widespread underperformance to one where vertical and horizontal strengths align with firm needs. However, counterfactuals reveal a trade-off: performance variance rises, with top firms gaining disproportionately, potentially widening disparities across companies. This dual outcome—higher valuations alongside greater dispersion—highlights the transformative potential of optimized CEO placement, while signaling caution about its uneven effects.

6.4. Determinants of Match Quality

We display correlations between CEO-firm match quality and various factors in Table 9.[12] Growth-oriented policies and richer local talent pools are associated with improved match quality, suggesting that reducing horizontal frictions can help firms secure their ideal CEO. At the same time, modest evidence of the negative effects of stricter non-compete enforcement suggests that relaxing certain vertical constraints on mobility could improve overall efficiency (Starr et al. 2018, Lipsitz and Starr 2022). Although correlations do not establish causality, they support the view that mitigating both vertical and horizontal impediments enhances CEO-firm matches.

6.5. Implications

In sum, actual CEO assignments reveal a complex interplay of vertical and horizontal differentiation. The market is not a simple ladder with universally superior CEOs at the top and firms at the bottom; rather, it is a complex landscape in which some CEOs excel only in specific contexts, while others possess universal appeal. Recognizing and addressing these dual dimensions of differentiation and the associated frictions are crucial for enhancing aggregate efficiency. The substantial valuation gains identified here emphasize the urgency of better aligning CEO types with firm environments. Future research should incorporate these richer market dynamics to better understand and address these inefficiencies (Lucas 1976).

7. Discussion and Conclusion

This study demonstrates that CEO-firm complementarities play a central role in determining firm performance—outweighing the explanatory power of CEO ability alone. By emphasizing contextual fit, we address a critical omission in existing research, which traditionally frames the CEO's influence as purely additive and independent of firm-specific factors. Our results underscore

[12]The sample attrition is due to merging firm data with historical HQ data. Corporate governance covariates result in a further sample reduction due to BoardEx coverage limitations.

that the true effectiveness of CEO leadership emerges when the executive's traits, experiences, and style align with the firm's unique strategic and cultural context.

By quantifying the strength of these complementarities, we bridge the conceptual gap between two influential theoretical streams that offer divergent accounts of CEO influence. UET posits that CEOs leave distinct imprints on their organizations, while competitive assignment models suggest that performance differences arise primarily through the efficient allocation of CEO ability. Our findings reconcile these perspectives: CEO "style" matters, but its effectiveness depends on firm-specific conditions, and while ability-based sorting occurs, it fails to guarantee optimal outcomes without the added dimension of complementarity. The evidence that current CEO-firm matches are far from optimal—and that even a random reassignment could yield better aggregate valuations—highlights the limitations of relying on ability alone, as competitive assignment models assume.

7.1. Theoretical Contributions

Our study moves beyond viewing CEOs as generic "inputs" or monolithic leaders whose personal attributes invariably improve performance. Instead, we show that the CEO's impact is inherently relational, contingent upon their organizational setting. By integrating CEO-firm complementarities into UET, we refine the concept of "style" to reflect the context-dependent efficacy of leadership. Simultaneously, by revealing misalignment and frictions in the executive labor market, we challenge the assumption of frictionless sorting in competitive assignment models. Future theoretical work can build on this insight, modeling how CEOs are assigned and how strategic fit evolves over time and shapes firm trajectories.

7.2. Methodological Contributions

On the methodological side, this study showcases how advanced econometric tools—particularly the BLM estimator—can disentangle CEO, firm, and match-specific effects in environments characterized by low mobility and endogenous matching. We ensure that technical artifacts do not drive our results by accounting for time-varying complementarities and deploying robustness checks with alternative estimators. This approach can guide future research into other contexts where person-environment fit is critical but challenging to measure using conventional methods.

7.3. Practical Implications

From a managerial perspective, our findings suggest that boards and search committees should look beyond general managerial ability when selecting CEOs. Instead of assuming that star talent will thrive anywhere, organizations should consider whether candidates' skills, experiences, and leadership styles complement the firm's strategic priorities, structural characteristics, and cultural norms. Compensation packages and performance evaluations should be tailored to recognize the evolving nature of CEO-firm fit, encouraging CEOs to adapt their leadership approaches as market

conditions and organizational strategies evolve.

7.4. Future Directions and Limitations

Our counterfactual scenarios are deliberately stylized, abstracting away from real-world frictions such as contractual impediments, personal constraints, and relational dynamics that influence CEO mobility. Future studies might incorporate these complexities, explore various organizational contexts (e.g., private firms or different national settings), or connect complementarities to broader stakeholder outcomes. Identifying specific attributes—such as technological expertise, prior functional roles, or cultural backgrounds—that generate the most significant complementarities would enhance our understanding of the drivers of CEO effectiveness.

7.5. Conclusion

In conclusion, this study reveals that the key to understanding CEO influence on firm performance lies in recognizing that leadership effectiveness depends on context-specific complementarities. We illuminate how contextual fit reconciles seemingly conflicting perspectives by bridging the gap between the CEO "style" emphasis of UET and the equilibrium sorting logic of competitive assignment models. Recognizing CEO-firm complementarities promises to enrich theory, enhance measurement, and inform governance practices, executive development, and public policy. As research continues to explore these contextual nuances, we will be better equipped to identify, foster, and reward the kinds of CEO-firm matches that optimize organizational success and contribute to overall economic vitality.

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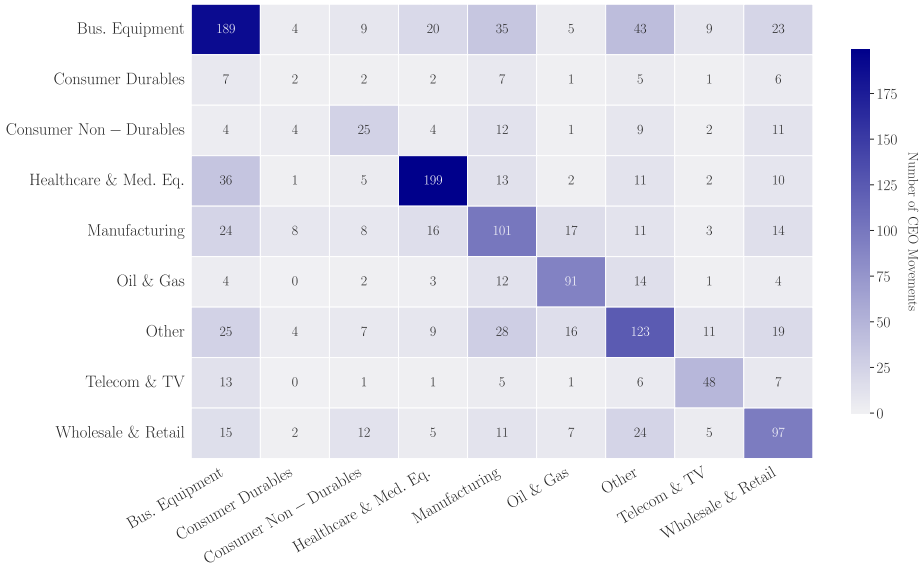
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8. Figures

(a) Between-industry CEO mobility



(b) Within- and between-industry mobility by firm size

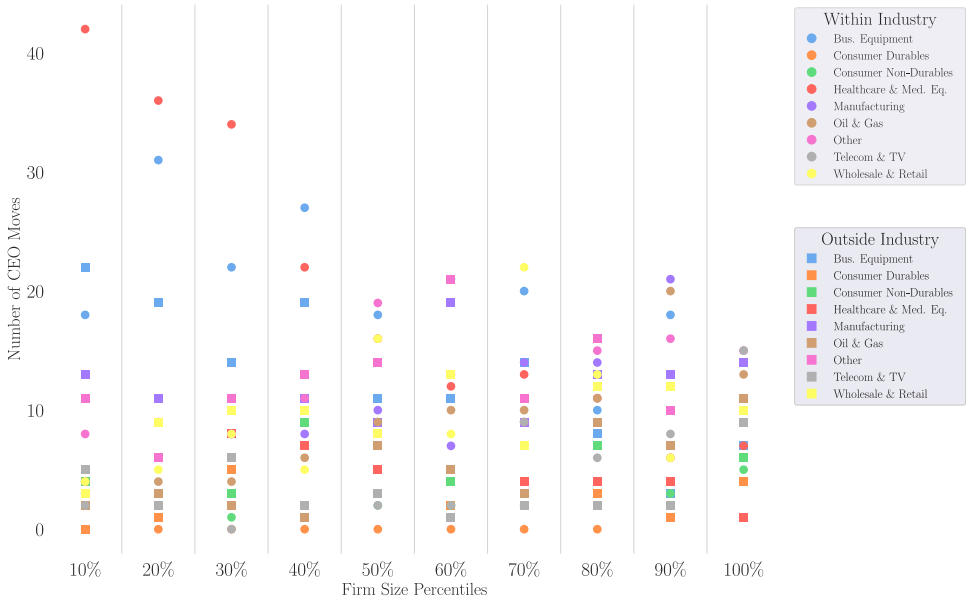


FIGURE 1. CEO mobility statistics within and between industries. Notes: The upper panel shows between-industry CEO mobility (based on Fama-French 10 industries). The lower panel shows within- and between-industry mobility by firm size quantiles. The "Outside industry" values refer to the number of CEOs who moved from that industry to another.

(a) Mean firm performance (Tobin's Q)

(b) CEO type proportions (Tobin's Q)

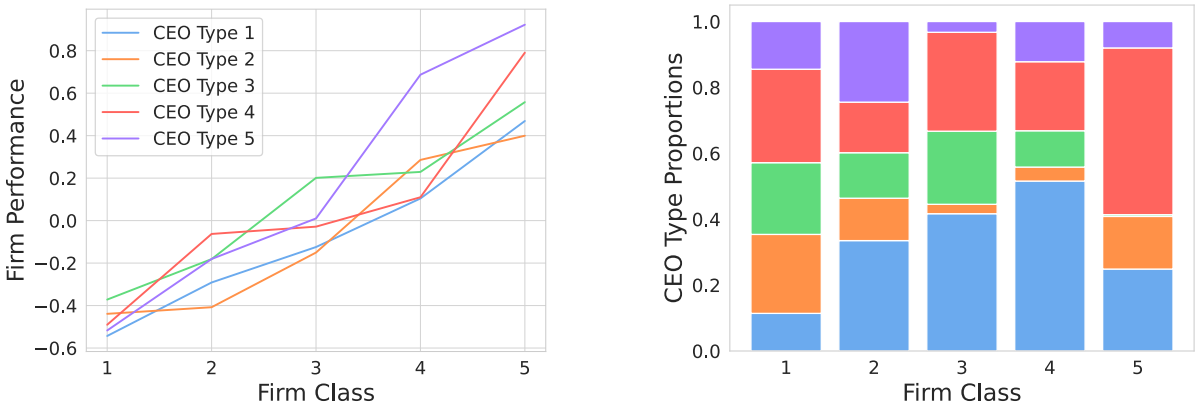


FIGURE 2. Main parameter estimates of the baseline BLM model (Tobin's Q). Notes: Estimates are based on model-reclassified firm classes. Panel (a) shows mean Tobin's Q by firm class (ordered by mean Tobin's Q) and CEO type. Tobin's Q (y-axis) is net of year × industry, year × size quartile, and year × U.S. state hosting firm headquarters set of dummies. Panel (b) shows the proportion of each CEO type within each firm class.

(a) Mean firm performance (ROA)

(b) CEO type proportions (ROA)

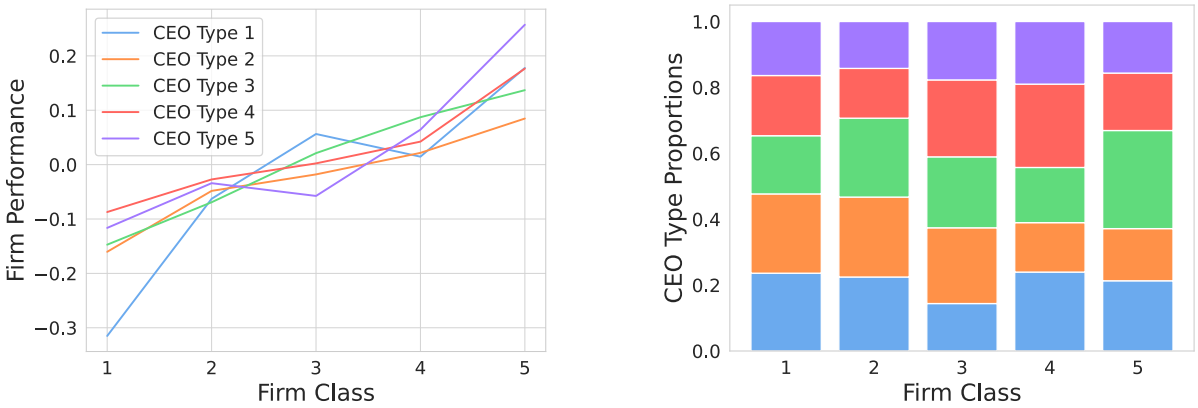


FIGURE 3. Main parameter estimates of the baseline BLM model (ROA). Notes: Estimates are based on model-reclassified firm classes. Panel (a) shows mean ROA by firm class (ordered by mean ROA) and CEO type. ROA (y-axis) is net of year × industry, year × size quartile, and year × U.S. state hosting firm headquarters set of dummies. Panel (b) shows the proportion of each CEO type within each firm class.

(a) CEO type proportions by firm size decile

(b) CEO type proportions by Tobin's Q decile

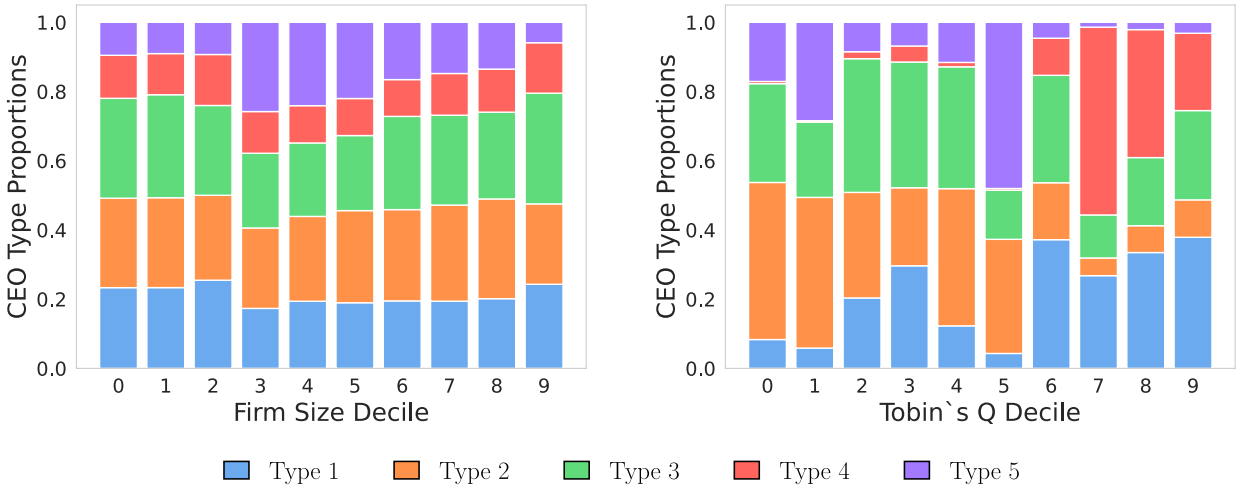
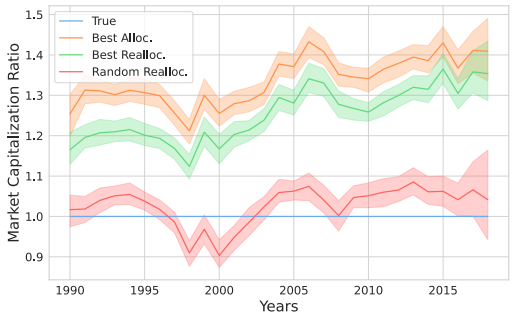


FIGURE 4. CEO type proportions by firm size and Tobin's Q deciles. Notes: The left panel shows proportions by firm size deciles (ordered by total assets), and the right panel by Tobin's Q deciles. All variables are deflated to their 1990-equivalent U.S. dollars. CEO types are estimated from the baseline BLM model (Tobin's Q specification).

(a) Time series of aggregate equity market valuations



(b) Distributional effects of alternative allocation strategies

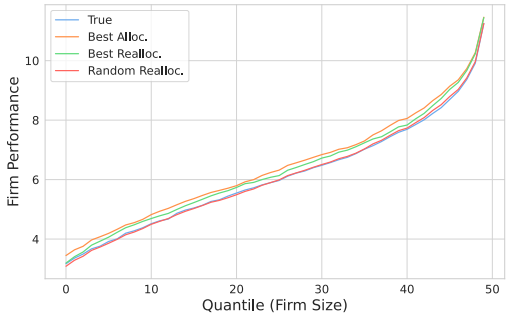


FIGURE 5. Counterfactual sorting estimates. Notes: Estimates are based on model-reclassified firm classes. Panel (a) shows time-series aggregate market capitalization under different reallocation strategies, with 100% (blue line) normalized as the actual outcome. Shaded regions indicate 2.5%–97.5% bootstrap quantile bands from 200 replications. Panel (b) shows the estimated log of Tobin's Q against firm size (total book assets) for various reallocation strategies. All CEO moves are constrained within industry $\times$ size quartile $\times$ year cells. Allocations and reallocations are capped at maximum and minimum Tobin's Q and firm-level market capitalization within industry $\times$ size quartile $\times$ year cells. Optimal allocation is based on estimated firm classes from the reclassified BLM.

(a) Optimal reallocation CEO type proportions

(b) Optimal allocation CEO type proportions

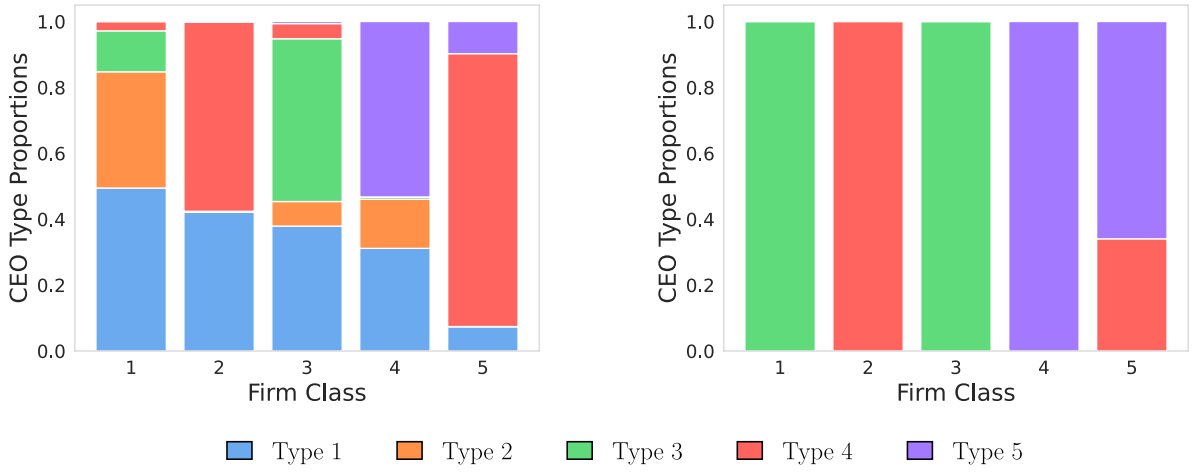
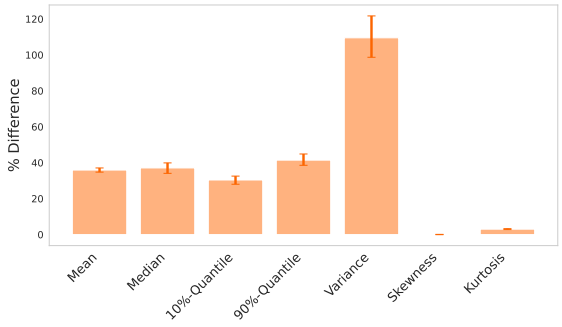
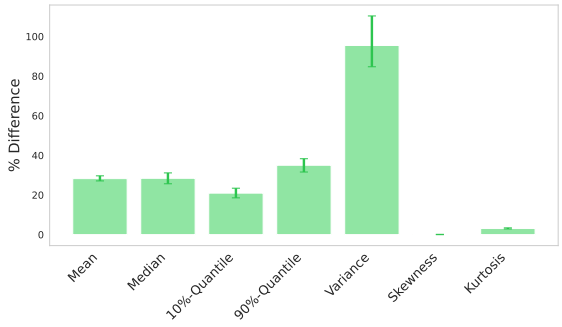


FIGURE 6. Differential reallocation sorting. Notes: The left panel (a) shows CEO-type proportions under the optimal reallocation strategy, where CEOs are reallocated based on CEO-type budgets from the baseline BLM. The right panel (b) shows CEO-type proportions under the optimal allocation strategy, conditioned on estimated firm classes. All CEO moves are constrained within industry × size quartile × year cells. Allocations and reallocations are capped at maximum and minimum Tobin's Q and firm-level market capitalization within industry × size quartile × year cells. Optimal allocation is based on estimated firm classes from the reclassified BLM.

(a) Best allocation



(b) Best reallocation



(c) Random allocation

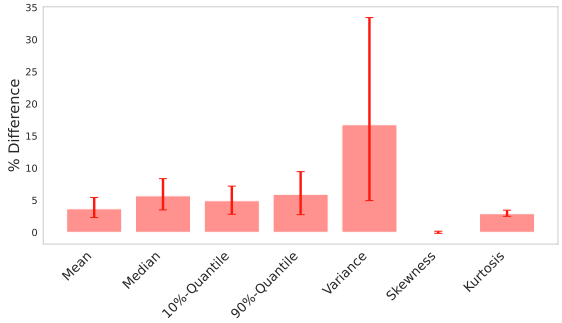


FIGURE 7. Distributional effects of different reallocation strategies. Notes: The panels show differences in key metrics (mean, median, 10% and 90% percentiles, variance, skewness, and kurtosis) of aggregate equity market capitalization relative to the original sample. Higher values indicate a higher expected aggregate market capitalization under that strategy. All CEO moves are constrained within industry × size quartile × year cells. Allocations and reallocations are capped at maximum and minimum Tobin's Q and firm-level market capitalization within industry × size quartile × year cells. Shaded error bars represent 2.5%–97.5% parametric bootstrap quantile bands based on 200 replications.

9. Tables

Table 1
Sample Summary Statistics

Variable	**Mean**	**Median**	**S.D.**	**P25**	**P75**
Tobin's Q	2.046	1.517	1.635	1.118	2.310
ROA	0.022	0.066	0.196	-0.006	0.119
Log of Assets	5.323	5.107	1.848	3.851	6.552
R&D Intensity	0.052	0.000	0.108	0.000	0.057
Capital Intensity	0.059	0.037	0.069	0.018	0.072
Leverage	0.237	0.191	0.240	0.025	0.364
Dividend Yield	0.023	0.000	0.085	0.000	0.018
Dividend Payer	0.351	0.000	0.477	0.000	1.000
Mobility Statistics					
N observations	N unique firms		N CEOs		N mover CEOs
92,651	10,238		17,114		1,556

Notes: This table presents summary statistics for firm-level variables used in the baseline analyses. The sample comprises industrial firms from the Compustat CRI disks from 1990 to 2018. The sample includes firms with non-missing observations on total assets and requires the CEO's tenure to be at least two years. All values are in 1990 CPI-adjusted US dollars. Tobin's Q is defined as the total market value of equity and debt scaled by book replacement costs. ROA is the return on assets, defined as EBIT/book assets. R&D intensity is R&D divided by book assets. Capital intensity is capital expenditures divided by book assets. Leverage is debt in current liabilities plus long-term debt divided by book assets. The dividend yield is dividends divided by book assets. The dividend payer variable is a dummy equal to one if the firm paid a dividend in that year. Mobility statistics refer to the following: Number of observations, Number of unique firms, Number of CEOs, and Number of mover CEOs (CEOs who worked in at least two firms in our sample as CEOs).

Table 2
Firm Cluster Summary Statistics

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Panel A. Mean Variables					
Tobin's Q	1.217	1.474	1.821	2.396	3.984
ROA	-0.002	0.026	0.028	0.029	0.022
Log of Assets	4.661	5.354	5.515	5.518	5.329
R&D Intensity	0.040	0.038	0.048	0.064	0.085
Capital Intensity	0.049	0.058	0.061	0.061	0.063
Leverage	0.224	0.269	0.244	0.228	0.188
Dividend Yield	0.011	0.016	0.022	0.028	0.043
Dividend Payer	0.252	0.338	0.383	0.386	0.371
Panel B. Distributional Characteristics					
10% Tobin's Q	0.696	0.882	0.995	1.194	1.821
90% Tobin's Q	1.832	2.195	2.913	4.043	7.099
Tobin's Q Variance	0.638	0.952	1.464	2.394	5.731
Tobin's Q Skewness	5.921	5.482	4.125	2.882	1.626
Tobin's Q Kurtosis	57.615	44.718	25.207	11.563	2.652
10% ROA	-0.167	-0.109	-0.151	-0.232	-0.391
90% ROA	0.119	0.138	0.159	0.192	0.273
ROA Variance	0.026	0.022	0.031	0.046	0.087
N	13,876	23,080	24,137	19,516	12,042

Notes: Panel A shows the means of firm clusters across different variables. Panel B shows distributional characteristics of Tobin's Q and ROA within each cluster. Clusters are estimated using the baseline BLM specification with five firm clusters and five CEO latent types using the reclassified BLM approach, as explained in the main text. Clusters are estimated using Tobin's Q as the dependent variable and are ordered based on mean Tobin's Q. All variable descriptions are in the Online Appendix B.

Table 3
Variance Decomposition of Firm Performance

	Tobin's Q		**ROA**	
	Estimate	***S.E.***	**Estimate**	***S.E.***
Firm Effect (ψ)	43.86%	(0.10)	32.57%	(0.17)
CEO Effect (α)	3.02%	(0.06)	3.03%	(0.15)
Sorting ($2\text{Cov}(\alpha, \psi)$)	2.89%	(0.05)	-0.02%	(0.06)
Complementarities ($\alpha \times \psi$)	4.30%	(0.08)	5.36%	(0.12)
Time-varying Complementarities ($\alpha \times \psi \times t$)	1.06%	(0.09)	1.30%	(0.24)
Residual (ε)	44.87%	(0.08)	57.76%	(0.28)
Total	100%		100%	

Notes: α = CEO effects; ψ = firm effects; Sorting = $2\text{Cov}(\alpha, \psi)$; $\alpha \times \psi$ = complementarities; $\alpha \times \psi \times t$ = time-varying complementarities; ε = residual. Estimates use five firm clusters and five CEO types. Standard errors are shown in parentheses, computed with 1,000 replications.

Table 4
Variance Decomposition – Tobin's Q – Robustness Check

	$\frac{\text{Var}(\alpha)}{\text{Var}(y)}$	$\frac{\text{Var}(\psi)}{\text{Var}(y)}$	$\frac{2\,\text{Cov}(\alpha,\psi)}{\text{Var}(y)}$	$\frac{\text{Var}(\alpha\times\psi)}{\text{Var}(y)}$	$\frac{\text{Var}(\alpha\times\psi\times t)}{\text{Var}(y)}$
			A. Baseline Model		
	3.02	43.86	2.89	4.30	1.06
			B. Different Number of Firm Clusters		
$K=8$	2.37	44.39	0.49	5.13	1.08
$K=4$	3.16	44.67	0.21	4.33	1.00
			C. Different Number of CEO Types		
$L=4$	0.51	35.69	0.25	3.73	1.48
$L=6$	5.21	45.84	0.78	4.24	1.12
			D. Add CEO Tenure and Age Controls		
	4.34	42.66	3.36	4.17	0.96
			E. Require at Least Three Years of CEO Tenure		
	2.54	46.32	0.86	5.10	1.02

Notes: α = CEO effects; ψ = firm effects; Sorting = $2\text{Cov}(\alpha,\psi)$; $\alpha\times\psi$ = complementarities; $\alpha\times\psi\times t$ = time-varying complementarities. Estimates use five firm clusters and five CEO types. Panel D includes a third-order polynomial in CEO tenure and firm age.

Table 5
Variance Decomposition – ROA – Robustness Check

	$\frac{\text{Var}(\alpha)}{\text{Var}(y)}$	$\frac{\text{Var}(\psi)}{\text{Var}(y)}$	$\frac{2\,\text{Cov}(\alpha,\psi)}{\text{Var}(y)}$	$\frac{\text{Var}(\alpha\times\psi)}{\text{Var}(y)}$	$\frac{\text{Var}(\alpha\times\psi\times t)}{\text{Var}(y)}$
			A. Baseline Model		
	3.03	32.57	-0.02	5.36	1.30
			B. Different Number of Firm Clusters		
$K = 8$	2.43	46.76	-2.18	6.30	2.01
$K = 4$	1.42	38.86	-4.98	4.46	1.39
			C. Different Number of CEO Types		
$L = 4$	1.28	40.25	2.42	4.96	1.47
$L = 6$	1.99	39.98	-4.32	5.48	1.26
			D. Add CEO Tenure and Age Controls		
	1.09	39.56	2.38	5.24	1.71
			E. Require at Least Three Years of CEO Tenure		
	2.37	44.39	0.49	5.91	1.08

Notes: α = CEO effects; ψ = firm effects; Sorting = $2\text{Cov}(\alpha,\psi)$; $\alpha\times\psi$ = complementarities; $\alpha\times\psi\times t$ = time-varying complementarities. Estimates use five firm clusters and five CEO types. Panel D includes a third-order polynomial in CEO tenure and firm age.

Table 6
Robustness Check – Alternative Estimators

Estimator	**Tobin's Q**			**ROA**		
	$\frac{\text{Var}(\alpha)}{\text{Var}(y)}$	$\frac{\text{Var}(\psi)}{\text{Var}(y)}$	$\frac{2\,\text{Cov}(\alpha,\psi)}{\text{Var}(y)}$	$\frac{\text{Var}(\alpha)}{\text{Var}(y)}$	$\frac{\text{Var}(\psi)}{\text{Var}(y)}$	$\frac{2\,\text{Cov}(\alpha,\psi)}{\text{Var}(y)}$
Baseline BLM	3.02%	43.86%	2.89%	3.03%	32.57%	−0.02%
Static BLM	3.64%	32.45%	2.62%	2.29%	37.75%	−1.38%
CRE	—	49.49%	0.07%	—	55.97%	2.32%
FE-HE	11.15%	43.78%	1.16%	12.99%	39.80%	4.92%

Notes: α = CEO effects; ψ = firm effects; sorting = $2\,\text{Cov}(\alpha,\psi)$. Baseline BLM refers to the BLM specification as explained in the main body of the paper. Static BLM refers to the BLM estimator without structurally estimated endogeneity and state dependence (Bonhomme et al. 2019). CRE refers to the Correlated Random Effects estimator (Bonhomme et al. 2023). Baseline BLM, Static BLM, and CRE models are estimated with five firm classes and five CEO latent types, equivalent to the benchmark specification used in the baseline analyses. FE-HE refers to the Two-Way Fixed Effects (AKM) model with firms clustered into five clusters using the same k-means procedure as for BLM. Estimates are heteroscedasticity-corrected using the method proposed by Kline et al. (2020) to account for limited mobility bias.

Table 7
Multinomial Regression of CEO Latent Types on CEO Covariates

	Model 1				Model 2			
Variables	**Type 2**	**Type 3**	**Type 4**	**Type 5**	**Type 2**	**Type 3**	**Type 4**	**Type 5**
Highest Education	0.230***	0.097***	0.063***	0.230***	0.293***	0.114***	0.083***	0.244***
	(0.017)	(0.012)	(0.002)	(0.011)	(0.014)	(0.016)	(0.005)	(0.010)
Ivy Undergraduate	−0.069***	−0.189***	0.120***	−0.003	−0.127***	−0.193***	0.107***	−0.012
	(0.008)	(0.019)	(0.013)	(0.019)	(0.033)	(0.024)	(0.017)	(0.021)
Year Became CEO	−0.005**	−0.014***	−0.020***	−0.008***	−0.004	−0.013**	−0.019***	−0.007***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.001)	(0.002)
Year Born	0.026***	0.009***	0.014***	0.025***	0.025***	0.007**	0.012***	0.024***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.004)	(0.003)	(0.001)	(0.001)
Depression Baby	1.323***	0.797***	−0.013	0.351***	0.950***	0.670***	−0.110	0.293***
	(0.032)	(0.087)	(0.024)	(0.035)	(0.114)	(0.065)	(0.059)	(0.054)
Mover	0.889***	0.202***	0.336***	0.016	1.144***	0.302***	0.424***	0.077*
	(0.035)	(0.025)	(0.014)	(0.015)	(0.197)	(0.067)	(0.059)	(0.037)
Output Exp.	0.037	−0.256***	0.069**	−0.139***	0.028	−0.274***	0.058	−0.147***
	(0.041)	(0.025)	(0.026)	(0.020)	(0.115)	(0.047)	(0.045)	(0.034)
Throughput Exp.	0.282***	0.352***	0.504***	0.019	0.355	0.373***	0.508***	0.019
	(0.047)	(0.023)	(0.036)	(0.067)	(0.265)	(0.074)	(0.094)	(0.085)
Firm Class	—	—	—	—	0.867***	0.339***	0.301***	0.215***
	—	—	—	—	(0.090)	(0.048)	(0.029)	(0.028)
CEO Industry Experience Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,053				2,053			

Notes: Multinomial logistic regression of CEO types on a set of CEO and firm-level covariates. The base outcome is Type 1 (the "lowest" type, sorted on mean Tobin's Q) CEO. Functional experience includes three dummies (Output Experience, Throughput Experience, and Peripheral Experience), with Peripheral Experience excluded. The industry with the most experience includes a set of dummies associated with the industry where the CEO spent the most time in their career (using BoardEx definitions of industry). Standard errors are clustered at the CEO type level and shown in parentheses.
Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8
Reallocation Exercise Results (×100) with Robustness Tests

Allocation	**Mean**	**Median**	**10%-Q**	**90%-Q**	**Var.**	**Skew.**	**Kurtosis**
A: Vary Number of Firm Classes - K = *8*, L = *5*							
Best Allocation	34.15	35.98	27.58	33.80	130.80	0.25	0.80
	(0.61)	(1.26)	(0.99)	(1.67)	(6.65)	(0.04)	(0.15)
Best Reallocation	30.43	32.22	23.73	30.59	122.30	0.26	0.81
	(0.64)	(1.33)	(1.09)	(1.64)	(6.94)	(0.04)	(0.15)
Random Reallocation	8.42	10.29	8.33	9.95	35.10	0.07	0.16
	(0.68)	(1.35)	(1.08)	(1.62)	(5.95)	(0.07)	(0.22)
B: Vary Number of Firm Classes - K = *4*, L = *5*							
Best Allocation	37.01	40.07	33.49	38.25	97.45	-0.05	-0.13
	(0.98)	(2.01)	(1.32)	(1.97)	(10.27)	(0.08)	(0.25)
Best Reallocation	24.68	26.46	20.34	27.73	67.06	-0.05	-0.14
	(0.88)	(1.67)	(1.35)	(2.09)	(8.32)	(0.07)	(0.23)
Random Reallocation	7.59	10.25	8.54	9.89	22.97	-0.05	-0.24
	(0.76)	(1.35)	(1.14)	(1.85)	(5.95)	(0.06)	(0.17)
C: Vary Number of CEO Types - K = *5*, L = *4*							
Best Allocation	26.68	29.98	25.71	29.61	65.94	-0.11	-0.35
	(0.82)	(1.57)	(1.25)	(1.94)	(8.01)	(0.07)	(0.19)
Best Reallocation	20.58	22.55	18.08	23.72	62.52	-0.00	-0.05
	(0.81)	(1.43)	(1.34)	(1.78)	(7.49)	(0.07)	(0.20)
Random Reallocation	5.73	8.04	6.75	7.83	20.10	-0.05	-0.22
	(0.70)	(1.25)	(1.05)	(1.66)	(5.54)	(0.06)	(0.18)
D: Vary Number of CEO Types - K = *5*, L = *6*							
Best Allocation	35.53	36.43	33.63	39.91	104.21	-0.01	-0.09
	(0.65)	(1.66)	(1.26)	(1.45)	(7.01)	(0.05)	(0.15)
Best Reallocation	28.35	28.62	24.82	33.27	87.93	-0.00	-0.07
	(0.70)	(1.55)	(1.27)	(1.65)	(7.13)	(0.05)	(0.15)
Random Reallocation	5.00	7.16	7.01	7.65	16.64	-0.06	-0.26
	(0.72)	(1.33)	(1.11)	(1.62)	(5.48)	(0.06)	(0.18)

Notes: This table reports differences in means, medians, 10% and 90% quantiles, variances, skewness, and kurtosis between Best Allocation, Best Reallocation, and Random Allocation strategies and the baseline outcome under four robustness test specifications. Higher values indicate that the counterfactual has a higher value of the focal statistic than the baseline outcome. All CEO relocations are constrained within industry × size quartile × year cells. All allocations and reallocations are capped at maximum and minimum Tobin's Q and firm-level market capitalization within industry × size quartile × year cells. We display parametric bootstrap standard errors in parentheses (computed using 200 replications).

Table 9
OLS Regressions of Standardized Match Quality on Covariates

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Log Assets	-0.020	-0.028	0.051	-0.027	-0.029	0.046
	(0.030)	(0.030)	(0.036)	(0.032)	(0.031)	(0.038)
R&D Intensity	0.190	0.163	0.034	0.177	0.168	0.074
	(0.204)	(0.204)	(0.257)	(0.203)	(0.203)	(0.259)
R&D Control	0.064	0.062	0.076	0.059	0.060	0.096
	(0.045)	(0.045)	(0.062)	(0.046)	(0.046)	(0.063)
Capital Intensity	1.362***	1.349***	1.330***	1.290***	1.288***	1.314***
	(0.158)	(0.158)	(0.214)	(0.161)	(0.161)	(0.216)
Leverage	-0.587***	-0.568***	-0.485***	-0.550***	-0.543***	-0.459***
	(0.069)	(0.068)	(0.087)	(0.070)	(0.070)	(0.088)
Dividend Payer	-0.118***	-0.113***	-0.103***	-0.103***	-0.102***	-0.090***
	(0.026)	(0.026)	(0.032)	(0.026)	(0.026)	(0.032)
Dividend Yield	1.328***	1.319***	1.282***	1.401***	1.403***	1.407***
	(0.167)	(0.167)	(0.193)	(0.170)	(0.170)	(0.200)
Non-competition Score		-0.056*	-0.010		-0.063**	-0.029
		(0.031)	(0.037)		(0.030)	(0.035)
Firms in Industry within 60 Miles		0.003***	0.004***		0.002***	0.003***
		(0.001)	(0.001)		(0.001)	(0.001)
Board Independence			0.022			0.036
			(0.095)			(0.096)
Board Size			-0.007			-0.005
			(0.007)			(0.007)
Board Busyness			-0.015			-0.011
			(0.017)			(0.017)
Number of Blockholders			0.002			0.004
			(0.006)			(0.006)
Percent Blockholders			0.000			0.000
			(0.000)			(0.000)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State of HQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Size Decile × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	No	No	No	Yes	Yes	Yes
R^2	0.464	0.466	0.486	0.483	0.483	0.506
N	44,699	44,699	26,529	44,699	44,699	26,529

Notes: The table presents the results of an OLS regression of standardized match quality on various covariates. Standardized match quality is calculated using the firm's cluster computed with the BLM reclassification approach, as described in the text. Columns (1)-(3) include firm fixed effects, year fixed effects, state of headquarters fixed effects, and firm size decile × year fixed effects. Columns (4)-(6) additionally include industry × year fixed effects, using the Fama-French 49 industry classification. Standard errors are clustered at the firm level and are shown in parentheses.
Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Online Appendix

Section A provides details on the CEO mobility dataset. Section B explains the construction of key variables. Section C contains details on the identification of the AKM model. Section D details the identification and implementation of the BLM model. Section E explains the implementation of the *k-means* clustering algorithm. Section F details result on the Tobin's Q determinants regressions. Section G presents results of variance decomposition using raw values of Tobin's Q and ROA. Section H describes identifying and estimating the TFP measures of firm performance and displays robustness checks using TFP for variance decomposition. Section I contains additional counterfactuals.

A. Data Description

We construct a comprehensive panel of CEOs of U.S. publically traded firms using information from the Compustat Research Insight CDs. A shorter panel from the same data sources was previously constructed by Fee et al. (2013). The discs include data on each firm's top four executives taken from the firms' U.S. Securities and Exchange Commission (SEC) filings. We use discs from the summer of each year, from 1990 to 2018. The sample excludes financial firms (SIC codes 6000–6999), utilities (SIC codes 4900–4949), and international firms. The sample excludes firms with less than $10 million in book assets (measured in 1990 dollars). Firms that cross the $10 million threshold are included in the sample until one year after they no longer meet the threshold. We follow Fee et al. (2013) and define the CEO as the top manager holding either the title of CEO or the dual titles of Chairman and President. When a firm drops from the panel and later reappears with the same CEO, we assume no CEO turnover occurred during the missing period. We verify CEO transitions manually using information from the firms' financial fillings, Factiva and LexisNexis searches, corporate websites, and press releases.

B. Variable Description

B.1. Firm Variables

Capital intensity – Ratio of reported capital expenditures to total assets.
Dividend payer – Dummy variable equal to one if the firm paid a dividend.
Dividend yield – Ratio of dividends to book equity.
Firm age – Number of years since the firm's original founding date. If the founding date is unavailable, it is proxied using the date of the first financial filing available in Compustat.
Firms in industry within a 60-mile radius – Number of public firms headquartered within a 60-mile radius of the focal firm's headquarters address, within the same Fama-French 10 industry.
Leverage – Ratio of short-term and long-term debt to book equity.
NCA score – Standardized score indicating the enforcement of non-compete agreements (NCA) in each US state.
R&D control – Dummy variable equal to one if the firm reports R&D spending.
R&D intensity – Ratio of reported R&D spending to total assets.
Return on assets (ROA) – Earnings before interest and taxes scaled by total assets.
Standardized match quality – Estimated match quality of the CEO-firm match minus the average within-cluster match quality, scaled by the standard deviation of within-cluster match quality. Clusters refer to firm clusters estimated using BLM.
Tobin's Q – Total market value of equity and debt scaled by book replacement costs.
Total assets – Total book assets.

B.2. Corporate Governance Variables

Board busyness – Average number of other public boards that directors on the board serve on.
Board independence – Ratio of independent directors to the total number of directors on the board.
Board size – Number of directors on the board.
Number of blockholders – Number of investors who own at least 5% of outstanding shares.
Percent of shares owned by blockholders – Percentage of outstanding shares held by blockholders (investors who own at least 5% of outstanding shares).

B.3. CEO Variables

CEO age – Age of the CEO.
CEO Depression Baby – Dummy variable equal to one if the CEO was born in the 1930s.
CEO tenure – Number of years the individual has been the firm's CEO.
CEO functional experience – Dummy variables indicating whether the CEO spent most of their career in an output (sales-oriented), throughput (operations, process, or engineering), or peripheral (legal, accounting, or HR) role.

CEO highest education – Categorical variable indicating the highest education level of the CEO:

- 0: Did not complete undergraduate education
- 1: Completed undergraduate education
- 2: Master's degree
- 3: Ph.D.

CEO industry experience – Dummy variables indicating the industry in which the CEO spent most of their career, using BoardEx industry definitions.
CEO Ivy undergraduate education – Dummy variable equal to one if the CEO completed undergraduate education at one of the Ivy League universities.
Mover CEO – Dummy variable equal to one if the CEO was a CEO of two or more publicly traded firms in our sample.
Year became CEO – The year when the CEO first became a CEO in a publicly traded US firm.
CEO year of birth – The year the CEO was born.

C. AKM Identification

The Abowd, Kramarz, and Margolis (AKM) model decomposes firm performance into CEO and firm effects using a two-way fixed effects framework (Abowd et al. 1999). Identification of these effects requires certain conditions to be met. Below, we present these identification conditions and discuss potential issues that may arise, such as limited mobility bias, which can affect the estimation of variance components.

The performance of firm j managed by CEO i at time t can be expressed as:

$$Y_{it} = \alpha_i + \psi_j + X_{it}\beta + \varepsilon_{it}$$

where:

- Y_{it}: Performance of firm j managed by CEO i at time t.
- α_i: CEO fixed effect.
- ψ_j: Firm fixed effect.
- X_{it}: Vector of time-varying covariates.
- β: Coefficient vector for covariates.
- ε_{it}: Idiosyncratic error term.

C.1. Identification Conditions

C.1.1. Exogeneity.– For OLS to provide unbiased estimates of the fixed effects and coefficients, the error term must be uncorrelated with the regressors:

$$\mathbb{E}[\varepsilon_{it} \mid \alpha_i, \psi_j, X_{it}] = 0$$

This exogeneity condition implies that the idiosyncratic shocks affecting firm performance are not systematically related to the CEOs' movements between firms or the observed covariates. In other words, CEOs do not move based on unobserved factors affecting firm performance. Violating this assumption (e.g., if CEOs move to firms based on unobserved productivity shocks) leads to biased estimates. However, CEOs sorting based on their permanent ability (α_i) or the permanent component of firm performance (ψ_j) does not violate the identifying assumptions.

C.1.2. Sufficient Mobility of CEOs.– CEOs must switch firms sufficiently to provide the variation needed to identify the fixed effects of CEOs and firms separately (Abowd et al. 2002).

- At least some CEOs must manage multiple firms over time.

- The mobility of CEOs across firms creates links between different firms and CEOs, which is necessary to disentangle the individual effects.

If the mobility network is disconnected into $K > 1$ components, fixed effects are identified only within these separate components, up to an additive constant. This means we cannot compare fixed effects across disconnected groups.

Mathematically, if the mobility network $\mathcal{G}$ is disconnected:

$$\mathcal{G} = \bigcup_{k=1}^{K} \mathcal{G}_k, \quad \mathcal{G}_k \text{ are disconnected subgraphs}$$

Then the rank of the design matrix $\mathbf{D}$ is reduced by K, and we have:

$$\text{rank}(\mathbf{D}) = N_\alpha + N_\psi + \text{rank}(\mathbf{X}) - K$$

where N_α is the number of CEO fixed effects and N_ψ is the number of firm fixed effects.

C.2. Limited Mobility Bias

While the OLS estimators of the fixed effects $\hat{\alpha}_i$ and $\hat{\psi}_j$ are unbiased under the exogeneity assumption, limited mobility of CEOs across firms affects the precision of these estimates and can bias the estimated variance components. This issue is known as the *limited mobility bias* (Kline et al. 2020, Bonhomme et al. 2023).

C.2.1. Impact on Variance Estimation.– Due to limited mobility, the estimation error in the fixed effects can be substantial. When calculating the variances of the estimated fixed effects, these estimation errors inflate the variance estimates, leading to an overestimation of the true variances of the fixed effects.

The variance of the estimated CEO effects can be decomposed as:

$$\text{Var}(\hat{\alpha}_i) = \text{Var}(\alpha_i) + \text{Var}(\text{Estimation Error}_i)$$

Similarly, for the firm effects:

$$\text{Var}(\hat{\psi}_j) = \text{Var}(\psi_j) + \text{Var}(\text{Estimation Error}_j)$$

Since the estimation error variances $\text{Var}(\text{Estimation Error}_i)$ and $\text{Var}(\text{Estimation Error}_j)$ are positive and can be large when mobility is limited, the estimated variances $\text{Var}(\hat{\alpha}_i)$ and $\text{Var}(\hat{\psi}_j)$ overstate the true variances $\text{Var}(\alpha_i)$ and $\text{Var}(\psi_j)$.

D. Dynamic BLM Model Implementation

This section outlines the framework for analyzing CEO-firm assignment patterns and matching frictions. Our approach builds on models of matched employer-employee data, allowing us to explore two-sided heterogeneity and the impact of CEO characteristics on firm outcomes (Bonhomme et al. 2019). Specifically, we investigate how mismatches in the CEO assignment process affect firm performance and aggregate market valuations.

D.1. Model Setup

Consider an economy with N CEOs and J firms, where each CEO is employed at a single firm at any given time, denoted by j_{it}, representing the firm with which CEO i is affiliated at time t. CEO-firm assignments change over time, capturing the dynamics of the CEO labor market and reflecting various factors such as CEO mobility, firm demand for specific CEO types, and assignment frictions.

We categorize firms by their class $k(j_{it}) \in \{1, \ldots, K\}$, representing groups with similar characteristics (Bonhomme and Manresa 2015). This classification allows us to capture firm heterogeneity in a tractable way, grouping firms based on common attributes such as size, industry, or productivity levels. CEO types, denoted α_i, may be discrete or continuous, capturing unobserved CEO heterogeneity, such as skill levels, managerial style, and other latent characteristics relevant to firm outcomes.

We are interested in understanding how these CEO and firm characteristics jointly affect outcomes such as firm market valuation and how mismatches—instances where CEO-firm pairs are suboptimal—contribute to performance losses. This framework enables us to quantify the cost of mismatches and to simulate alternative allocations to assess potential improvements in aggregate outcomes.

The model has four time periods. Identification is based on observing performance changes around CEO movement from one firm to another ('mover CEOs'). Conceptually, we represent CEO performance equations differently for movers and stayers.

Firm performance equation for mover CEOs:

$$
\begin{aligned}
Y_2 &= A_{2\mathrm{ma}} + A_{2\mathrm{mb}} + \varepsilon_{2\mathrm{m}} \\
Y_3 &= A_{3\mathrm{ma}} + A_{3\mathrm{mb}} + \rho_{\mathrm{m3|2}} \left(Y_2 - A_{2\mathrm{ma}} - A_{2\mathrm{mb}}\right) + \varepsilon_{3\mathrm{m}} \\
Y_1 &= A_{12} + \rho_{1|2} \left(Y_2 - A_{2\mathrm{ma}}\right) + \varepsilon_1 \\
Y_4 &= A_{43} + \rho_{4|3} \left(Y_3 - A_{3\mathrm{ma}}\right) + \varepsilon_4
\end{aligned}
$$

where $A_{2\mathrm{ma}}$ and $A_{3\mathrm{ma}}$ are the mean performance conditional on the current CEO and firm match in periods two and three for mover CEOs, $A_{2\mathrm{mb}}$ is the endogenous mobility term, and $A_{3\mathrm{mb}}$ is the state dependence term.

Firm performance equation for stayer CEOs:

$$
\begin{aligned}
Y_2 &= A_{2\mathrm{s}} + \varepsilon_{2\mathrm{s}} \\
Y_3 &= A_{3\mathrm{s}} + \rho_{s3|2}\left(Y_2 - A_{2\mathrm{s}}\right) + \varepsilon_{3\mathrm{s}} \\
Y_1 &= A_{12} + \rho_{1|2}\left(Y_2 - A_{2\mathrm{ma}}\right) + \varepsilon_1 \\
Y_4 &= A_{43} + \rho_{4|3}\left(Y_3 - A_{3\mathrm{ma}}\right) + \varepsilon_4
\end{aligned}
$$

where $A_{2\mathrm{s}}$ and $A_{3\mathrm{s}}$ are the mean performance conditional on the current CEO and firm match in periods two and three for stayer CEOs.

Each A is an nl by nk matrix. $A_{2\mathrm{ma}}$ and $A_{2\mathrm{mb}}$ only depend on firm class k and not CEO type l. ρ is a persistence parameter of firm performance and is a scalar.

D.2. Markovian Structure

The dynamic model assumes a first-order Markov process for performance dynamics. Specifically, the firm performance for a CEO in period $t+1$ depend on the previous period's performance Y_{it}, their type α_i, the current firm class k_{it+1}, and the previous firm class k_{it}:

$$
Y_{it+1} = \rho_t Y_{it} + a_{t+1}(k_{it+1}) + b_{t+1}(k_{it+1})\alpha_i + X'_{it+1}c_{t+1} + v_{it} \tag{2}
$$

where v_{it} is an error term.

D.3. Mobility Decision

The probability that a CEO moves to a new firm is a function of current performance Y_{it}, firm class k_{it}, and type α_i. The mobility probability is denoted by:

$$
P(m_{it+1} = 1 \mid Y_{it}, k_{it}, \alpha_i) \tag{3}
$$

where $m_{it+1} = 1$ indicates a job move.

D.4. Identification

In accordance with Assumption 2, we derive the bivariate cdf of firm performance Y_{i1} and Y_{i4} for CEOs who change firms between periods 2 and 3:

$$
\begin{aligned}
&\Pr\Big(Y_{i1} \leq y_1, Y_{i4} \leq y_4 \mid Y_{i2} = y_2, Y_{i3} = y_3, k_{i1} = k_{i2} = k, k_{i3} = k_{i4} = k', m_{i1} = 0, m_{i2} = 1, m_{i3} = 0\Big) \\
&\quad = \sum_{\alpha=1}^{L} G^f_{y_2,k\alpha}(y_1) G^b_{y_3,k'\alpha}(y_4) p_{y_2y_3,kk'}(\alpha)
\end{aligned} \tag{4}
$$

where $G^f_{y_2,k,\alpha}(y_1)$ is the forward cdf of firm performance Y_{i1} in firm class k for a CEO of type α, conditioned on staying in the firm and having firm performance y_2 in period 2.

Similarly, $G^b_{y_3,k',\alpha}(y_4)$ denotes the backward cdf of firm performance Y_{i4} in firm class k' for a CEO of type α, conditioned on staying in the firm and having firm performance y_3 in period 3. The term $p_{y_2y_3,kk'}(\alpha)$ represents the type distribution of CEOs who transition from firm class k to k', generating firm performance y_2 and y_3 in periods 2 and 3.

The joint cdf of firm performance in periods 1 and 2 for CEOs who do not change firms is given by:

$$\Pr\left(Y_{i1} \leq y_1, Y_{i2} \leq y_2 \mid k_{i1} = k_{i2} = k, m_{i1} = 0\right) = \sum_{\alpha=1}^{L} G^f_{y_2,k\alpha}(y_1) F_{k\alpha}(y_2) q_k(\alpha) \tag{5}$$

The identification, assuming known firm classes, relies on exploiting changes in firm performance before and after a CEO moves between firms. Bonhomme et al. (2019) show that identification of mixtures of dynamic models in matched panel data requires at least four observations of, in our contexts, firm performance. In practice, we use several approaches to constructing firm classes to gauge the sensitivity of our results to assumptions concerning the clustering approaches. In principle, the model can be estimated with every firm class representing a unique fixed effect. However, as described in the main body of the paper, the incidental parameter problem and low CEO mobility between firms require us to partition the firms into a finite number of classes.

D.5. Estimation Strategy

Based on the identification strategy, the estimation is implemented using the following multi-step procedure:

D.5.1. Step 1: Firm Classification Using k-means Clustering.– Firms are grouped into K classes using a clustering algorithm based on the distribution of firm performance. The objective is to minimize:

$$\min_{k(1),\ldots,k(J),\mu_1,\ldots,\mu_K} \sum_{j=1}^{J} \left(y_j - \mu_{k(j)}\right)^2 \tag{6}$$

where y_j denotes the observed performance measure (e.g., Tobin's Q or ROA) of firm j, $k(1), \ldots, k(J)$ denotes a partition of firms into K clusters, and $\mu_1, \ldots, \mu_K$ are the mean performance values of the clusters..

D.5.2. Step 2: Expectation-Maximization (EM) Estimation.– Given the estimated firm classes $k(j)$, we estimate the parameters θ by maximizing the following log-likelihood functions:

$$\begin{aligned} &\sum_{i=1}^{N_m} \sum_{k=1}^{K} \sum_{k'=1}^{K} 1\{\hat{k}_{i2} = k\} 1\{\hat{k}_{i3} = k'\} \times \ldots \\ &\times \ln\left(\sum_{\alpha=1}^{L} p_{kk'}(\alpha; \theta_p) f^f_{Y_{i2},k\alpha}(Y_{i1}; \hat{\rho}_{1|2}, \hat{\theta}_{ff}) f^m_{kk'\alpha}(Y_{i2}, Y_{i3}; \hat{\theta}_{fm}) f^b_{Y_{i3},k'\alpha}(Y_{i4}; \hat{\rho}_{4|3}, \hat{\theta}_{fb}) \right), \end{aligned} \tag{7}$$

and

$$\sum_{i=1}^{N}\sum_{k=1}^{K} 1\{\hat{k}_{i2}=k\}\times\ldots \\ \times\ln\left(\sum_{\alpha=1}^{L} q_k(\alpha;\theta_q) f^f_{Y_{i2},k\alpha}(Y_{i1};\hat{\rho}_{1|2},\hat{\theta}_{ff}) f^s_{k\alpha}(Y_{i2},Y_{i3};\hat{\theta}_{fs}) f^b_{Y_{i3},k'\alpha}(Y_{i4};\hat{\rho}_{4|3},\hat{\theta}_{fb})\right). \tag{8}$$

where N_m are is numbers of mover CEOs, $p_{kk'}(\alpha)$ is the probability of type α moving between firms of class k and k', and $f_{k\alpha}(Y_{i1})$ and $f_{k'\alpha}(Y_{i2})$ are the type-specific performance densities.

We estimate $\hat{\theta}_p$, $\hat{\theta}_{ff}$, $\hat{\theta}_{fm}$, $\hat{\theta}_{fb}$ (parameters that define the performance distributions for CEOs across different periods and firm classes) based on (7), and then $\hat{\theta}_q$, $\hat{\theta}_{fs}$ (parameters that model the proportions of CEO types in various context, and the probabilities of CEOs transitioning between firm classes) based on (8) using the expectation–maximization (EM) algorithm in both cases (Dempster et al. 1997). Equations (7) and (8) are standard single-agent correlated random-effects log-likelihood functions.

D.5.3. Step 3: Firm Class Reclassification.– After the EM step, we update firm classes to maximize the model log-likelihood. We adapt the reclassification approach for the static BLM shown in Bonhomme et al. (2019) to the dynamic BLM estimator. More specifically, we estimate and update the firm classes using the following reclassification approach:

$$\begin{aligned}\tilde{k}(j)=\arg\max_{k=1,\ldots,K}\Bigg\{&\sum_{i=1}^{N_s}\mathbf{1}\left(j_{i2}=j\right)\ln\left(\sum_{\alpha=1}^{L} q_k\left(\alpha;\hat{\theta}_q\right) f^f_{k\alpha}\left(Y_{i1};\,\hat{\rho}_{1|2},\,\hat{\theta}_{ff}\right) f^b_{k\alpha}\left(Y_{i4};\,\hat{\rho}_{4|3},\,\hat{\theta}_{fb}\right)\right)\\ &+\sum_{i=1}^{N_m}\mathbf{1}\left(j_{i2}=j\right)\sum_{k'=1}^{K}\mathbf{1}\left(\hat{k}_{i3}=k'\right)\ln\left(\sum_{\alpha=1}^{L} p_{kk'}\left(\alpha;\,\hat{\theta}_p\right) f^f_{k\alpha}\left(Y_{i1};\,\hat{\rho}_{1|2},\,\hat{\theta}_{ff}\right)\right.\\ &\qquad\left.\times f^m_{kk'\alpha}\left(Y_{i2},\,Y_{i3};\,\hat{\theta}_{fm}\right) f^b_{k'\alpha}\left(Y_{i4};\,\hat{\rho}_{4|3},\,\hat{\theta}_{fb}\right)\right)\\ &+\sum_{i=1}^{N_m}\mathbf{1}\left(j_{i3}=j\right)\sum_{k'=1}^{K}\mathbf{1}\left(\hat{k}_{i2}=k'\right)\ln\left(\sum_{\alpha=1}^{L} p_{k'k}\left(\alpha;\,\hat{\theta}_p\right) f^f_{k'\alpha}\left(Y_{i1};\,\hat{\rho}_{1|2},\,\hat{\theta}_{ff}\right)\right.\\ &\qquad\left.\times f^m_{k'k\alpha}\left(Y_{i2},\,Y_{i3};\,\hat{\theta}_{fm}\right) f^b_{k\alpha}\left(Y_{i4};\,\hat{\rho}_{4|3},\,\hat{\theta}_{fb}\right)\right)\Bigg\}\end{aligned} \tag{9}$$

We require that each reclassification improve the model log-likelihood. Since we perform a full EM estimation, the new EM estimates may give a worse likelihood than the estimates from the reclassified model. In that case, we revert to the previous estimates.

E. *K-means Alghoritm*

K-means is an unsupervised machine learning technique that groups observations into similar clusters based on specified variables (Hartigan 1975). In our application, since we have a single observation per firm-year, the *K-means* algorithm is estimated as:

$$\min_{k(1),\ldots,k(J),\mu_1,\ldots,\mu_K} \sum_{j=1}^{J} \left(y_j - \mu_{k(j)}\right)^2 \tag{10}$$

where: y_j denotes the observed performance measure (e.g., Tobin's Q or ROA) of firm j, $k(1),\ldots,k(J)$ denotes a partition of firms into K clusters, $\mu_1,\ldots,\mu_K$ are the mean performance values of the clusters.

We minimize (10) concerning all possible partitions and cluster mean values. This objective function seeks to assign firms to clusters such that the sum of squared differences between each firm's performance and the mean performance of its assigned cluster is minimized.

In their respective specifications, we use the observed values of Tobin's Q and ROA as performance measures for clustering.

F. Firm Cluster Regressions

In this section, we estimate regressions of Tobin's Q on ROA, firm size (*Log of Assets*), R&D Intensity, Capital Intensity, Leverage, Dividend Yield, and Dividend Payer status within each of the five firm clusters. The purpose is to gain further insight into how these clusters differ in terms of key value drivers. We run separate regressions for each cluster and summarize all resulting coefficients in Figure F.1.

The findings reveal three key insights:

1. **Return on Assets (ROA) consistently boosts valuation**. Across all five clusters, ROA exhibits a positive and statistically significant coefficient. However, the effect is largest in Clusters 3–5, indicating that more profitable firms in higher-growth or innovation-oriented clusters receive a greater market premium.
2. **Firm size (*Log of Assets*) has divergent impacts**. While increasing size benefits firms in Cluster 1, it is negatively associated with Tobin's Q in Clusters 2–5. This suggests that, for more dynamic or innovation-focused firms, investors may view excessive scale as limiting flexibility or growth potential.
3. **R&D Intensity and Dividend Policy entail trade-offs**. All clusters show a positive relationship between R&D Intensity and Tobin's Q, with the effect especially pronounced in Clusters 4 and 5. Meanwhile, a higher Dividend Yield generally raises valuations, but simply being a Dividend Payer exerts a negative influence. This trade-off is most pronounced in high-innovation clusters, indicating that reinvesting earnings into R&D often takes precedence over distributing profits to shareholders.

Collectively, these results underscore the importance of profitability, research investments, and strategic resource allocation in shaping firm valuations across the five clusters.

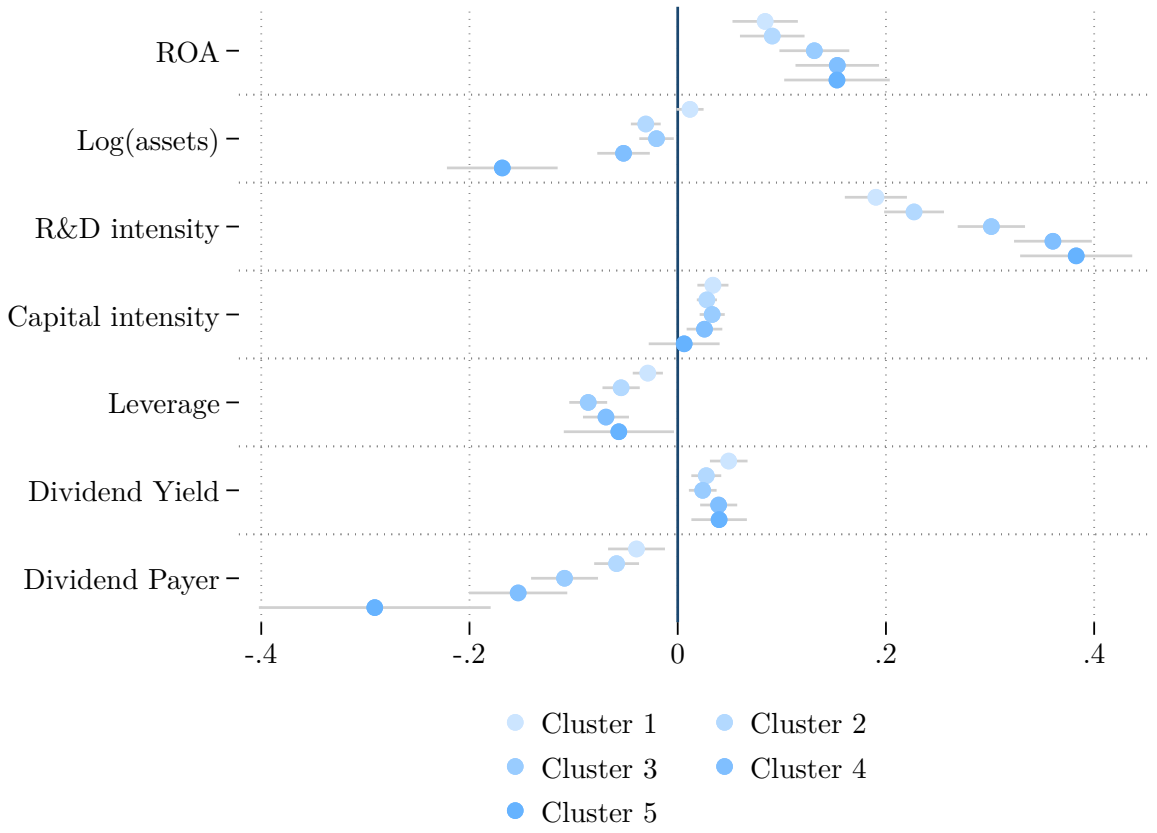


FIGURE F.1. Within-cluster determinents of Tobin's Q. Notes: This figure displays standardized OLS regression coefficients for each covariate, highlighting their relative importance in explaining Tobin's Q across different clusters. Each marker represents a point estimate of the partial effect of the corresponding variable on Tobin's Q, controlling for all other factors in the model. Error bars show the 95% confidence intervals, indicating both the precision of the estimates and whether they differ significantly from zero. Standard errors are clustered at firm level.

G. Alternative Tobin's Q and ROA Variables

Table G.1
Variance Decomposition of Firm Performance Using Raw Variables

	Tobin's Q		**ROA**	
	Estimate	**Std. Error**	**Estimate**	**Std. Error**
Firm Effect (ψ)	34.73%	(0.10)	40.84%	(0.05)
CEO Effect (α)	8.50%	(0.06)	6.84%	(0.03)
Sorting ($2\text{Cov}(\alpha, \psi)$)	5.54%	(0.05)	4.34%	(0.02)
Complementarities ($\alpha \times \psi$)	12.17%	(0.10)	16.23%	(0.09)
Time-varying Complementarities ($\alpha \times \psi \times t$)	4.13%	(0.05)	1.13%	(0.03)
Residual (ε)	34.93%	(0.10)	31.88%	(0.07)
Total	**100%**		**100%**	

Notes: In the table, we present variance decomposition results using raw values of Tobin's Q and ROA. α refers to CEO effects, ψ refers to firm effects, and the covariance between α and ψ represents sorting. $\alpha \times \psi$ denotes complementarities, $\alpha \times \psi \times t$ indicates time-varying complementarities, and ε is the residual. Estimates use five firm clusters and five CEO types. Standard errors are shown in parentheses, computed with 1,000 replications.

H. Production Function Results

In this section of the appendix, we present the variance decomposition results for production function estimates of firm performance. We estimate both the Levinsohn and Petrin (LP) (Levinsohn and Petrin 2003) and Olley and Pakes (OP) (Olley and Pakes 1996) production functions to estimate total factor productivity (TFP). We apply the Ackerberg, Caves, and Frazer (ACF) correction to account for potential functional dependence issues in LP and OP production functions (Ackerberg et al. 2015).

H.1. Cobb-Douglas Production Function

The Cobb-Douglas production function is a widely used specification in empirical analyses of production. In logarithmic form, it is expressed as:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \epsilon_{it},$$

where:

- y_{it} is the logarithm of output for firm i at time t,
- k_{it} is the logarithm of capital input,
- l_{it} is the logarithm of labor input,
- ω_{it} represents firm-specific productivity shocks observed by the firm but unobserved by the econometrician,
- ϵ_{it} is an idiosyncratic error term.

H.2. Olley-Pakes (OP) Approach

The Olley-Pakes method addresses the simultaneity bias arising from the correlation between input choices and unobserved productivity shocks ω_{it}. The key idea is to use investment i_{it} as a proxy for the unobserved productivity. Under the assumption that investment is a strictly increasing function of productivity for a given level of capital, we can invert this relationship:

$$i_{it} = f(k_{it}, \omega_{it}) \quad \Longrightarrow \quad \omega_{it} = f^{-1}(k_{it}, i_{it}).$$

This invertibility allows us to control for the unobserved productivity by expressing it as a function of observable variables. Additionally, the OP approach models productivity as following a first-order Markov process:

$$\omega_{it} = E[\omega_{it} \mid \omega_{it-1}] + \xi_{it},$$

where ξ_{it} is an innovation uncorrelated with past productivity. This framework helps to mitigate biases due to simultaneity and selection in estimating production functions.

H.3. Levinsohn-Petrin (LP) Approach

The Levinsohn-Petrin method extends the proxy variable approach by using intermediate inputs, such as materials m_{it}, instead of investment to proxy for unobserved productivity shocks. This is particularly useful in datasets where investment is infrequent or contains many zero observations. The LP approach relies on the assumption that intermediate input demand is a monotonic function of productivity and capital:

$$m_{it} = f(k_{it}, \omega_{it}) \quad \Longrightarrow \quad \omega_{it} = f^{-1}(k_{it}, m_{it}).$$

By inverting this relationship, the unobserved productivity ω_{it} can be expressed in terms of observable variables. The LP method effectively addresses the endogeneity of input choices and allows for consistent estimation of production function parameters using widely available data on intermediate inputs.

H.4. Ackerberg-Caves-Frazer (ACF) Approach

The Ackerberg-Caves-Frazer method refines the proxy variable approaches by tackling identification issues arising from the simultaneity in the choice of variable inputs and the proxy variable. In the OP and LP methods, labor l_{it} and the proxy variable (investment i_{it} or materials m_{it}) are often determined simultaneously based on the firm's productivity shock ω_{it}, leading to collinearity problems. The ACF approach modifies the timing assumptions of input decisions:

$$\begin{aligned} m_{it} &= m(k_{it}, \omega_{it}), \\ l_{it} &= l(k_{it}, \omega_{it}). \end{aligned}$$

While the proxy function f is invertible in ω_{it}, the simultaneity in labor decisions complicates identification. The ACF method circumvents this issue by adjusting the estimation strategy to separate the effects of labor input from the proxy variable, thereby enhancing the identification of all input coefficients in the production function.

H.5. TFP Estimates

We estimate TFP at an industry level (using Fama-French 49 industry definitions) and include a complete set of year dummies as controls using a value-added production function. All variables are winsorized at 1%/99% and deflated to 1990-equivalent US dollars, consistent with the sample construction for the baseline BLM models. The residual from the estimate shows how much a firm diverges from other firms in the industry regarding productivity while allowing for differential factor loadings in the cross-section.

Table G.1 presents the variance decomposition results. The table shows that the variance decomposition results for both OP and LP estimates align with our baseline results using ROA, which is more closely related to TFP estimates than the forward-looking Tobin's Q.

Table H.1
Variance Decomposition of Firm Performance

	TFP (OP)		**TFP (LP)**	
	Estimate	**Std. Error**	**Estimate**	**Std. Error**
Firm Effect (ψ)	61.34%	(0.70)	63.71%	(0.13)
CEO Effect (α)	0.69%	(0.20)	0.83%	(0.30)
Sorting ($2\text{Cov}(\alpha, \psi)$)	0.92%	(0.02)	-1.32%	(0.07)
Complementarities ($\alpha \times \psi$)	4.29%	(0.20)	3.87%	(0.10)
Time-varying Complementarities ($\alpha \times \psi \times t$)	0.92%	(0.07)	1.03%	(0.10)
Residual (ε)	31.84%	(0.70)	31.88%	(0.70)
Total	**100%**		**100%**	

Notes: In the table, α refers to CEO effects, ψ refers to firm effects, and the covariance between α and ψ represents sorting. $\alpha \times \psi$ denotes complementarities, $\alpha \times \psi \times t$ indicates time-varying complementarities, and ε is the residual. Estimates use five firm clusters and five CEO types. TFP (LP) refers to residual TFP estimated using the Levinsohn and Petrin method, while TFP (OP) refers to the Olley and Pakes method. We apply ACF bias correction in both cases. Standard errors are shown in parentheses, computed with 1,000 replications.

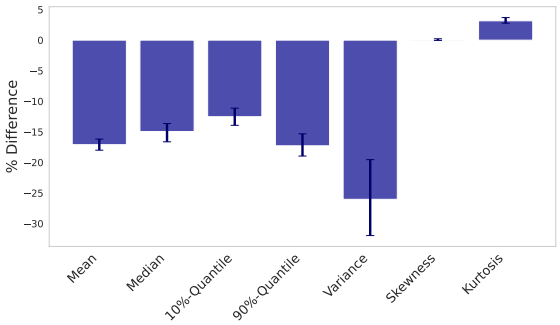
I. Alternative Counterfactual Scenarios

In this section of the Online Appendix, we present the results of alternative counterfactual scenarios aimed at *minimizing* aggregate equity valuations. Comparing these counterfactuals with the best reallocation and allocation scenarios allows us to gain additional insights into how the distribution of CEOs affects aggregate outcomes. Both counterfactual scenarios impose the same constraints as the optimal counterfactuals discussed in the main paper.

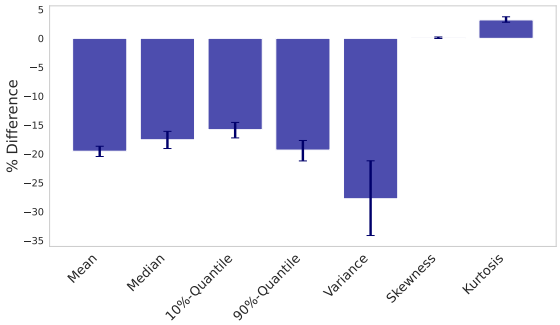
In the first counterfactual, aggregate equity valuation is minimized by reallocating CEOs to firms with the lowest mean match performance. In the second counterfactual, we simulate a CEO distribution that minimizes aggregate equity valuation conditional on estimated firm classes.

Figure I.1 presents the results of these counterfactuals. Panels (a) and (b) illustrate the distributional effects of these scenarios. Both alternative counterfactuals result in aggregate equity valuations over 20 percentage points lower than the baseline estimate. There are minimal differences in the distributional effects of both scenarios; however, they also exhibit reduced variance compared to the baseline. Combined with the results of the optimal counterfactuals, this suggests that optimizing for higher equity valuation comes at the cost of increased performance dispersion. Differences in skewness and kurtosis are minimal, consistent with the optimal counterfactuals, reflecting the constraints used in the optimization process.

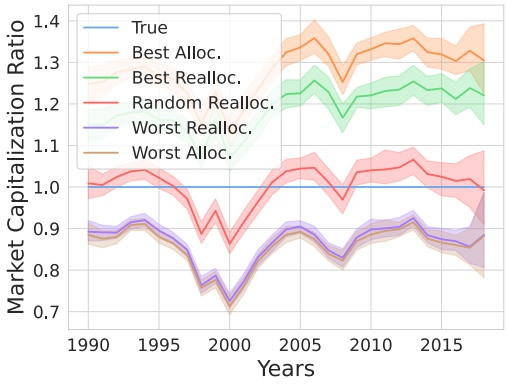
Panel (c) shows the time series of all counterfactual outcomes relative to the baseline. Both alternative counterfactuals display cyclicality, consistent with the behavior of optimal counterfactuals. The contrast between the optimal and the worst possible allocation is striking, highlighting that aggregate equity valuation can vary by approximately 50 percentage points compared to the baseline, depending on how CEOs are matched with firms. This further emphasizes the aggregate effects of CEO-firm matching.



(a) Worst Reallocation



(b) Worst Allocation



(c) Time Series of Aggregate Equity Market Valuations

FIGURE I.1. Effects of alternative counterfactuals. Notes: Panels (a) and (b) show the differences in key metrics (mean, median, 10% and 90% percentiles, variance, skewness, and kurtosis) of aggregate equity market capitalization between various reallocation strategies and the original sample. Panel (c) shows the time-series evolution of aggregate equity valuations across different counterfactuals, with baseline outcome normalized to 100%. Higher values indicate that the counterfactual has a higher expected aggregate market capitalization within focal key metric. All CEO moves are constrained within industry × size quartile × year cells. Allocations and reallocations are capped at maximum and minimum Tobin's Q and firm-level market capitalization within industry × size quartile × year cells. Optimal allocation is based on estimated firm classes from the reclassified BLM. We display parametric bootstrap 2.5%–97.5% quantile bands in error brackets and shaded regions computed using 200 replications.

Online Appendix References

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