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AGING AT THE VERY TOP

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ABSTRACT

This paper documents that the age at which CEOs are appointed has risen sharply over the past several decades. Using newly assembled data covering a wide set of firms, we show that this increase is concentrated outside the largest listed firms and driven primarily by longer and more diverse external career paths prior to CEO appointment. These patterns are difficult to reconcile with explanations based on demographics, schooling, or tenure, and are instead consistent with a matching framework in which rising demand for generalist human capital leads firms to trade off peak ability for accumulated experience. We investigate the forces behind this shift. Using variation in consulting networks, we establish that firms place greater weight on diversified managerial experience as operating environments have become increasingly uncertain and complex. We also provide evidence for a supply-side response in which prospective CEOs broaden their skill portfolio as demand for generalist skills rises.

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1 Introduction

We uncover a striking evolution in the age of CEOs over the last decades and study its underlying forces. Between 2000 and 2023, the average age of CEOs in the United States has increased by ten years (Figure 1), five times the increase for the college-educated labor force. Similar patterns have emerged in Europe. Longer tenures or entrenchment cannot fully explain this trend, as age at appointment has risen almost as sharply from 47-48 to 55 over the same time span. Using comprehensive data on CEOs alongside their employment histories, we consider a variety of potential explanations and conclude that the patterns we observe are indicative of firms' increased demand for generalist human capital. We also discuss how executives alter their career paths in response to these changes in skill demand.

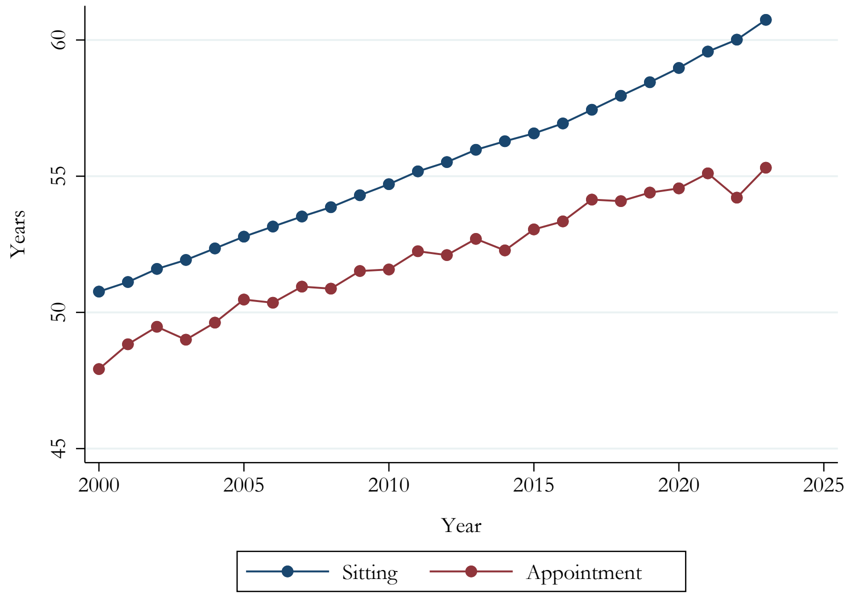
We document a number of important changes in the career profiles of managers and executives over the sample period. First, individuals who eventually become CEOs accumulate roughly ten years more external experience compared to 2000, whereas internal experience has remained almost unchanged during this period. This pattern holds true both for external and internal appointments, and is particularly pronounced in smaller firms. Second, we consider the composition of this additional experience. At appointment, today's CEOs have held a larger number of positions across more firms and industries than their counterparts in 2000. Third, turnover has increased with shorter spells in each position. Fourth, the increase in the number of positions dominates the faster turnover, so that CEOs' employment histories have become longer, leading to the increased age of CEOs upon appointment.

We evaluate several potential explanations for this aging of corporate leadership, including demographic trends, agency conflicts, and rising concentration, but conclude that none of these can account for the magnitude of the observed age increase. We then turn to changes in market forces that affect the matching of firms and CEOs. To formalize this mechanism, we develop a many-to-one matching model with the following ingredients. Workers have multidimensional skills: they vary in both age-adjusted ability (which peaks at mid-career) and experience (which increases in age). Firms differ in productivity (related to firm size) and have multiple positions with hierarchically ranked productivity levels. We provide conditions on the shape of the productivity functions under which the equilibrium assignment is consistent with the key empirical patterns. Our main result characterizes how an increase in the value of experience shifts top positions toward older workers, especially at lower-productivity, or smaller, firms. We further show that, under mild assumptions, CEOs in smaller firms are younger on average.

Aging at the very top of the corporate ladder can have substantial effects on a variety of firm outcomes, e.g., because of older CEOs' distinct management style (Bertrand and Schoar, 2003; Schoar and Zuo, 2016) or preferences (Jenter and Lewellen, 2015). A key takeaway from this literature is that CEO age is negatively associated with business dynamism and firm risk.[1] Thus, our findings reveal not only how firms adjust to changing economic conditions, but also how these decisions in turn shape broader trends. Because our dataset spans a much wider universe than the

[1] See Appendix Section D for a detailed discussion of the nexus between CEO age and firm-level outcomes.

Figure 1: Average CEO Age Over Time



Notes: The plot shows the average age of CEOs over time, separately for sitting CEOs and CEOs at appointment. The sample includes 50,510 CEOs in the United States, for which we obtain information from BoardEx.

large, listed firms typically studied, we can document systematic differences in CEO hiring patterns across the firm size distribution. Smaller firms offer fewer opportunities to accumulate generalist experience internally and rely more heavily on external hiring, whereas larger firms can cultivate such skills through internal assignments. Since smaller firms tend to be younger and account for a disproportionate share of job creation and innovation (Haltiwanger et al., 2013), and since today's large firms began as small firms, understanding how executive skill demand shapes leadership selection at smaller firms provides crucial insights for aggregate economic performance.[2]

We use granular data from BoardEx and LinkedIn to track firms' hiring decisions and executives' career trajectories in the United States. To shed light on the rising value of experience, we focus on two dimensions along which firms' operating environment has evolved. First, economic uncertainty has increased (Baker et al., 2016). Second, the CEO role has become more complex, as evidenced by firms simultaneously expanding across geographies and business lines while navigating a growing set of regulatory constraints (Dessein and Santos, 2006; Pan, 2017). These forces can lead firms to seek leaders with generalist skills, which are more closely tied to accumulated experience than to raw ability. As executives require longer career paths to build such diverse capabilities, firms appoint older CEOs.

In support of these hypotheses, we first establish that in the face of rising industry-level uncertainty, firms demand different profiles in their prospective CEOs. A challenge in relating industry-level uncertainty to the demand for CEO characteristics is that uncertainty itself may be

[2]These considerations are particularly concerning in light of decreasing firm entry rates, which have been traced back to increased entry costs (Kozeniauskas, 2025) as well as demographic changes (Hopenhayn et al., 2022).

correlated with the pool of available CEO candidates. To address this, we use spatial variation in the availability of generalists in the form of strategy consultants. This strategy allows us to study the differential response in CEO appointments to industry-level shocks across space, while controlling for time-varying geographic and sectoral heterogeneity. Exploiting plausibly exogenous variation in travel time to the offices of the top three strategy consulting firms—stemming from office openings and air route expansions—we find that demand for generalist skills in response to greater industry-level uncertainty increases, leading firms to appoint older CEOs whenever other generalists are less readily available. The results are stronger for small firms where generalist human capital is more difficult to accumulate internally, consistent with the larger gradient in external experience of small firms' CEOs over time that we document. Therefore, the value added of generalist consultants as substitutes for experience is arguably higher for small firms.

To assess how overlapping trends in the complexity of organizational structures may have contributed to the rising value of generalist human capital, we extend our identifying framework using the following proxies: business diversification (measured by the number of distinct VP-level roles within firms), spatial diversification within the U.S., and trade-induced variation in economic complexity. Across all these measures, we find qualitatively similar results.

Next, we investigate how executives have adapted their career strategies in light of firms' growing demand for generalist skills. One interpretation of prospective CEOs' increased turnover across positions, firms, and industries is that they respond strategically to the increasing premium for broad managerial capabilities. To explore this hypothesis, we start from the idea that executives learn about career-enhancing opportunities through professional networks. If the acquisition of generalist skills is revealed to be an important career ingredient, they may become more willing to accept lower-level positions and reduced pay in the short run in exchange for building a generalist skill set that enhances their long-term career prospects.

To test this, we study changes in employees' career paths after they learn about CEO appointments of former peers. Individuals who worked contemporaneously at the same firm and seniority level as well as in the same metro area with the newly appointed CEO (of another firm) respond by increasing their own job mobility more strongly than colleagues who shared the same firm and seniority level but were located in different metro areas. On average, these treated individuals accept reduced compensation in the short run in exchange for the presumed value of additional experience. This is reflected in the higher prevalence of downward switches across firms—where employees move to positions at lower seniority levels—but also in more frequent transitions across industries. These responses to information shocks are stronger for coworkers with longer shared tenure, for those that exhibit more mobility on the way to the top, and for workers in small firms.

Taken together, our findings support the idea that both the demand and the supply of generalist skills have shaped the age profile of CEO appointments since the early 2000s. We leverage this insight to decompose the overall age trend and show that around 37% of the variation in CEO age can be attributed to sectoral changes, reflecting changes in skill demand. A further 28% can be explained by geographical factors, capturing supply-side forces. The remaining share can be traced back to the interaction of these two dimensions.

Our analysis makes the following contributions. First, we provide novel systematic documentation of CEO aging trends and their relationship to changing career patterns, and link them to the increasing value of generalist human capital. Second, we provide a matching model that rationalizes and interprets these patterns. Third, we develop identification strategies that separately estimate demand- and supply-side factors contributing to these changes. Fourth, we demonstrate how professional networks transmit information about optimal career strategies in the market for CEOs, leading to widespread behavioral changes among executives.

Related Literature: Our paper speaks to several strands of the literature. A number of studies have explored the changing demand for CEO skills over time. Murphy and Zabojnik (2004, 2007) and Frydman (2019) link the rise in executive compensation and the increasing prevalence of external CEO hiring during the end of the 20$^{\text{th}}$ century to a shift toward generalist skills.[3] Custódio et al. (2013) document a pay premium for generalist CEOs, while Adams et al. (2018a) highlight the importance of diversified skill sets among board members.

Other research has more directly analyzed shifts in skill requirements using data from job postings and interviews. Kaplan and Sorensen (2021) show that CEOs, compared to other executives, have higher levels of general ability, execution orientation, strategic focus, and analytical skills. Following the financial crises, Decressin et al. (2025) document a shift away from interpersonal skills toward a stronger emphasis on execution orientation, which they find to be positively correlated with firm performance. Similarly, Deming (2021) emphasizes the increasing importance of decision-making skills, and Deming (2017) and Fuller et al. (2021) show that social skills have become more valued in the labor market. Kaplan and Sorensen (2021) argue that too much weight is placed on social skills in the selection of CEOs. Moreover, Deming and Silliman (2024) report that higher-level skills, such as the ability to allocate individual tasks, have gained increasing importance over time.[4]

The evolution of CEO skill demand has frequently been examined in conjunction with changes in firm characteristics, using two-sided matching models. This literature has sought to explain rising executive compensation through assortative matching of managerial talent and firm size (Gabaix and Landier, 2008; Terviö, 2008). This relationship may be driven by the multiplicative

[3] A large literature discusses the role of CEO hiring patterns, as the share of internal compared to external appointments is informative about frictions in this labor market. In the S&P 500, the majority of CEOs are promoted internally (Cziraki and Jenter, 2021). Relatedly, Hamori and Kakarika (2009), Koch et al. (2017) and Lyman et al. (2025) underscore the importance of internal work experience for CEOs of large listed organizations. In contrast, Gompers et al. (2023) examine private equity buyouts and find that most CEOs are hired externally. Other studies also point toward a competitive market for CEOs. Cappelli (2010) and Cappelli and Hamori (2004) date the shift from internal development programs toward external hiring to around 1980. Bai and Mkrtchyan (2023) show that outside hiring generates productivity gains, and Gao et al. (2015) document that companies increase executive pay after managers leave for other firms.

[4] A related literature has focused on variation across individuals by exploring how managerial styles influence firm outcomes (Bertrand and Schoar, 2003; Schoar and Zuo, 2016; Bennedsen et al., 2020; Nguyen, 2025). These styles are malleable, shaped by early-career experiences (Schoar and Zuo, 2017), and vary with firms' ownership and governance structures, e.g. in family firms (Bertrand and Schoar, 2006; Bertrand et al., 2008; Mullins and Schoar, 2016). Fee et al. (2013) complement this work by demonstrating that boards deliberately select candidates who implement strategies aligned with their own objectives.

impact of managerial skills in large firms (Edmans et al., 2009), or by the fact that larger firms pay efficiency wages to discourage shirking, as the signal of managerial quality is more diffuse (Gayle et al., 2015). Using these models, closely related to our findings, Gayle et al. (2015) emphasize the importance of general human capital in the CEO market, while Pan (2017) highlights the nexus between firm scope (i.e., diversification) and CEO experience in relevant industries. Dow and Raposo (2005) model CEO selection based on firms' strategic needs, showing how demand for change management capabilities shapes the matching of CEOs to firms. We demonstrate that such adaptive capabilities are tied to accumulated generalist experience, explaining why firms requiring strategic flexibility appoint older rather than younger CEOs.

Our work further contributes to the literature that examines how technological and institutional changes influence human capital accumulation and how human capital is traded in labor markets. This debate has been shaped by the distinction between firm-specific and general human capital (as introduced in Becker, 1964). Generalist skills are often measured by work experience in multiple firms and industries, capturing skills that are transferable across different organizations or roles (Custódio et al., 2013). Conversely, as noted by Lazear (2009), few skills are inherently firm-specific, but many combinations of skills or skill requirements are. Following this reasoning, the extent to which human capital is firm-specific or general mainly depends on market thickness, as documented in Sauvagnat and Schivardi (2024) for the market for executives. Beyond the firm level, the evidence points toward human capital that is specific to industries (Neal, 1995), occupations (Sullivan, 2010), and individual tasks (Gibbons and Waldman, 2004). Similarly, Dessein and Santos (2006) investigate firms' adaptability—defined as the level of discretion granted to workers—in an environment with uncertainty and task bundling. They show that more adaptive organizational structures, in response to increased uncertainty, tend to feature more bundled jobs, thereby increasing the demand for generalists.

Our supply-side channel also resonates with a broader literature that highlights the importance of on-the-job human capital accumulation in driving wage growth (see, e.g., Adda and Dustmann, 2023; Jedwab et al., 2023). In this context, firm characteristics have been shown to play a crucial role in shaping human capital development. These characteristics include coworkers (Jarosch et al., 2021; Nix, 2020; Gong et al., 2018), export shares (Macis and Schivardi, 2016), firm size (Arellano-Bover, 2024), and firm connectivity (Del Prato, 2023). Arellano-Bover (2024) documents large differences in firms' abilities to offer on-the-job learning opportunities, emphasizing the importance of general human capital. In line with this, Groes et al. (2015) find that occupational mobility follows a U-shaped pattern with respect to wages, suggesting that higher earners are more likely to transition to other jobs.

Lastly, we add to the literature on age trends in high-skill professions and their consequences. Older CEOs' management styles reflect their different incentives compared to their younger counterparts, including distinct wealth concerns and career horizons (Dechow and Sloan, 1991; Antia et al., 2010), future career concerns (Li et al., 2017), and different compensation structures involving pensions and deferred benefits (Sundaram and Yermack, 2007). Empirically, CEO age has been shown to be negatively related to firm growth and innovation, for instance, in terms of investment and sales (Acemoglu et al., 2022a), firm value and operating performance (Cline and Yore, 2016), R&D expenditure (Serfling, 2014; Li et al., 2017), artificial intelligence (AI) usage (Yotzov et al., 2026), and radical innovation (Acemoglu et al., 2022a). Yet, given that managers can shape firms' risk exposure (Schoar et al., 2024), older CEOs tend to increase firms' diversification across business segments (Serfling, 2014), while younger CEOs take on more risk by pursuing acquisitions (Yim, 2013), aggressive takeovers (Levi et al., 2010), and strategic restructuring (Li et al., 2017).[5] Even though the role of CEO age in shaping firm-level outcomes has received widespread attention, changes in age structures over time have been relatively understudied. One reason may be the lack of comprehensive panel data covering firms beyond the largest ones, for which CEO age has remained relatively similar over the last century.[6]

Similar trends appear beyond corporate leadership: the average age of scientists has been increasing over the past decades, particularly among grant winners.[7] Daniels (2015) attributes this trend to longer pre-grant career paths, while Fons-Rosen et al. (2023) point to slower hiring and delayed retirements. Jones (2010) and Jones and Weinberg (2011) show that both the age at which Nobel Prize-winning discoveries are made and the age at which the prize is awarded have increased over the course of the 20$^{\text{th}}$ century. In many fields, such as the judiciary, individual performance tends to decline with age (Ash and MacLeod, 2024). One possible explanation is that aging is associated with changes in cognitive abilities (Salthouse, 2012; Waelchli and Zeller, 2013; Singh-Manoux et al., 2012), physiological capacity, and various forms of human capital (MacLeod, 2016). Additionally, older individuals may experience motivational shifts, placing greater emphasis on maintenance and loss prevention over growth (Ebner et al., 2006), and may tolerate lower effort.

Aging professionals can also have effects on others. Ash and MacLeod (2024) identify negative productivity spillovers to younger judges, likely due to shifts in workload distribution within teams. A higher concentration of older workers has been shown to hinder younger workers' career outcomes in local labor markets (Mohnen, 2025) and slow down younger colleagues' promotion prospects in internal labor markets (Bianchi et al., 2023). These dynamics have important distributional consequences along demographic dimensions, including age (Bianchi and Paradisi, 2024) and gender (Arellano-Bover et al., 2024). The evidence in d'Astous et al. (2025) indicates that older workers may be productive complements to younger workers, especially in industries with high physical capital intensity.

[5] We provide an extensive summary of the literature in Appendix Section D.1.

[6] Taussig and Joslyn (1932) report that the median age of American business leaders in the early 1930s ranges between 50 and 54. Warner et al. (1967) states that the typical management hire in the early 1950s was around 50 years old. Frydman (2019) tracks the 50 largest US corporations over time, for which CEO age has remained almost unchanged throughout the second half of the 20th century. For CEOs in the Fortune 100, Cappelli et al. (2024) find a slight decline in average CEO age during 1980 and 2000, followed by a rebound by 2020. For European countries, analyses based on small samples of very large listed companies yield mixed conclusions. While Freye (2010) and Sluyterman and Westerhuis (2022) find no clear age trend in CEO age at appointment throughout the second half of the 20$^{\text{th}}$ century for Germany and the Netherlands, respectively, Adams et al. (2023) document a decline in the UK of about five years.

[7] https://grants.nih.gov

2 Data

The main empirical analysis relies on data on CEOs from BoardEx and employment biographies from Revelio Labs, which we combine with company-level covariates and information on the availability of strategy consultants. This section contains details on the data.

BoardEx: We use CEO data from BoardEx, a product offered by *Delinian*. This dataset provides comprehensive details on executives' employment histories and demographic characteristics. While BoardEx includes individuals from both North America and continental Europe, our analysis focuses primarily on the United States. We define CEOs as individuals with the job title "CEO" categorized as "Executive Director," following BoardEx's classification. This yields a sample of 50,510 CEOs in the United States (17,962 in Europe) with available age data, of whom roughly 22% (25%) are appointed at Compustat (listed) firms.

For the descriptive analysis, we transform the data into a panel, capturing employment status as of January 1st each year. In cases of overlapping employment periods, we prioritize more senior positions and those with earlier start dates.[8] Following the literature (Cziraki and Jenter, 2021), we exclude CEO appointments of less than 12 months. We focus on a CEO's first appointment per firm, omitting CEO reappointments and subsequent board appointments at the same firm. Internally appointed CEOs are defined as those employed by the firm in some other capacity during the last observation prior to their appointment; all others are considered externally appointed.[9] Among internally appointed CEOs, we further distinguish those who initially joined the firm at a managerial level and those who entered at lower levels.

Summary statistics for the descriptive analysis for the U.S. are shown in Table A1, Panel A.[10] The average CEO age at appointment is 52. Around 20% of CEOs are appointed internally, split evenly between those first entering the firm at the managerial level and those joining below it. Given the prevalence of private firms in our sample, the median firm has 141 employees. Importantly, the dataset extends well beyond the S&P 500 or S&P 1500 firms covered in most prior work, and the resulting firm characteristics differ accordingly. For example, in the S&P 1500 the average CEO age at appointment is 54, around 50% of CEOs are appointed internally, and the median firm employs nearly 4,000 workers.[11]

[8]The seniority ranking applied is as follows (in descending order): *CEO*, *Other Executive Director*, *Senior Manager*, *Supervisory Director*, and *All Other Employees*. Throughout this paper, we define seniority as an individual's hierarchical position within a firm, distinguishing it from the concept of relative tenure compared to coworkers, as used for instance in Buhai et al. (2014).

[9]Therefore, external insiders, i.e., returning executives who account for less than 4% of all appointments, are classified as externally appointed.

[10]For the remaining analysis on the U.S., we start with a slightly larger sample of executives. Focusing on age at appointment, we calculate average CEO age at the firm-year level between 2000 and 2022, thereby accounting for Co-CEOs, individuals appointed CEO at multiple companies, and those who held the same position multiple times at the same company. We then merge this variable with the company-level variables described below. Summary statistics for this sample are reported in Table A1, Panel B.

[11]Using an alternative data preparation approach in Appendix Section E, the share of internally appointed CEOs increases to 32% for the overall sample, 68% for the S&P 1500, and 73% for the S&P 500. The latter figure is very close to

Employment Biographies: We also utilize employment biography data provided by Revelio Labs, which compiles this information by scraping LinkedIn profiles. The dataset encompasses employment details for nearly 500 million workers across approximately 1.8 billion employment spells. The linked employer-employee data include the start and end dates of employment spells, alongside a seniority ranking based on job titles ranging from 1 (lowest) to 7 (highest).[12] Revelio Labs also imputes salaries for each employment spell. The data cover the period from 2019 to 2023 but are backfilled, implying that we can observe employment spells from earlier periods to the extent that they are reported by the respective individual.

Compared to BoardEx, this dataset offers the advantage of including information on rank-and-file employees. Another key strength of the data is that it assigns individual employment spells to 145 metropolitan statistical areas (MSAs). We use this information to determine the headquarters of the firms included in BoardEx. For this purpose, we define the location of a firm's headquarters as the modal MSA of its executives in the two highest seniority levels, provided they are at least at seniority level 4, which corresponds to the managerial level. Among other variables, we compute firm-level employment as the number of individuals employed at a firm at the beginning of each year. To ensure that time trends are not driven by increased reporting in later periods, we exploit the overlap of our dataset with Compustat and scale the measure by the year-specific ratio of average employment in Compustat to our employment counts.

To merge the employment biographies with BoardEx at the firm level, we proceed as follows. First, we clean company names on both sides by applying standard data normalization techniques and removing previous company names. Second, we consecutively merge on ISIN and CIK, manually verifying the merges since these identifiers can change over time. Third, for the unmerged companies, we perform an exact merge on company names. Fourth, we apply a fuzzy merge algorithm based on *term frequency-inverse document frequency* on the remaining unmerged company names. For the employment histories, we retain only firms with more than 10 employment spells in Northern America. The procedure is highly efficient, as it vectorizes the data into a sparse matrix and fits a k-nearest neighbors algorithm. We then randomly select 1,000 matches, which we manually classify into good and bad matches. In this way, we determine a precision threshold of 0.85, at which 95% of the matches can be considered accurate.[13] Overall, we are able to merge firm-level details for 65% of the CEOs in the BoardEx sample.

Company-Level Covariates: We complement the individual-level data with firm-level information. We obtain annual balance-sheet information from Compustat, which we merge with the U.S. BoardEx data using CRSP identifiers. We focus on the balance-sheet items revenue (*revt*) and employment (*emp*). For both variables, we drop negative values and winsorize below the 1$^{\text{st}}$ and above the 99$^{\text{th}}$ percentile.

Cziraki and Jenter (2021), who find that 72% of S&P 500 CEOs are promoted internally. In Appendix Section E, we also document that our main descriptive results are insensitive to the data processing approach used.

[12] For examples, see here.

[13] For additional detail on the fuzzy merge algorithm, we refer to Van Dijcke et al. (2023).

We then construct symmetric growth rates γ_{jt} accommodating entry and exit as $\gamma_{jt} = 100 \times \frac{x_{jt}-x_{jt-1}}{0.5(x_{jt}+x_{jt-1})}$, where x_{jt} is the variable of interest for firm j at time t. Given the non-negativity restriction, this implies values between -200 and 200. Using these growth rates, we construct volatility measures defined as the cross-sectional standard deviation of γ_{jt} within NAICS-4 industries.

MSA-Level Data: Our identification strategy in Section 5.1 exploits plausibly exogenous variation in the supply of (former) strategy consultants, focusing on the presence of MBB (*McKinsey & Company*, *Boston Consulting Group*, and *Bain & Company*) offices across the United States between 2000 and 2023. The data on office expansions are obtained through manual searches of the *archive.org* platform and cross-checked for the years 2001 to 2013 with information from Weinstein (2025).

The identification also leverages information on flight times between MSAs. We use the *28DS - T-100 Domestic Segment Data (World Area Code)* provided by the *Bureau of Transportation Statistics* (BTS), which include monthly information on flight connections by carrier in the United States from 1990 onwards. We restrict the data to regular flight connections, which we define as all scheduled direct flights with a flight distance exceeding 50 miles and, per year and direction, more than 1,000 passengers and at least one departure per week. We then aggregate all flights to the MSA-year level and calculate the travel time as the average ramp-to-ramp time across all flights between two MSAs in that period.[14]

3 Descriptive Evidence and Potential Explanations

3.1 Aging at the Very Top

In Figure 1, we document a consistent increase in CEO age since the year 2000. For the overall sample of CEOs contained in BoardEx, average age rose by more than 10 years to 61 in 2023. Average age at appointment also increased noticeably from less than 48 to 55 years, suggesting that the aging trend is unlikely to arise solely from longer tenures, later retirement, or CEO entrenchment. The age increase is pervasive and not limited to specific segments of the distribution of newly appointed CEOs. Figure A1, Panel (a), plots the quartiles of the age distribution over time, revealing an upward shift throughout the sample period. Similarly, in Panel (b), we observe the same trend for all CEOs, irrespective of their order of appointment.

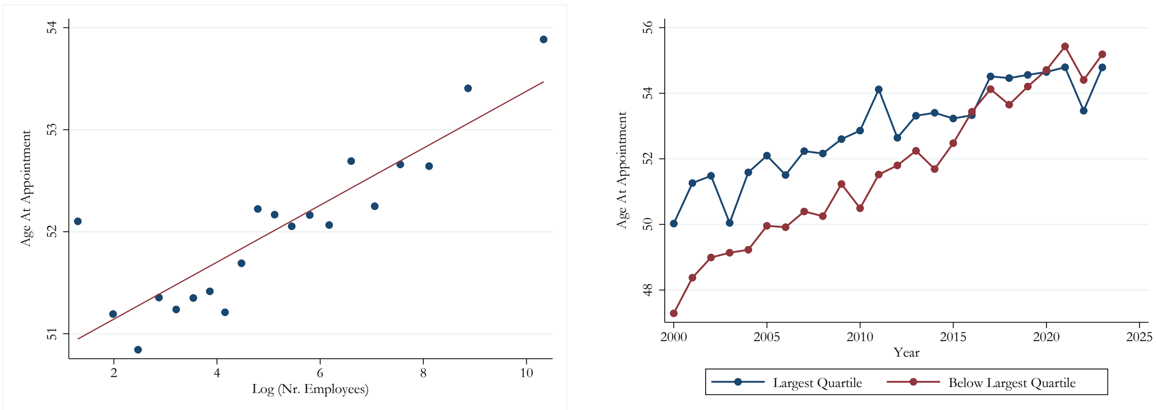
Next, we examine heterogeneity in the CEO age trend across the firm size distribution, with results shown in Figure 2. The binscatter plot in Panel (a) demonstrates that average CEO age at appointment and firm size exhibit a strongly positive relationship. In Panel (b), we separately plot age at appointment for firms in the largest size quartile and for smaller firms, showing that the latter group is primarily responsible for the overall age increase.

[14] To assign airports to MSAs, we obtain airport coordinates from the *Master Coordinate Table* provided by the BTS and map these coordinates into core-based statistical areas (CBSAs) using the 2013 version of the *TIGER/Line Shapefiles*. We then manually aggregate the CBSAs into the MSAs as defined by Revelio Labs.

Figure 2: CEO Age at Appointment and Firm Size (Number of Employees)

(a) Binscatter Average CEO Age vs. Firm Size

(b) Average CEO Age over Time by Firm Size



Notes: Panel (a) shows a binscatter plot of age at appointment against the natural logarithm of the number of employees. Panel (b) plots age at appointment separately for those in the largest firm quartile and for those in the other three quartiles. Size quartiles are generated separately by year.

To place these findings from our sample period starting in 2000 into historical perspective, we draw on data on 1,000 executives from the *Great American Business Leaders of the 20th Century* database. As we show in Figure A2, the average CEO age in this sample barely changed between 1940 and 1990. However, this is due to a combination of an increase in age at appointment alongside a decline in tenure. Moreover, in contrast to the bulk of the literature (e.g., Frydman, 2019), we observe an increase in average CEO age during the 1990s, possibly due to the fact that the number of annual observations is substantially larger in our data and, thus, contains a larger number of smaller firms.

3.2 Potential Explanations

One explanation for the CEO age trend is that it reflects an efficient market response to changes in the importance and availability of experience among CEOs. Given that many features of firms and the economy more broadly have changed since 2000, we first consider a range of potential alternative explanations. This section reviews several competing narratives and argues that none of these convincingly account for the documented age patterns.

CEO Aging as a Demographic Inevitability: One possible explanation centers on demographic shifts, which have accompanied the age increase among executives. We present several pieces of evidence that suggest that demographics can only account for a small fraction of the CEO aging trend. First, as we report in Figure A3, Panel (a), the age increase among CEOs in the United States is more than three times that of the overall labor force. This gap is even more pronounced when comparing to college-educated workers, who arguably constitute the relevant baseline population. Second, we document a similar increase in CEO age across a sample of countries in Europe (Figure A4), despite large differences in demographic trajectories and the timing of cohort sizes such as the baby boomers. Relatedly, our long-run analysis suggests that average CEO age has remained stable for most of the 20th century, in spite of the substantial demographic changes during this period. Third, we further examine the role of the age distribution in driving the aging trend by leveraging the cross-country variation in our data, with results reported in Figure A5. Specifically, we regress average CEO age by year and country on the share of the labor force within each 10-year age bin, controlling for country and year fixed effects (Panel b). Multiplying the estimated coefficients by the change in each bin's share over time (Panel a) and summing across bins, we find that shifts in the labor force age distribution account for 1.9 years of the overall increase in CEO age.

Optimal Response to Managerial Entrenchment: A second competing explanation refers to possible increases in rent seeking or entrenchment by CEOs. While entrenchment may directly raise the age of sitting CEOs by extending their tenure, our focus is on age at appointment, which is unaffected by this mechanism. However, entrenchment may also impact age at appointment indirectly through an anticipation channel. Specifically, boards of directors may attempt to prevent entrenchment by appointing older CEOs, who are potentially easier to replace after a shorter tenure. An empirical implication of this conjecture is that age at appointment and tenure should become more (negatively) correlated over time. Figure A6 examines the joint distribution of age at appointment and tenure by plotting their time-varying correlation. As expected, the two variables are negatively correlated, but the association attenuates throughout our sample period, which contradicts the hypothesis.[15]

Rising Market Concentration: A third potential explanation is that rising market concentration may have influenced CEO appointments. As shown by Bao et al. (2022), increasing market power accounts for a substantial share of the growth in top executive compensation. Relatedly, Fee and Hadlock (2000) document a positive link between product market concentration and management turnover. In our context, higher market concentration could also imply a reduced supply of CEO positions at smaller firms. To test this idea, we correlate CEO age at appointment with market concentration measures from the Economic Census. The results, presented in Table A2, reveal a statistically insignificant association (with a contradictory sign).

Changes in Education Paths: A fourth set of hypotheses centers on the role of human capital in the labor market for CEOs, either due to prolonged educational paths or due to changes in skill accumulation on the job. We examine the former using education data from BoardEx, with results shown in Figure A7. Overall, we observe an increase of approximately one year in the age at highest degree over the sample period (Panel a). This shift is primarily driven by higher age at graduation among postgraduate degree recipients and by a rising share of CEOs holding such

[15] These results are consistent with the overhaul in corporate-governance regulations since the 1980s (e.g., Edmans et al., 2017; Ma and Shleifer, 2025), which has increased scrutiny over managerial actions and reduced the potential for entrenchment. Moreover, Dow (2013) suggests that entrenchment plays a limited role in private firms, which are the focus of this paper.

degrees (Panels b and c). Given the modest size of these changes relative to the aging magnitudes we have documented, we conclude that extended education alone cannot account for the rise in CEO age. In contrast, the observed increase in the length and diversity of prior experience supports the view that on-the-job human capital accumulation is the key driver of our results.

Another line of reasoning in this context suggests that firms may have reduced their investment in executive training since the beginning of our sample period. Consequently, only older candidates would have the necessary experience to be appointed CEO. However, the evidence points in the opposite direction: the employment share in professional and management development training has more than doubled (Figure A8), alongside a broader expansion in business education (Acemoglu et al., 2022b).

Sample Composition: A fifth concern is that BoardEx oversamples larger and older firms relative to the population of US firms. To address this consideration, we compare our sample to the Business Dynamics Statistics and reweigh CEO age at appointment by the inverse frequency of firms in each category (firm size, firm age, NAICS-2 or NAICS-4 industries) relative to the population. Figure A9 shows that the 7-8 year increase in CEO age is robust across all reweighting schemes, confirming that compositional shifts cannot explain the age increase at appointment. In Appendix Section E, we also document that the more pronounced age trend among smaller firms is not a mere artifact of the sample composition.[16]

Changes in Firm- and Individual-Level Observables: Sixth, we assess to what extent the age trend can be explained by observable factors. To this end, we regress CEO age at appointment on a linear time trend starting in 2000 and normalized to range between 0 and 1. We sequentially introduce an array of covariates. The estimated coefficients on the time trend are shown in Figure A10. Absent controls, the predicted age difference between 2000 and 2023 is more than 7 years. This estimate remains stable after accounting for fixed effects at the NAICS-4 level, a firm's listing status, and whether the CEO was hired internally or is female. Next, we consider firm size and age. Controlling for the former is essential given the interplay between age, accumulated skills, and firm size. Firm age is also important, as firm formation tends to be concentrated among younger individuals (Liang et al., 2018), though to a lesser extent than commonly assumed (Azoulay et al., 2020). An increase in firm age could thus entail a mechanical increase in CEO age. Notably, when adjusting for the natural logarithm of employment and firm age, the estimate shrinks only slightly. However, the coefficient drops markedly to less than 4 years, once restricting the data to the firm sample contained in Compustat, and remains unchanged thereafter. Hence, while changes in firm fundamentals cannot mechanically account for the rise in CEO age, the results suggest a crucial role of smaller and unlisted firms in driving the aggregate patterns.

[16] This result also speaks against the role of superstar firms being the driving force behind the overall age increase. Notably, the narrowing gap in CEO age between smaller and larger firms is consistent with broader structural trends, including the declining contribution of superstar firms to aggregate US productivity growth since 2000 (Gutiérrez and Philippon, 2019).

Reversion to Older CEOs after the Dot-com Crisis: A final possible concern relates to the timing of the starting point of our sample. Specifically, the bursting dot-com bubble in the late 1990s may have disproportionately affected young firms led by young CEOs, thereby mechanically increasing average CEO age afterwards. To assess this, we combine data from Execucomp on executives in the S&P 1500 between 1992 and 2000 with delisting information from CRSP. We then test whether firms delisted for involuntary reasons or through mergers and acquisitions were managed by younger CEOs. The estimates are shown in Figure A11. For sitting CEOs, we find that firms delisted for involuntary reasons had in fact significantly younger CEOs, whereas this pattern does not hold for M&A-related delistings. Crucially, however, we find no such difference in CEO age at appointment. If anything, CEOs appointed toward the end of the sample window at delisted firms were older than those appointed at firms that did not delist. An interpretation of these patterns is that delisted firms were disproportionally managed by their founders, who entered office at relatively young ages before the beginning of the sample and remained in place throughout the 1990s, thereby aging beyond the sample mean. Still, the evidence does not support the notion that our results are driven by a rebound effect following the late 1990s.

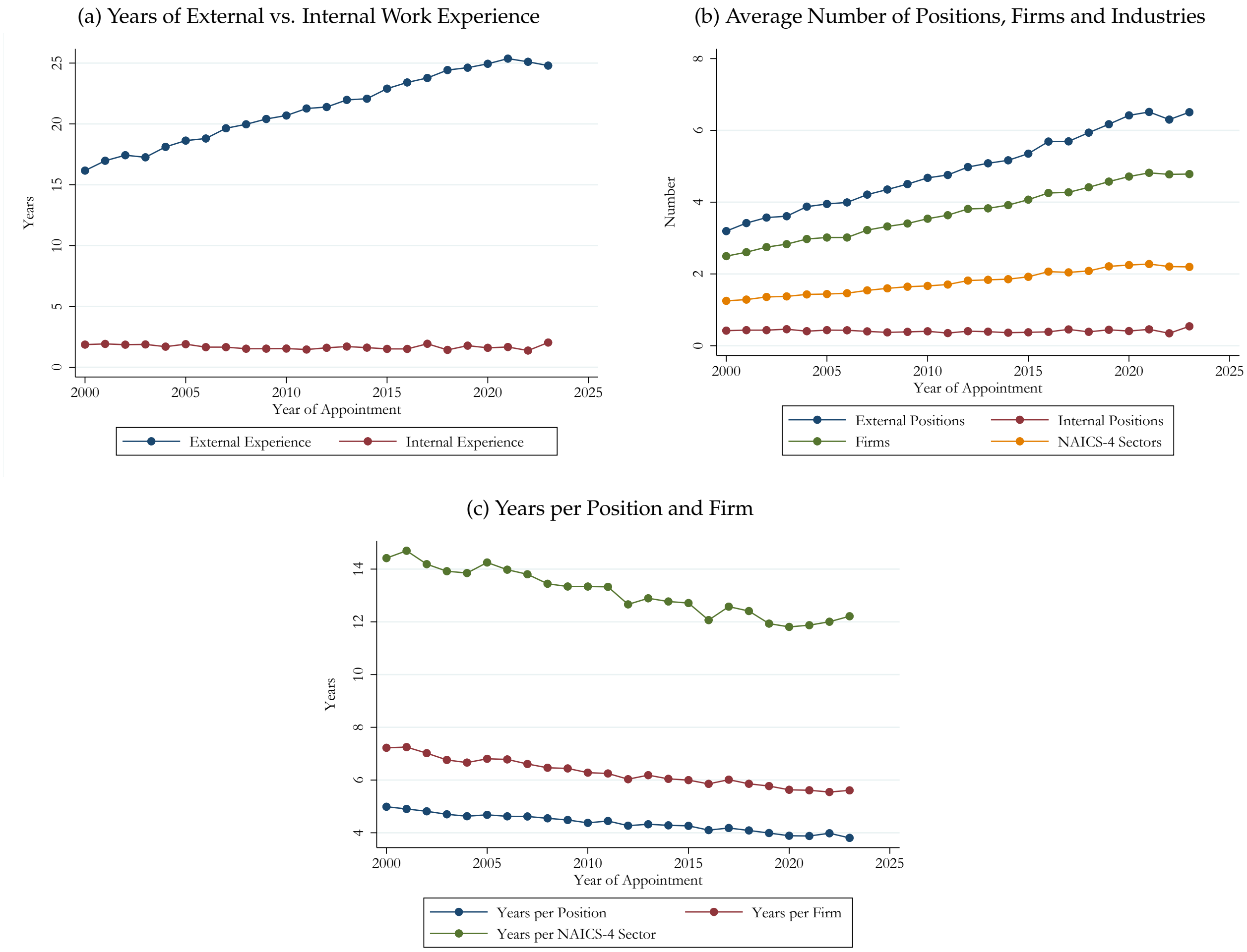
3.3 Changes in Career Paths and Generalist Skills

We now examine how prospective CEOs allocate the additional time prior to reaching top positions and the extent to which this increase in experience reflects the accumulation of generalist human capital. In Figure 3, we highlight the increased importance of external work experience. Panel (a) displays the average number of years spent outside and inside the firm over time. External work experience has increased strongly since the early 2000s, fully accounting for the upward trend in CEO age, whereas internal experience—measured as the time between joining the firm and becoming CEO—–has remained relatively stable throughout our sample period. As we discuss below, the share of internal appointments also shows little variation over time. Zooming in on external mobility, Panel (b) reveals a sharp increase in job mobility and the number of external positions held before entry into the firm. Before assuming the CEO role, individuals spend more time in multiple roles across a wider range of firms and sectors nowadays. At the same time, the number of years spent in each position, firm, and sector has decreased substantially since 2000 (Panel c).[17] We interpret these patterns as evidence in favor of the idea that prospective CEOs transition across different positions, firms, and sectors to gather a broader skill set—pointing to a shift toward a *boundaryless career* in this segment of the labor market (Arthur and Rousseau, 1996).[18]

[17]These results may be surprising, given that they stand in contrast to a strand of literature that shows a slight increase in tenure among the overall workforce during our sample period (Farber, 2010; Hyatt and Spletzer, 2016).

[18]In addition to reflecting skill accumulation, years of work experience can be an important factor on their own, as they may indirectly reveal a candidate's age during the interview process. In the United States, the *Age Discrimination in Employment Act* prohibits age-based discrimination in the workplace for individuals over 40. Although it is not illegal, asking applicants directly about their age is uncommon and generally considered inappropriate. This lack of explicit age information during interview processes may be less pertinent in recent years, as birth dates have become publicly accessible in many cases.

Figure 3: Work Experience Prior to CEO Appointment Over Time



Notes: The figure plots work experience of CEOs over time. Panel (a) plots average external and internal work experience prior to appointment. Panel (b) shows the average number of positions, separately for external and internal positions, as well as the number of firms and industries a prospective CEO worked in. Panel (c) shows the average number of years per position and firm.

Even though our results highlight the importance of generalist skills, the broadening of career paths has not unfolded uniformly across backgrounds. In Figure A12, we show that an increasing share of CEOs previously held positions as CFO or COO, but this trend is confined to those who served in these roles at other companies. Furthermore, Decressin et al. (2025) document that CEOs appointed after the Great Financial Crisis score more highly in analytical skills and execution orientation, at the expense of lower levels of interpersonal skills and charisma.

As another way to highlight the rising importance of external experience, we distinguish between externally and internally appointed CEOs, further stratifying the latter into those entering the firm at the managerial level or below. Within this classification, three factors may account for the rise in CEO age: increases in (*i*) external or (*ii*) internal experience within each group, or (*iii*) level differences in CEO age across groups, combined with shifts in group composition. As

Figure A13 shows, a combination of (*i*) and (*iii*) drives the age trend. Average age rose across all groups but more so for externally appointed CEOs, while the level was highest for those entering at the managerial level (Panel a). Panel (b) shows that since 2000, the share of external appointments has been stable, while managerial-level entries nearly doubled as lower-level entries declined. Meanwhile, both internally and externally appointed CEOs join firms at later career stages with more external experience (Panel c), whereas internal experience grew only for the shrinking group of those entering at less senior positions (Panel d). Overall, late entry, both within and across ports of entry, has thus become increasingly common.

In our sample, the share of internally appointed CEOs is relatively low.[19] As we show in Table A3, this is due to the comprehensive coverage of smaller firms, which are more likely to hire CEOs externally, whereas larger firms tend to favor internal candidates.[20] Among other factors, this heterogeneity across the firm size distribution has been ascribed to differences in internal talent pools among potential applicants and corporate governance practices (Kaplan and Sorensen, 2021).[21] Given that prospective CEOs are gaining increasing amounts of external experience (Appendix Figure A15), the prevalence of external hiring among smaller firms is consistent with our finding that these firms account for most of the upward trend in CEO age.

Lastly, we examine the extent to which these time trends among CEOs differ from those of other senior employees who did not become CEOs. If executive skill requirements have evolved, these changes should be most pronounced among CEOs relative to less senior executives and increasingly reflected in their career paths over time. To draw this comparison, we classify all non-supervisory directors in the BoardEx data based on the most senior position they reached throughout the sample and analyze their career paths leading up to the first appointment at that seniority level. In Figures A16 and A17, we replicate Figure 3, showing the differential effects for CEOs compared to non-CEO executives and non-executive managers, respectively. In terms of levels, CEOs accumulate more external experience than both other groups, spanning a greater number of positions, firms, and industries. These differences are stronger for non-executive managers, who are more distant from the CEO position. Over time, most of these gaps become larger. Notably, the increasing accumulation of external experience is driven by the number of external positions for CEOs relative to non-CEO executives. For CEOs compared to non-executive managers, this development is to a greater extent driven by years of experience across different firms and industries. In the latter comparison, internal experience also exhibits a widening gap, owing to a decline in internal experience among non-executive managers (Figure A17, Panel a). Taken together, this suggests that broad external experience is not only an important factor in the selection of CEOs but also that its relevance has grown over time.

[19] With the data processing approach used in the main paper, around 20% of the appointments are internal. Under the alternative preparation method described in Appendix Section E, the share is at 32%.

[20] This result holds when firm size is measured by employment and becomes even more pronounced when stratifying by a firm's listing status. Figure A14 illustrates that these two effects are cumulative, as a firm's listing status remains relevant even after accounting for the number of employees.

[21] In turn, these hiring practices directly affect economic outcomes, as more productive firms recruit more talented trainees and promote managers internally (Friedrich, 2023).

4 Model

To provide a framework to understand and interpret the patterns that we have documented, we study a frictionless many-to-one matching model with transfers between workers and firms. Workers are heterogeneous along two dimensions: ability and experience at appointment.[22] Firms differ in terms of productivity, and feature multiple hierarchical positions with associated productivity requirements.[23] Assortative matching implies that more productive firms are matched with more productive CEOs, which we capture empirically by proxying firm productivity with firm size.[24] The model predicts that CEOs in higher-productivity (larger) firms are older on average, generates a negative correlation between CEO ability and age, and produces an aging of CEOs in response to an increase in the importance of experience for CEO productivity.

Framework: There is a continuum of workers and firms. Workers are indexed by ability $a \in [a_L, a_H]$ and age $t \in [0, T]$. Firms have productivity $z \in [\underline{z}, \bar{z}]$ with distribution G and *capacity* (mass of job positions) $m(z) \geq 0$. Total capacity in the entire economy is $M := \int m(z)\, dG(z)$. Positions or job slots are a continuum, with the *top slot* in each firm being a measure-zero point. Within each firm, positions are indexed by k, with productivity

$$z(k) := z - \beta(k-1), \qquad \beta > 0,$$

so that higher-ranked positions are associated with higher productivity. For the formal analysis in the appendix, it is convenient to work with the induced one-dimensional distribution of slot productivity generated by (z, k). In particular, CEO slots correspond to $k = 1$, implying that the productivity of the CEO equals firm productivity z.

Worker productivity has two components: an *age-adjusted ability* component $x(a, t)$ and an *experience* component $y(t)$. We adopt the additive specification

$$x(a, t) \equiv a + h(t),$$

and define the scalar *worker score*

$$\phi(a, t; \alpha) \;:=\; (1-\alpha)\big[a + h(t)\big] + \alpha\, y(t), \qquad \alpha \in [0, 1).$$

[22]This distinction parallels a large literature in psychology that differentiates between two forms of cognitive functioning (Cattell, 1971): fluid intelligence, capturing the capacity to develop new skills independently from prior knowledge, and crystallized intelligence, reflecting abilities derived from previous learning and experience (Salthouse, 2009; Schaie, 2005; Baltes and Mayer, 1999).

[23]See Corblet (2025) and Choné et al. (2024) for recent empirical contributions on many-to-one matching with multidimensional skills.

[24]We therefore use firm productivity and size interchangeably throughout this section.

We assume that h is twice continuously differentiable, strictly concave, and single-peaked with maximizer t^*; y is twice continuously differentiable, strictly increasing, and concave.[25] We assume throughout that a and t are independent with continuous densities.

Firm-worker output at position k is multiplicatively separable in firm-side productivity:

$$\pi\big(z(k), a, t; \alpha\big) \;=\; z(k)\,\phi(a, t; \alpha).$$

This functional form is consistent with the idea that changes in CEO talent scale with firm productivity, or analogously, firm size (Gabaix and Landier, 2008; Terviö, 2008; Edmans et al., 2009).

Remark 1. Because utility is transferable and the surplus takes the form $\pi(s, a, t; \alpha) = s\,\phi(a, t; \alpha)$, which has increasing differences in (s, ϕ), the efficient and stable assignment is positively assortative between slot productivity and worker score: more productive slots are filled by higher-score workers.

Main Theoretical Results: Appendix A includes a formal analysis of this environment and provides sufficient conditions for three core implications:

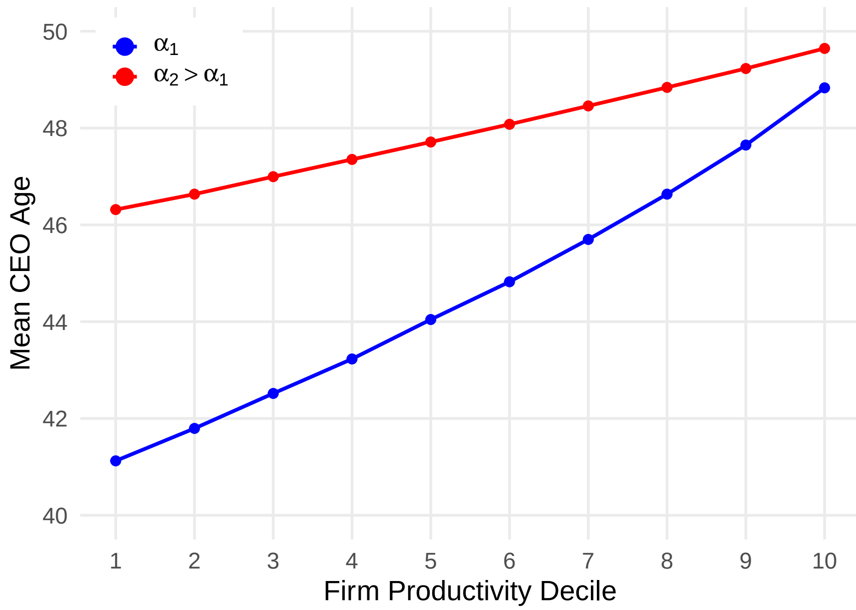
(i) *Larger (higher-z) firms have older CEOs on average.* Larger firms have more productive workers. If higher productivity makes higher ages more likely (a stochastic monotonicity property), then selecting workers with higher productivity leads to a stochastically older group. Positive assortative matching transfers this conclusion to firms: more productive firms, which match with higher-score workers, have stochastically older workers.

(ii) *Age and ability of CEOs are negatively correlated.* As older workers benefit from the positive contribution of age to the score, they can clear a given threshold with lower ability, whereas younger workers must compensate with higher ability. This selection induces a negative relationship between ability and age among appointed CEOs.

(iii) *Increasing the weight on experience raises average CEO age.* Higher α shifts selection toward older workers at all ranks, which lowers the relative ability threshold required for older workers and increases the probability that older workers qualify for top positions. This generates a first-order stochastic dominance increase in the age distribution of CEOs.

[25] These functional forms are motivated by findings from psychology. The eventual decline of the function h reflects the evolution of energy levels and fluid intelligence. The latter typically increases during youth, peaks in early adulthood, and subsequently declines with age. Cross-sectional studies tend to identify this peak in individuals' twenties, followed by a rapid decline. Longitudinal studies suggest a later peak, occurring up to the forties or fifties, as well as a slower decrease afterwards (for a review, see Desjardins and Warnke, 2012). The decline in fluid intelligence correlates with a general slowing of cognitive processes (Schaie, 1989) as well as diminished attention, memory capacity, and motivation (Ng and Feldman, 2008). The function y captures a variety of gains from age, including broadening networks, having faced a longer history of challenges to learn from, as well as crystallized intelligence. The latter tends to increase steadily until around the mid-fifties and then either remains stable or shows only a modest decline thereafter (Schaie, 2005). This decline is mostly confined to individuals with lower skill-usage, while white-collar professionals and those with higher education levels continue accumulating skills beyond their forties (Hanushek et al., 2025).

Figure 4: Illustrative Age Profiles at the Top Position by Firm Productivity



Notes: The figure plots illustrative CEO age profiles across firm productivity deciles for two values of α: $\alpha_1 = 0.4$ (blue line) and $\alpha_2 = 0.8$ (red line). We simulate 100,000 workers with ability $a \sim U(0, 200)$ and age $t \sim U(0, 50)$. Skills are defined as $h(t) = -0.04t(t - 50)$ and $y(t) = -0.1t(t - 150)$. On the firm side, we draw 1,000 firms with productivity $z \sim U(0, 1)$, capacity $m = 100$, and hierarchical decay parameter $\beta = 0.08$. Within each firm, the CEO corresponds to the top slot ($k = 1$). We exploit the assortative matching implied by the model and compute the average CEO age within each firm productivity decile. The simulation is repeated 500 times, and results are averaged across all replications.

To understand the intuition for part (iii), consider two simplifications of the model as benchmark cases. If there were only one firm, it is natural to expect that this firm would shift older workers to more senior positions when experience becomes more valuable. However, if there were many firms and only one worker per firm, such a reallocation cannot hold for every firm because of aggregation: if workers in some firms get older, others must get younger. In particular, as experience becomes more highly valued by all firms, the equilibrium shadow value of experience must also adjust, potentially leading some firms to economize on experience, especially in less senior positions. Thus, while the partial-equilibrium logic is straightforward, the general-equilibrium channel introduces conflicting forces. There are a variety of conditions one can impose to guarantee that the distribution of workers in top positions stochastically increases when α increases. In the Appendix we provide sufficient conditions in terms of the induced conditional tail densities.[26]

Figure 4 illustrates the theoretical predictions using a simulation and plots the predicted CEO age profiles across the firm productivity distribution for different values of α.[27] Given the link between firm productivity and size, the age profiles can be compared to the empirical age patterns over time across the firm size distribution. For a given α_1 (blue line), CEO age increases with firm size. When $\alpha_2 > \alpha_1$ (red line), CEOs are generally older than under α_1. In the given parametrization, the gradient

[26] A related option is to ensure that CEO positions are in a thin upper tail of the most productive workers in the economy, a condition that is difficult to describe qualitatively.

[27] See the figure notes for details on the parametric specification.

in CEO age over the firm size distribution is also less pronounced than for α_1. This heterogeneity is driven by two forces. First, due to the concavity of y, any increase in α produces stronger reordering among younger workers. As smaller firms draw from that part of the distribution, their assigned CEO age shifts more. Second, larger firms already select high-ability workers due to assortativity, which constrains how much their CEO age can adjust when α increases. In the numerical example, the average correlation between experience and ability for $\alpha = \alpha_1$ is negative at -0.981, which drops to -0.997 for $\alpha = \alpha_2$. This discrepancy exists across the entire firm size distribution, but to a stronger extent for smaller firms (Figure A18).

Turnover: We conclude the theory discussion by outlining how the model speaks to the increasing turnover that we observe in our data. Although the model is static, it suggests a simple benchmark for turnover pressure when the importance of experience changes over time. Starting from a baseline environment with weight α_1, consider the workers who initially occupy the top θ positions. As α rises, these workers may move up or down in the frictionless ranking because experience becomes more heavily weighted. The Appendix summarizes this by measuring the cumulative rank movement of these baseline top workers as the economy transitions from α_1 to α_2. While this does not model realized turnover directly, it provides a simple measure of how much the target assignment would need to be reorganized in response to changes in α. A key implication is that larger increases in α generate greater reshuffling pressure, that is, they require more reallocation of workers across positions.

Empirical Evidence on Model Predictions: First, the model predicts that the age distribution of CEOs in larger firms first-order stochastically dominates that in smaller firms. Panel (a) of Figure 5 plots the cumulative distribution functions of CEO age at appointment by firm size quartile, after residualizing with respect to NAICS-4 industry and year fixed effects. The plots closely match the expected pattern: relative to smaller firms, larger firms appoint substantially fewer CEOs at younger ages, in particular below age 45.[28]

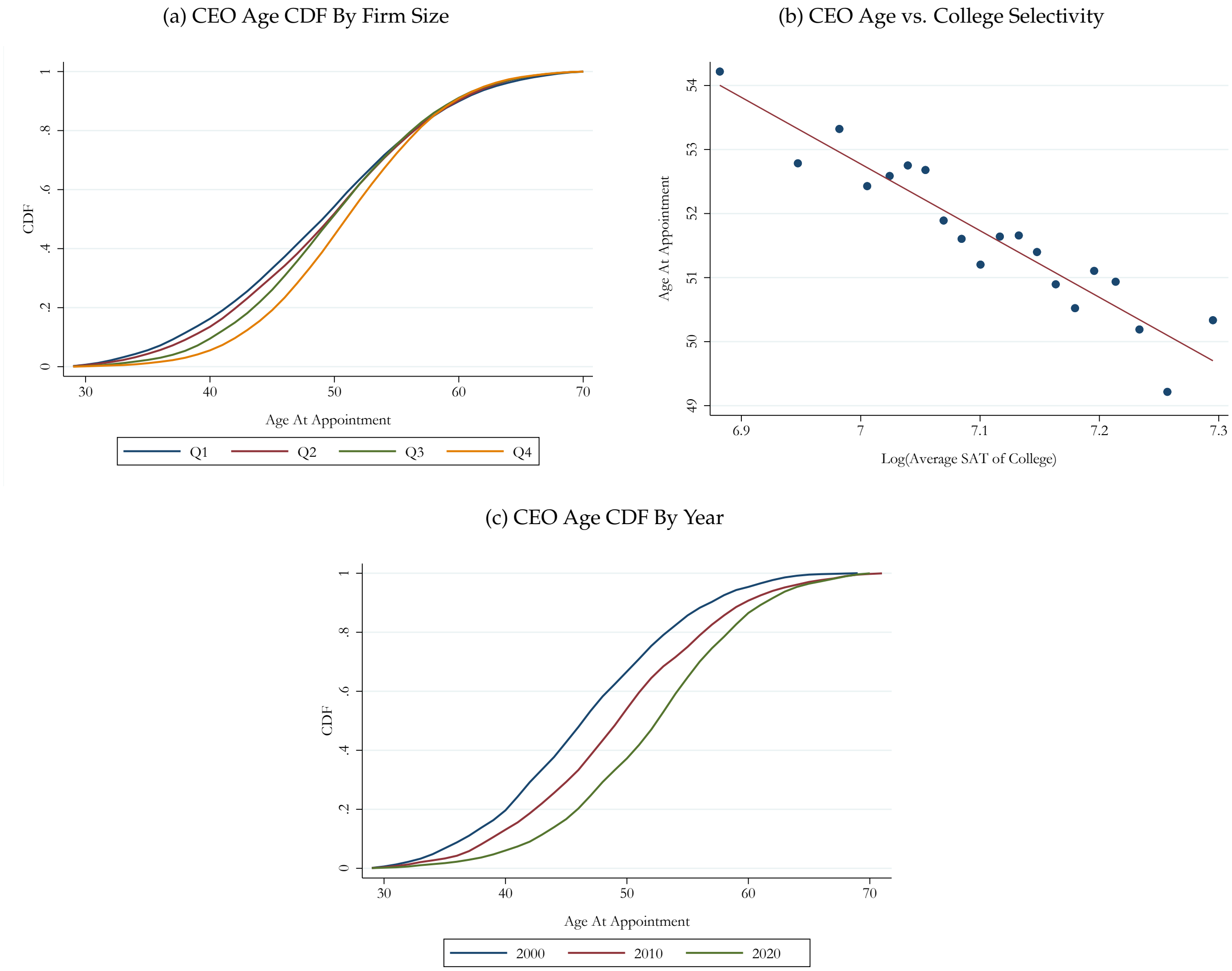
Second, selection generates a negative association between CEO age at appointment and ability in the model. Even though age and ability are independently distributed in the population, conditioning on CEO appointment creates a collider bias, predicting a negative correlation between the two variables. To test this in the absence of a direct measure of ability, we use information on educational backgrounds to construct different proxies for college selectivity.[29] Consistent with our theory, college selectivity is negatively correlated with CEO age at appointment (Panel (b) of Figure 5 and Table A4), indicating that age and ability act as substitutes in the selection of CEOs.

Third, Panel (c) of Figure 5 plots the cumulative distribution of CEO age at appointment for the years 2000, 2010, and 2020, conditional on employment and NAICS-4 fixed effects. Assuming that

[28]Consistent with this, Adams et al. (2018b) show that both cognitive and non-cognitive skills matter for CEO selection, with a stronger role for non-cognitive skills. These skills include traits such as social maturity, emotional stability, and persistence, which may partly reflect accumulated experience.

[29]As college attendance is correlated with SAT performance and, in turn, with intelligence (for a review, see Frey, 2019), these measures closely mirror the ability component used in the theoretical analysis.

Figure 5: Empirical Evidence for Theoretical Predictions



Notes: Panel (a) shows the cumulative distribution function of CEO age at appointment by employment quartile. CEO age and the natural logarithm of firm employment are residualized with respect to NAICS-4 and year fixed effects, with the sample mean added back. Employment quartiles are constructed from these residuals, and the top and bottom percentiles of the age distribution are trimmed. Panel (b) focuses on a CEO's first postsecondary degree, identified either by the stated degree name or, if missing, by the first degree recorded in BoardEx. We exclude first postsecondary degrees obtained from institutions outside of the United States. The plot binscatters age at appointment against the natural logarithm of the institution's average SAT admission score in 2001, taken from Chetty et al. (2020). Controls include the natural logarithm of employment and firm age. Panel (c) shows the cumulative distribution function of CEO age at appointment by year. CEO age is residualized with respect to the natural logarithm of firm employment and NAICS-4 fixed effects, with the sample mean added back, and the top and bottom percentiles of the age distribution are trimmed.

the weight on experience has increased over time, we expect the entire age distribution of CEOs age at appointment to shift to the right throughout the sample period. Indeed, the age distribution in more recent years first-order stochastically dominates that in previous periods.[30]

[30]Across the firm size distribution, the heterogeneous age trends (Figure 2) closely mirror the simulated response to changes in α (Figure 4).

Potential Extensions: First, for the concept of a CEO position to be meaningful, firms must have multiple, hierarchically ordered positions. In the model, CEO productivity is exogenous, and the remainder of the hierarchy plays only a limited role. However, the model could be extended to allow for productivity to depend on the team composition, which would potentially generate additional richness without changing the main qualitative predictions of the model. Second, the model considers firm heterogeneity in terms of productivity, which we empirically proxy by firm size. A natural extension with equivalent results would be to allow firm size $m(z)$ to depend on productivity, with $m(z)$ increasing in z.[31] Third, the model assumes that all workers are matched to some firm. Allowing for potential unemployment would imply that the least productive and disproportionately young workers remain unmatched, which would strengthen our existing results.

5 Identifying Demand and Supply of Generalist Skills

5.1 Demand for Generalists in the Face of Greater Uncertainty and Complexity

So far, we have documented that CEOs have become more mobile between positions and firms prior to their appointment, possibly in order to gather generalist skills across a range of functional areas. In this section, we propose a demand-side channel: heightened uncertainty and complexity may require executives with more generalist skill sets,[32] resulting in firms appointing executives who have taken longer career paths before reaching CEO positions and are, thus, older upon appointment. We seek to identify the causal effect of changes in firms' economic environment on the characteristics of appointed CEOs, in particular their level of generalist skills. We start with uncertainty and later extend our empirical framework to a range of measures capturing economic complexity. The rationale for this approach is that while uncertainty and complexity have generally increased over time (cf. Figure A19), different components thereof may matter more at different points in time, which we remain agnostic about.

Empirical Strategy: The ideal experiment would induce random variation in firm-level uncertainty or complexity, bolstering demand for generalist skills among some firms. However, finding exogenous variation in uncertainty or complexity that operates solely through this channel is challenging. Moreover, even then, comparing CEO age across high- and low-uncertainty (complexity) firms would recover the estimand of interest only if the supply of potential CEOs were sufficiently elastic.

To address these issues, our empirical approach exploits information on both the demand and the supply side. Specifically, we use plausibly exogenous variation in the availability of generalist skills and study its *differential* effect on CEO appointments in high- vs. low-uncertainty (complexity) environments. As a supply shifter, we rely on spatial variation in firms' access to elite strategy

[31] We could further allow for heterogeneity in α. If larger firms tend to place higher value on experience in general and if smaller firms become more similar to larger ones over time, our results should hold under less stringent assumptions.

[32] This reasoning is supported by management studies arguing that firm diversification and industry complexity increase the value of generalist skills (see, e.g., Mueller et al., 2021).

consultancies across the United States. These consultancies, with a broad outlook across firms and industries, provide firms with additional manpower in their management teams, allowing them to quickly adjust to changing market environments (Ernst and Kieser, 2002; Glückler and Armbrüster, 2003).[33] In other words, the presence of external strategy consultants reduces firms' dependence on hiring older CEOs as a means to navigate uncertainty. Consultants effectively substitute for these experienced executives by supplying the generalist skills that become particularly valuable in high-uncertainty or high-complexity environments. Therefore, we expect that firms in areas with better access to elite consultancies are less likely to appoint older CEOs when faced with higher uncertainty (complexity). This reasoning builds on Yonker (2017), who documents the prevalence of CEO appointments from local labor markets, and on Knyazeva et al. (2013) and Sauvagnat and Schivardi (2024), who emphasize the role of the local supply of managerial talent, specifically the thickness of the market for executive skills, in shaping firm-level outcomes.

On the supply side, the empirical strategy is based on the idea that the consulting industry is highly concentrated, but to a heterogeneous extent across time and space. We focus on the three firms commonly considered the most prestigious: *McKinsey & Company*, *Boston Consulting Group*, and *Bain & Company*. Throughout our sample period, these companies (henceforth MBB) have seen a substantial expansion, increasing their number of offices from 25 in 2000 to 47 in 2022 (Figure 6, Panel a). Despite this growth, their offices remain clustered in relatively few cities. As illustrated in Panel (b) of Figure 6, while the number of MSAs with any MBB presence has increased substantially, so has the number of MSAs hosting all three MBB offices. In 2022, this latter group accounted for roughly 80% of all offices, concentrated in merely 12 cities. This spatial variation will constitute one ingredient in capturing firms' exposure to consultancy services in our empirical approach.

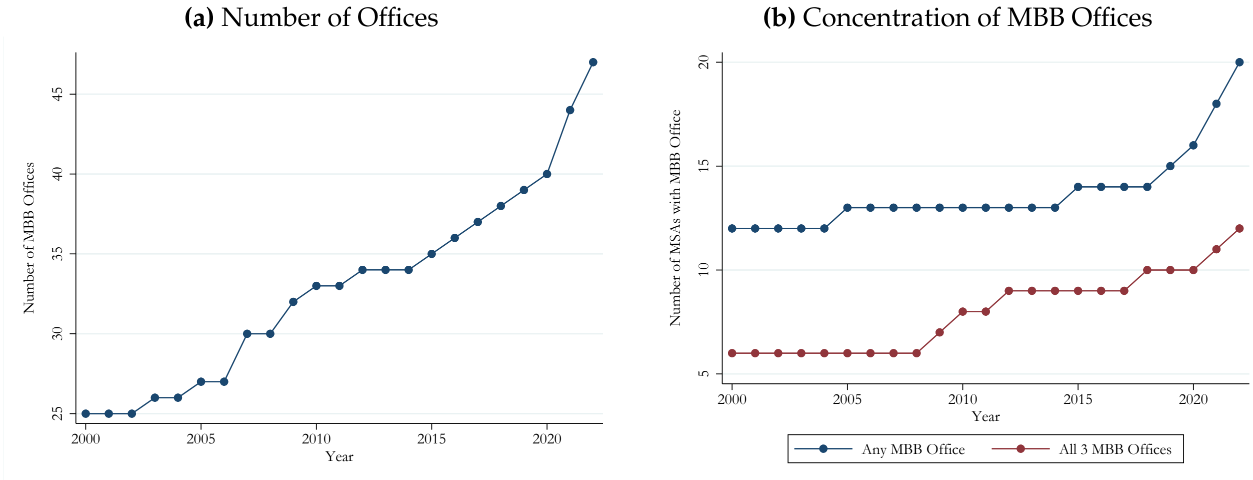
We hypothesize that increasing the geographical proximity between consultancies and their clients enhances the dominance of the consultancies, as consultants typically work on-site, arriving from their office location and staying from Monday until Thursday. In other words, having an MBB office nearby implies an increase in the availability of generalist skills. However, the timing and location of new office openings may be correlated with existing firm networks (Glückler, 2006) or local economic conditions, since consultancies tend to expand into areas with high demand for their services. To address this potential endogeneity issue, we do not use direct exposure to an MBB office (i.e., a consultancy being located in the same MSA) but, instead, construct a proxy for indirect exposure by exploiting variation in flight times. This approach, inspired by Giroud (2013), creates additional variation that we exploit in our empirical analysis.

Starting with uncertainty, we can spell out the regression equation of interest. Specifically, considering a CEO appointment in firm j, MSA m, industry i and year t, we estimate the following specification:

$$Age_{jt} = \beta\, Uncertainty_{it} \times Travel\ Time_{mt} + \gamma_{mt} + \phi_{it} + X_{jt} + \epsilon_{jt}, \tag{1}$$

[33] The empirical evidence highlights that consultancies improve firm performance through productivity-enhancing channels, in particular restructuring, with little support for rent-seeking effects (Bruhn et al., 2018; Bijnens et al., 2025).

Figure 6: Expansion of MBB Offices Across the United States



Notes: The figure shows the evolution of MBB offices (*McKinsey & Company*, *Boston Consulting Group*, and *Bain & Company*) in the United States over time. Panel (a) shows the total number of offices, and Panel (b) plots the number of MSAs with at least one or all three offices, respectively. The data are obtained from *archive.org* and cross-checked with information from Weinstein (2025).

where Age_{jt} denotes CEO age at appointment obtained from BoardEx, $Uncertainty_{it}$ is an uncertainty (or complexity) measure at the industry-time level[34], and $Travel\ Time_{mt}$ is the flight time to closest MBB office. The fixed effects γ_{mt} and ϕ_{it} are at the MSA-year and NAICS-4-year level, respectively, eliminating the standalone coefficients on $Uncertainty_{it}$ and $Travel\ Time_{mt}$. Finally, the vector of controls, X_{jt}, includes the natural logarithm of the number of employees and of firm age.

The coefficient of interest is β, which captures the differential effect of higher uncertainty on CEO age upon appointment, conditional on the availability of young generalists (i.e., MBB consultants). This interpretation hinges on two assumptions. First, proximity to an MBB office tilts the age composition of the available generalist talent pool, expanding firms' access to younger generalists more than to older ones. Second, the part of the variation in uncertainty that is associated with CEO age responds to travel time due to changes in firms' demand for generalist skills. The fixed effects control for all time-varying characteristics at the levels of MSAs and industries, implying that our empirical approach relies solely on the fluctuations generated by the interaction of uncertainty and travel time. We expect firms to appoint older CEOs if uncertainty is high and the available supply of other generalists is low due to exogenous reasons, as experienced executives typically provide the generalist expertise that firms seek in such situations. Since travel time is negatively related to the availability of young generalists, this implies a positive sign for the estimated β as firms in high-uncertainty industries are then left with an older pool of available generalists.

We emphasize that this exercise is *not* aimed at suggesting that increased MBB exposure causally contributed to the selection of older CEOs. If anything, one would expect the opposite effect, given the expansion of offices and flight routes in conjunction with the substitutive relationship between

[34]For the baseline specification, we use the cross-sectional standard deviation of the symmetric growth rate of firm revenue within each NAICS-4 industry.

consultants and more experienced executives. Instead, we exploit the supply of consultants as a source of variation to probe our mechanism of interest.

To measure firms' travel time to the closest MBB office, we rely on time-varying flight times that we compute as described in Section 2, considering only direct connections. Combining these data with information on the expansion of MBB offices across the United States, we calculate the minimal flight time to any MBB office at the MSA-year level. The final sample covers all observations between 2000 and 2022, excluding those in which an MBB office is present in a given year.[35] As we show in Appendix Table A5, reductions in travel time translate into higher inflows of employees from these firms. Conditional on time-varying firm-level controls as well as fixed effects at the firm and industry-year level, a one-hour reduction in flight time increases inflows by about 19% (Column 1).

Results on Uncertainty: We use the cross-sectional standard deviation of the symmetric growth rate of firm revenue within each NAICS-4 industry as our main measure of uncertainty. This variable has the advantage that it captures broader, industry-wide fluctuations and is unaffected by idiosyncratic shocks experienced by individual firms. Appendix Figure A20 plots the measure over time, alongside uncertainty indices from Baker et al. (2016) and Baker et al. (2019). All three series reveal a secular increase in uncertainty since around 2000 compared to the 1980s and 1990s.

The results obtained from estimating Equation (1) are shown in Table 1. Column (1) includes the results from a regression with controls only, showing a positive and significant coefficient on the interaction term. By consecutively adding fixed effects for MSAs, NAICS-4 industries, years, and combinations thereof, the estimated coefficient remains consistently significant at the 5%- or 1%-level. Quantitatively, the estimated coefficient from our preferred specification (Column 4) is large and lends itself to an intuitive interpretation: One additional hour of travel time, evaluated at one standard deviation above mean uncertainty, translates into an increase in CEO age of 0.6 years.

We provide additional evidence for our mechanism in four ways. First, we corroborate the robustness of the result from Table 1, Column (4) by conducting a number of robustness checks, presented in Table 2. In Column (1), we use the standard deviation of revenue growth at the NAICS-2 level, rather than the NAICS-4 level, as a proxy for uncertainty. The estimated coefficient remains comparable, supporting the idea that broader economic turbulences shift the demand for older CEOs. Similarly, in the remaining regressions, the results remain highly significant and quantitatively consistent across the board. In Column (2), we replace the standard deviation of revenue growth with stock return volatility. In Column (3), we use lagged values of travel time. In Column (4), we discretize the linear measure of travel time to the nearest MBB office by constructing a dummy for above-median values of travel time. In Column (5), we examine the influence of the current age of the firm's other executives, a factor that could play a significant role in CEO selection. In the case of internal appointment, other executives are part of the pool of potential

[35]We impose this restriction because direct exposure to office entry is more likely to reflect strategic considerations, whereas exposure through flight connections is less prone to such endogeneity concerns. As we show in Column (5) of Table 2, however, our main result is insensitive to this choice.

Table 1: MBB Availability, Uncertainty and CEO Age

	CEO Age			
	(1)	(2)	(3)	(4)
Travel Time	0.216	-0.710		
	(0.271)	(0.893)		
Industry-Level SD	-0.471	-0.657**	-0.732*	
	(0.338)	(0.307)	(0.378)	
Travel Time × Industry-Level SD	0.454**	0.625***	0.476**	0.632***
	(0.186)	(0.232)	(0.212)	(0.212)
R^2	0.033	0.088	0.230	0.360
Observations	15,679	15,676	15,235	14,132
MSA fixed effects		✓		
Year fixed effects		✓		
MSA-Year fixed effects			✓	✓
Naics4 fixed effects			✓	
Naics4-Year fixed effects				✓

Notes: The dependent variable in all regressions is CEO age upon appointment, obtained from BoardEx. *Travel Time* denotes the flight time (in hours) to the closest office, which we construct from MBB office openings combined with flight data from the Bureau of Transportation Statistics. *Industry-Level SD*, calculated as the cross-sectional standard deviation of the symmetric growth rate of firm revenue within a firm's NAICS-4 industry, is standardized to mean zero and standard deviation one. The sample is restricted to those MSAs without MBB presence. All regressions control for firm size by including the natural logarithm of employment and firm age (extracted from the employment history data). Standard errors are double-clustered at the NAICS-4 industry and MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

candidates, while for external appointments older board members may favor older CEOs due to similarity attraction (Davidson et al., 2006). However, the estimated coefficients remain qualitatively unaffected. In Column (6), we use the full sample, which includes metro areas with an MBB office and, thus, a travel time of zero. Lastly, in Column (7), we restrict the sample to firms in metro areas that do not experience any office entry throughout the entire sample period.

Second, we provide more direct evidence that the treatment shifts CEO appointments in smaller firms toward older candidates with more generalist skills, while leaving CEO appointments in larger firms essentially unchanged. We do so by splitting the sample at the median employment level and reporting the corresponding estimates in Panels A (smaller firms) and B (larger firms) of Table 3. Column (1) shows that the effect on CEO age is entirely driven by smaller firms. The remaining columns further probe our main mechanism. Column (2) and (3) document that treated smaller firms appoint CEOs with significantly more experience outside of the current industry, measured either as years spent in other NAICS-4 or NAICS-2 industries. We also consider years within the same NAICS-4 industry (Column 4) and firm (Column 5) as placebos, both with insignificant responses. Column (6) and (7) reveal an increase in the breadth of CEOs' prior industry experience among smaller firms, captured by the number of distinct NAICS-4 industries worked in, with very similar conclusions drawn from OLS and quasi-Poisson estimations. By contrast, the estimated coefficients for larger firms are consistently insignificant.

Table 2: MBB Availability, Uncertainty, and CEO Age—Robustness

	CEO Age						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Travel Time × Industry-Level SD	0.527**	0.702**	0.640***	0.366**	0.528*	0.628***	0.572*
	(0.219)	(0.315)	(0.205)	(0.149)	(0.284)	(0.148)	(0.327)
R^2	0.365	0.371	0.360	0.360	0.381	0.252	0.397
Observations	14,954	13,856	14,132	14,132	12,289	33,006	10,912
MSA-Year fixed effects	✓	✓	✓	✓	✓	✓	✓
Naics4-Year fixed effects	✓	✓	✓	✓	✓	✓	✓
Change Compared to Baseline	NAICS-2 SD	Return Volatility	Lagged	Discretized	Board Age	Full Sample	Never Office

Notes: The dependent variable in all regressions is CEO age upon appointment, obtained from BoardEx. *Travel Time* denotes the flight time (in hours) to the closest office, which we construct from MBB office openings combined with flight data from the Bureau of Transportation Statistics. *Industry-Level SD*, calculated as the cross-sectional standard deviation of the symmetric growth rate of firm revenue within a firm's NAICS-4 industry, is standardized to mean zero and standard deviation one. The sample is restricted to those MSAs without MBB presence. All regressions control for firm size by including the natural logarithm of employment and firm age (extracted from the employment history data). We deviate from this setup in the following ways: Column (1) uses the standard deviation of revenue growth within NAICS-2 sectors; Column (2) uses stock return volatility, calculated as the within-year volatility of monthly stock returns aggregated up by taking the NAICS-4-specific median, with data taken from the Center for Research in Security Prices; Column (3) uses the first lag of travel time; Column (4) replaces the linear measure of travel time to the nearest MBB office with a dummy for above-median travel time; Column (5) controls for average executive age constructed from the employment history data; Column (6) uses the entire sample including those metro areas with an MBB office; Column (7) restricts the sample to firms in MSAs that do not experience any office entry throughout the entire sample. Standard errors double-clustered at the NAICS-4 industry and MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Third, we scrutinize our empirical approach through the lens of a difference-in-differences framework, for which we show event-study estimates in Figure 7. To this end, we estimate the effect of MBB entry in MSAs linked by a direct flight connection, improving access to the closest consultancy compared to the counterfactual of no MBB entry. Separate estimations for sectors with high and low levels of uncertainty reveal no differential pre-trend between the two groups and a positive response in low-uncertainty sectors. In contrast, CEO age in high-uncertainty sectors declines gradually and persistently following the treatment. As an additional test for pre-trends, we conduct a placebo exercise, in which we replace travel time in levels by future changes relative to the current period. The estimated coefficients, shown in Figure A21, are statistically indistinguishable from zero across all horizons.

Fourth, we plot the coefficient on the interaction term separately for 5-year sub-periods. The estimated coefficients, shown in Figure A22, can be interpreted as the elasticity of CEO age with respect to variation in uncertainty, evaluated at a given level of travel time. The estimates are consistently positive and statistically significant for the periods 2010–2014 and 2020-2023. Together with the increase since 2005–2009, this provides tentative evidence of a gradual rise in the value of generalist human capital in the aftermath of the financial crisis.

Results on Complexity: Beyond the secular shift in uncertainty, firms' simultaneous expansion across geographies and business areas, coupled with the need to operate in multiple regulatory environments, has created new layers of complexity. These changes along several, possibly correlated

Table 3: MBB Availability, Uncertainty, and Generalists by Firm Size

	CEO Age	Yrs. Oth. NAICS-4	Yrs. Oth NAICS-2	Yrs. Same NAICS-4	Yrs. Internal	No. NAICS-4	No. NAICS-4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Smaller Firms							
Travel Time × Industry-Level SD	0.897**	0.573**	0.665***	-0.255	0.183	0.124***	0.127***
	(0.437)	(0.219)	(0.189)	(0.427)	(0.358)	(0.037)	(0.035)
Observations	5,932	5,932	5,932	5,932	5,932	5,932	5,696
MSA-Year fixed effects	✓	✓	✓	✓	✓	✓	✓
Naics4-Year fixed effects	✓	✓	✓	✓	✓	✓	✓
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	Poisson
Panel B: Larger Firms							
Travel Time × Industry-Level SD	0.287	0.105	0.496	-0.564	-0.135	-0.099	-0.061
	(0.686)	(0.595)	(0.509)	(0.550)	(0.525)	(0.063)	(0.076)
Observations	6,055	6,055	6,055	6,055	6,055	6,055	5,539
MSA-Year fixed effects	✓	✓	✓	✓	✓	✓	✓
Naics4-Year fixed effects	✓	✓	✓	✓	✓	✓	✓
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	Poisson

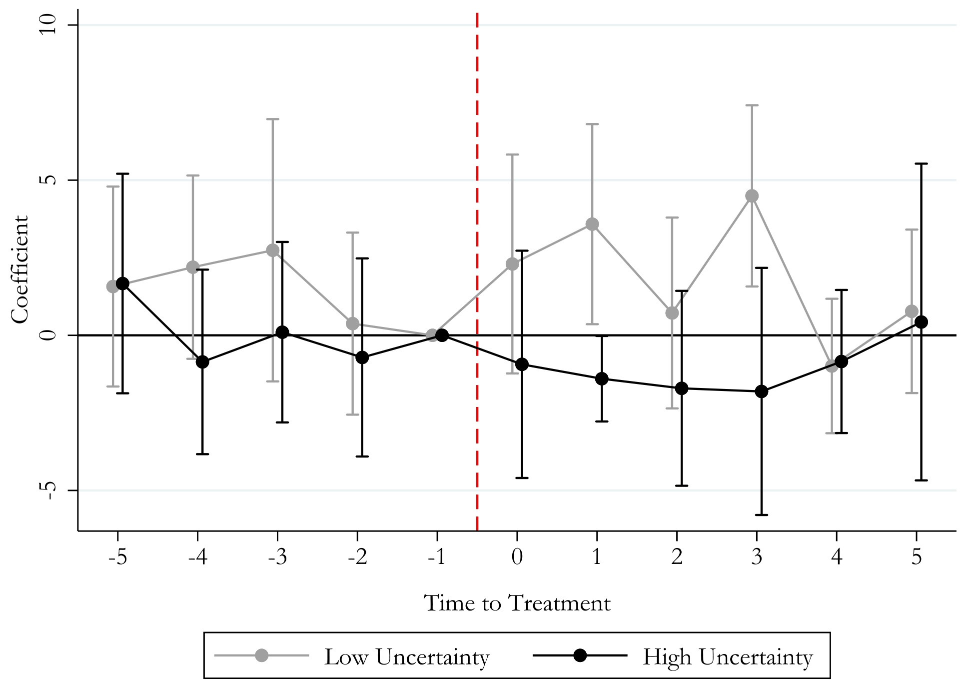
Notes: The dependent variables refer to the time, firm, or industry of CEO appointment: CEO age (Column 1), years of experience in other NAICS-4 industries (Column 2), years of experience in other NAICS-2 sectors (Column 3), years of experience in the same NAICS-4 industry (Column 4), years of international experience within the same firm (Column 5), and the number of NAICS-4 industries the CEO has worked in (Column 6 and 7). *Smaller Firms* are defined as those with below-median employment, while *Large Firms* comprise those above the median. *Travel* denotes the flight time (in hours) to the closest office, which we construct from MBB office openings combined with flight data from the Bureau of Transportation Statistics. *Industry-Level SD*, calculated as the cross-sectional standard deviation of the symmetric growth rate of firm revenue within a firm's NAICS-4 industry, is standardized to mean zero and standard deviation one. The sample is restricted to those MSAs without MBB presence. All regressions control for firm size by including the natural logarithm of employment and firm age (extracted from the employment history data). Column (1) to (6) are estimated using OLS, while Column (7) uses quasi-Poisson estimation. Standard errors are double-clustered at the NAICS-4 industry and MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and compounding dimensions have potentially contributed to the rising value of generalist human capital. To assess our mechanism along these different dimensions, we introduce a set of proxies for economic complexity to our identifying framework. As before, we estimate the differential effect of these industry-level measures across MSAs with varying local supply of generalist skills, captured by flight time to the closest MBB office. The results are summarized in Table 4.

First, we construct a measure of business diversification from the employment history data by counting the number of vice presidents (VPs) in distinct job roles.[36] VPs are transparently identifiable in the employment history data, with their titles revealing the activities, product lines, or markets they are responsible for. As firms typically appoint VPs to oversee specific business functions, the number of VPs captures the extent of diversification at the operational level. As shown in Panel (a) of Figure A19, the average firm-level number of VPs in distinct roles has increased substantially over time. In Column (1) of Table 4, we use this count variable as our main explanatory variable, aggregated to the industry-specific median and transformed to its natural logarithm. To preclude that the respective coefficient is driven by structural time-varying differences across firms

[36]To identify job roles, we rely on the taxonomy developed by Revelio Labs, which assigns activities to job titles by matching descriptions from resumes and online profiles to responsibilities in job postings. It initially classifies 1,500 roles, which are then hierarchically clustered.

Figure 7: MBB Market Entry, Uncertainty and CEO Age—Event Study



Notes: The plot shows event-study estimates obtained from regressing CEO age at appointment (obtained from BoardEx) on indicators for time relative to treatment, separately for low- and high-uncertainty NAICS-4 industries. The treatment is defined as exposure to MBB market entry in an MSA linked by a direct flight connection. An MSA is classified as treated if the minimum travel time to an MBB office is reduced by at least 5% in response to that entry. To ensure sufficient pre-treatment periods, only treatments that occurred in 2005 or later are considered. Uncertainty is measured as the cross-sectional standard deviation of the symmetric growth rate of firm revenue within a firm's NAICS-4 industry. We take the median of this measure across all periods and define high-uncertainty sectors as those with above-median levels of this variable. The sample is restricted to those MSAs without MBB presence. The regression controls for fixed effects at the NAICS-4-MSA and NAICS-4-year level as well as the natural logarithm of employment and firm age (extracted from the employment history data). The endpoints are binned at $t = -6$ and $t = 6$, while $t = -1$ is omitted as the reference category. Point estimates are shown alongside 95% confidence intervals, which are obtained from standard errors double-clustered at the NAICS-4 industry and MSA level.

related to, e.g., size, we control for the interaction of travel time with the overall number of VPs.[37] Consistent with our hypothesis, the estimated interaction of travel time with the number of distinct VPs is positive and highly significant. Our interpretation is that firms tend to appoint older CEOs when demand for generalists stemming from business diversification increases and the supply of other generalist managers is low. In the baseline specification, we employ the job taxonomy at a granularity of 500 distinct roles. As reported in Table A6, very similar results obtain when using the taxonomy at higher or lower levels of disaggregation.

Next, we examine the role of spatial diversification within the United States. As documented in Rossi-Hansberg et al. (2021), large firms have expanded into an increasing number of local markets, with diverging implications for national and local concentration. We use the employment history

[37] Equivalently, our results are robust to using the ratio of the number of different VP roles to the total number of VPs.

Table 4: MBB Availability, Complexity Measures, and CEO Age

	CEO Age				
	(1)	(2)	(3)	(4)	(5)
Travel Time × No. VP Roles	4.683***				
	(1.549)				
Travel Time × No. VPs	-4.281***			-0.688**	1.641
	(1.401)			(0.346)	(1.093)
Travel Time × Spatial HHI, Bottom Decile		4.244***			
		(1.262)			
Travel Time × No. Offices		-0.568		-0.290	-3.050***
		(0.375)		(0.336)	(0.758)
Travel Time × Export Complexity, Above Median			3.374***		
			(0.544)		
Travel Time × No. Countries Export			-9.049**		-9.878***
			(3.487)		(1.569)
Travel Time × Complexity Index (3 Components)				1.071***	
				(0.224)	
Travel Time × Complexity Index (4 Components)					1.098***
					(0.262)
R^2	0.365	0.365	0.408	0.365	0.403
Observations	14,933	14,195	5,136	14,173	4,946
MSA-Year fixed effects	✓	✓	✓	✓	✓
Naics4-Year fixed effects	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓

Notes: The dependent variable in all regressions is CEO age upon appointment, obtained from BoardEx. *Travel Time* denotes the flight time (in hours) to the closest office, which we construct from MBB office openings combined with flight data from the Bureau of Transportation Statistics. In Column (1), *No. VP Roles* is a count variable measuring the number of distinct job roles (out of 500) in which a firm employs vice presidents, while *No. VPs* is a count variable of the number of VPs. We aggregate these measures to the year-specific median within NAICS-4 industries and use their natural logarithm. Further details are provided in Table A6. In Column (2), spatial diversification is measured as the Herfindahl-Hirschman index (HHI) of employee counts across offices, which we define as having at least 5 employees in an MSA-year observation. The variable *Spatial HHI, Bottom Decile* is derived from an indicator for firms in the lowest decile, aggregated to the NAICS-4-year level by assigning a value of one whenever at least half of the underlying indicators equal one. *No. Offices* denotes the natural logarithm of the median number of offices of each firm within a year and NAICS-4 industry. Further details are provided in Table A7. In Column (3), *Export Complexity, Above Median* is an indicator for above-median levels of export complexity, which we define as the weighted average economic complexity (Hidalgo and Hausmann, 2009) across export destinations, where the weights reflect the export shares of a NAICS-4 industry in a given year. Further details are provided in Table A8. In Column (4) and (5), we create a composite index of complexity by transforming all variables to standard normal (if necessary), and summing over the corresponding variables: *Industry-level SD*, *No. VP Roles*, *Spatial HHI, Bottom Decile* (3 components) and additionally *Export Complexity, Above Median* (4 components). The sample is restricted to those MSAs without MBB presence. All regressions control for firm size by including the natural logarithm of employment and firm age, both extracted from the employment history data. Standard errors are double-clustered at the NAICS-4 industry and MSA level. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

data to construct a Herfindahl-Hirschman Index (HHI) based on employee counts across offices, defining an office as having at least 5 employees in a given MSA and year. This measure has declined substantially since 2010, suggesting a marked rise in spatial diversification (see Panel (b) of Figure A19, where we invert the measure). Motivated by these observations, we construct an industry-level measure of high spatial diversification by assigning indicators to firms in the lower tail of the HHI distribution and computing the industry-specific median of this indicator by year. Column (2) of Table 4 presents the results for industries where at least half of the firms fall into the bottom decile of the spatial HHI, controlling for travel time interacted with the number of offices. Consistent with expectations, the estimated interaction for spatial diversification is positive and highly significant. Table A7 suggests that the results are robust to alternative definitions of spatial diversification, including the use of indicators for the bottom quartile of the HHI distribution, a threshold of 10 employees to define offices, and an indicator based on the share of individuals employed outside of a firm's headquarters.

Third, we are interested in trade-induced variation in economic complexity. We focus on sectoral exports, given that exporting is a relatively rare activity, involving fewer than 3% of U.S. firms in 2021,[38] which requires high levels of strategic skill. Specifically, export participation is strongly shaped by managerial experience and associated with a wage premium (Mion and Opromolla, 2014). These dynamics are further amplified by globalization: higher economic integration tends to increase managerial slack, in turn raising the importance of generalist human capital (Schymik, 2018). We operationalize these considerations by combining trade flows with the country-level economic complexity index (ECI) from Hidalgo and Hausmann (2009) into a measure of export complexity. The ECI is based on product-level trade data and captures both the diversity of a country's exports and the ubiquity of the products it exports. These dimensions are synthesized into a single continuous index that reflects the complexity of a country's product space relative to others. Based on these data, we construct the export-related economic complexity index (EECI) as the weighted average of the ECI of a sector's export destinations, with weights corresponding to the export shares of each NAICS-4 industry in a given year.[39] Column (3) of Table 4 shows the results for industries with above-median levels of EECI, interacted with travel time. The estimated coefficient is again positive and highly significant, even after controlling for the natural logarithm of the number of export destinations. We conduct a battery of robustness checks in Table A8. The findings remain unchanged when using the raw EECI, an indicator for the upper quartile, or when constructing the EECI based on 1999 export shares, the last year before the start of the sample period. The results are also robust to using EECI values derived from HS code data, and to controlling for the number of export destinations that account for at least 1% of sectoral exports. As a placebo test, Table A9 replicates these regressions using import shares, yielding small and insignificant coefficients across the board.

To summarize these results, we re-estimate the specification using the sum of all four normalized drivers for generalists. We show specifications with and without the EECI, since this variable is available only for manufacturing. Using the index constructed from industry-level uncertainty,

[38] Source: 2022 Annual Business Survey. Summary tables are available here.

[39] By construction, the ECI exhibits no trend on average. To be able to interpret the time series, we deduct the ECI of the US economy from the EECI. This difference can be interpreted as the distance of the export destinations to the US economy and has declined in absolute value, suggesting a convergence process since the late 1990s (Figure A19, Panel c).

business diversification, and spatial diversification, we find a strong positive coefficient (Column 4). The results are very similar when we augment the index with EECI (Column 5).

Substitutability of MBB Experience and Age: Our identification exploits spatial variation in access to consultancies. Such exposure may operate through the usage of their services, which is not captured by our data, or through hiring from these firms, which we document. The latter channel is relevant because current or former consultants can transition directly into CEO positions or enter firms in any other capacity. Consequently, our measure of the local supply of young generalists may partly reflect firms' hiring at lower organizational levels, so that the age of the subsequently appointed CEO does not purely reflect firms' demand for such skills at the level of the CEO.

To test how hiring from consultancies at different organizational levels affects CEO age, we examine labor market flows from these firms to other employers. In particular, we document that CEOs with prior MBB experience are younger on average, consistent with the idea that work experience in these firms fast-tracks the accumulation of generalist skills. Moreover, the inflow of former consultants into a firm is positively associated with CEO age, but only for executives without a consulting background. This suggests that consulting firms offer their employees an accelerated path to management-relevant human capital, whereas executives who rise through other channels take longer to acquire the same skills, which the firm nonetheless demands of its CEO despite having hired former consultants into non-CEO positions. Together, these findings indicate that consulting experience provides individuals with generalist skills that substitute for age and interact with executives' internal career paths to affect CEO age at appointment.

We establish these patterns by combining the CEO information from BoardEx with the employment history data. For a CEO w, appointed in firm j, industry i, MSA m, and year t, we estimate regressions of the following form:

$$Age_{wt} = \alpha\, MBB\ Exp_{wt} + \beta\, Inflows_{jt} + \delta\, MBB\ Exp_{wt} \times Inflows_{jt} + \gamma_{mt} + \phi_{it} + X_{jt} + \epsilon_{wt}, \quad (2)$$

where Age_{wt} denotes the CEO's age at appointment, $MBB\ Exp_{wt}$ indicates individual w's experience at one of the MBB firms, and $Inflows_{jt}$ captures the share of employees with MBB experience. Specifically, the latter is defined as the firm-level sum of employees with any MBB experience hired over the previous 10 years, divided by the total number of new employees hired in the firm over the same period. As before, the regression includes fixed effects at the MSA-year and the NAICS-4-year level. We also control for the natural logarithm of employment and firm age. The main coefficient of interest is δ, capturing the differential effect of MBB inflows on individuals with MBB experience, compared to those without.

The results are reported in Table A10. Inflows from MBB firms are consistently and positively associated with CEO age, which is inconsistent with the view that the CEO age trend is primarily driven by supply-side scarcity of executives. Individuals with experience in one of these firms tend to be appointed as CEOs at substantially younger ages, by more than 3 years. The estimated coefficient on the interaction term is negative, indicating that MBB experience can serve as a substitute for age. These findings are robust across all specifications, conditional on controls and across varying sets of fixed effects.[40] Using the coefficient from our preferred specification, which includes fixed effects at the NAICS-4-year and MSA-year level, a one standard deviation increase in MBB inflows translates into a CEO age increase of around 0.4 years for those without MBB experience. This suggests that if the local supply of young generalists in Tables 1 to 4 operates, among other margins of adjustment, to hiring former consultants at lower organizational levels, then our estimated effects on CEO age constitute lower bounds.

CEO Age and Firm-Level Outcomes: Finally, in Appendix Section D.3, we scrutinize how these shifts in the demand for certain skills lead to the appointment of systematically different types of CEOs, thereby causally affecting firm-level policies and outcomes. Our results reveal that the appointment of older CEOs, as a result of higher demand for generalists, leads to reduced R&D expenditure and innovation in computing-related technologies.

5.2 Supply-Side Factors

We next shift the focus to a potential supply-side response in the managerial labor market. In the descriptive analysis, we established that part of the increase in the aging of CEOs goes hand in hand with increased mobility across jobs prior to CEO appointments. In this section, we explore whether the rise in labor market turnover prior to CEO appointments is driven by executives' voluntary job switches aimed at acquiring generalist skills. Upward, or possibly lateral, moves are typically associated with career progression and compensation. In contrast, downward moves, i.e., job transitions to less senior positions across firms, tend to be associated with factors such as employer-employee mismatches, wage disparities, or shocks to product market competition that induce firm exit and worker reallocation.[41] Against this background, *voluntary* downward moves are unlikely to be motivated by short-term financial considerations. Instead, they suggest that executives may be willing to forego short-term wage growth for the sake of accumulating generalist skills by switching to less senior positions in new domains, e.g., to different functions or even industries.

Using employment biographies, we identify transitions between firms that involve moving to lower seniority levels ("downward switches") or maintaining the same level ("lateral switches") as well as across job categories.[42] Figure 8 plots the evolution of the share of CEOs who ever moved downwards or laterally prior to their appointment, across positions within or across firms (Panel a) or only across firms (Panel b). While all variables exhibit a striking and similar upward trend in absolute terms, the relative increase in the share of those CEOs who ever moved downward is much

[40] The results from a number of additional robustness checks are shown in Table A11.

[41] As documented in Fee and Hadlock (2004), forced turnover among non-CEO executives occurs at rates at least as high as those for CEOs.

[42] The use of seniority levels as a measure of career attainment (e.g., as documented in Amornsiripanitch et al., 2025) is motivated by a large literature highlighting the role of firm-level hierarchies in organizing production processes (for a survey, see Garicano and Rossi-Hansberg, 2015), with implications for individual career progression (Caicedo et al., 2019), wage growth (Bayer and Kuhn, 2023), and firm-level outcomes (Ewens and Giroud, 2025).

larger. Consistent with these findings, Figure A23 plots the shares of downward and lateral switches over total switches—as above—across positions (Panel a) and firms (Panel b). The probability of moving downward conditional on switching has increased substantially over time, while the conditional probability of switching laterally has only seen modest increases.

We examine whether these labor market mobility patterns reflect voluntary switches by testing whether they are partly caused by heterogeneous information shocks on the returns to job switching. Our labor market data are particularly well-suited to answer this question, given that they capture individuals' information sets about their network connections.

For workers to capitalize on opportunities for on-the-job learning across firms, they must be aware of such opportunities and believe that increased mobility will be beneficial for their careers. We therefore expect exposure to information supporting this idea to increase job turnover in subsequent periods. We operationalize this idea by leveraging the role of information flows via coworker networks. The importance of social networks in shaping labor market outcomes is well-documented, both theoretically (Montgomery, 1991; Dustmann et al., 2016) and empirically in the overall labor market (Bramoullé and Saint-Paul, 2010; Hensvik and Skans, 2016) and in the labor market for CEOs (Liu, 2014; Kim et al., 2023). Network ties can emerge for various reasons, including prior employment at the same firm (Cingano and Rosolia, 2012; Glitz, 2017; Saygin et al., 2021; Cornelissen et al., 2025), shared educational backgrounds (Oyer and Schaefer, 2009), or residential proximity (Bayer et al., 2008). Importantly, networks also affect firm policies (Shue, 2013) and misconduct among financial advisers (Dimmock et al., 2018).

The positive information shock that we explore is the event of a former coworker leaving the firm and later becoming CEO. Consistent with the idea of observational learning, individuals, witnessing their former colleagues' career progress, should become more likely to emulate these career moves and become more mobile across firms and industries. That is, we test whether individuals respond to such information shocks by increasing their own job mobility.

Specifically, consider a worker w in year t, who worked alongside a future CEO in firm j, MSA m, and seniority level s. We implement a difference-in-differences design by estimating equations of the following form:

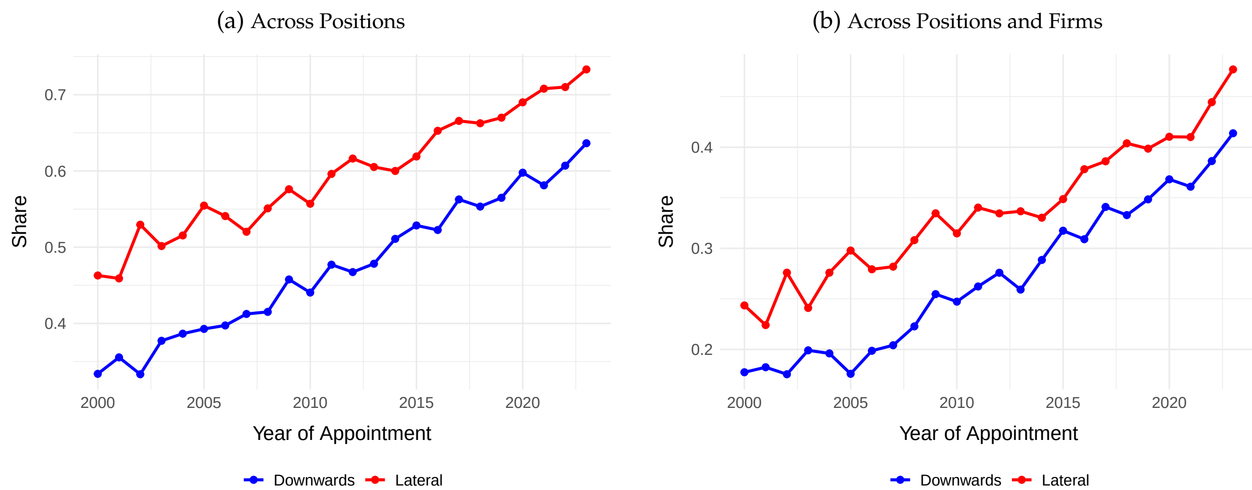
$$y_{wt} = \beta\, Treat_{jms} \times Post_{jst} + \gamma_w + \delta_{jst} + \epsilon_{wt}, \tag{3}$$

where y_{wt} is the outcome of interest, $Treat_{jms}$ is an indicator for treated individuals, and $Post_{jst}$ is an indicator for all periods following the CEO appointment of a former colleague. The fixed effects included, γ_w and δ_{jst}, are at the worker and firm-seniority-year level, respectively. The coefficient of interest is β, capturing the increase in job mobility following the CEO promotion event for workers associated with the CEO compared to the counterfactual.

To construct the sample, we start by identifying a list of CEO employment spells, considering only the first CEO appointment for each individual.[43] We then extract the employment histories of

[43] We focus on employment spells with the following attributes: (*i*) job title includes "CEO" or "Chief Executive Officer," (*ii*) seniority level of 7, (*iii*) ONET-code in the major group "11 - Management Occupations," (*iv*) the firm has at least 100 active employment spells in a given year, and (*v*) it is located in the United States.

Figure 8: Share of CEOs That Ever Moved Downwards or Laterally



Notes: Plots the share of CEOs by year of appointment that have ever switched downwards or laterally prior to their first CEO appointment. Panel (a) includes all switches across positions, and Panel (b) focuses on those across positions and firms. Switches are identified from a panel constructed from employment biographies from Revelio Labs, prioritizing more senior positions and those that started earlier in the case of overlapping spells.

these CEOs and retain all spells that meet the following criteria: they ended during the 10 years prior to the CEO appointment; they are at least at seniority level 4; and after these spells, the future CEO left the firm, but did not immediately become CEO. We label these as *connection spells*. The sample includes all individuals who had an employment spell in the same company and at the same seniority level, overlapping with a *connection spell* by at least 90 days. Thus, the sample encompasses all individuals who worked contemporaneously for at least 3 months in the same firm and at the same seniority level as a future CEO.

Among those individuals, the variable $Treat_{jms}$ is set equal to one for all those who were employed in the same MSA as their associated future CEO. In other words, the treatment group is composed of all individuals who have worked alongside a future CEO, that is, at the same company, the same seniority level, and in the same MSA. The control group comprises individuals that worked at the same company and seniority level but in other MSAs. The variable $Post_{jst}$ is an indicator for all periods following the former colleague's appointment to CEO, which typically takes place years after leaving the firm in question. Each individual enters the sample with the beginning of the spell that overlaps with the *connection spell*, but at the earliest in 1990, and exits the sample after at most 10 years following the CEO appointment, but at the latest at the end of the sample in 2023. In Table A12, we show summary statistics for the last year prior to the treatment, separately for the treatment and the control group. On average, individuals in the treatment group are slightly older, more experienced, and work at higher seniority levels, with somewhat higher imputed salaries, although these differences are small.

Our main outcomes comprise a set of indicators for job switches across firms between two consecutive observations.[44] With all fixed effects in place, this implies that the regressions estimate the change in the propensity to switch firms in response to the CEO appointment, comparing those who were working alongside the future CEO to those who were not. The causal effect is identified under a standard parallel trend assumption, which holds if—–conditional on all fixed effects and controls—–the change in the probability of switching firms would have been the same in both groups before and after the treatment. We are confident that this assumption is justified in our setting, given that the timing of the treatment is arguably quasi-random from the perspective of the treated individuals.

A burgeoning literature discusses potential biases arising from estimating difference-in-differences models with heterogeneous treatment timing using two-way fixed effects regressions (see, e.g., Goodman-Bacon, 2021; Roth et al., 2023). A key problem is that these designs generate flawed comparisons between a treatment group and a comparison group that has already been treated. To alleviate concerns about the validity of our approach, we exclude all individuals who were first assigned to a control group and then to a treatment group. If an individual is treated multiple times, we focus on the first treatment event. Finally, we only consider the first CEO appointment for each CEO. These restrictions ensure that the treatment is binary and that the sample includes only individuals who were either treated simultaneously with all other units in their firm-seniority group or who were never treated. In our preferred specification, we include fixed effects for all firm-seniority-year combinations. Consequently, our final estimate is a weighted average of canonical 2×2 difference-in-differences estimates generated by each of these firm-seniority-year combinations, following the logic of a stacked design (Wing et al., 2024). We also highlight that the control group is relatively large compared to the treatment group, accounting for 79% of all observations post-treatment observations and 77% of all individuals, further mitigating potential issues arising from negative weights (De Chaisemartin and d'Haultfoeuille, 2020).

We proceed by estimating Equation (3) on the employment history data. The baseline results are presented in Table 5, where the outcome variable is an indicator of switching between firms. Column (1) displays the coefficients from regressions that include the treatment and post indicators, their interaction, and year fixed effects. While the coefficient on the $Treat_{jms}$ is insignificant, the coefficient on the $Post_{jst}$ is negative, suggesting that job mobility during the post-treatment period tends to decrease—–possibly because people are at later stages of their careers and less likely to transition between firms. Finally, the estimated coefficient on the interaction term is positive but insignificant.

In the subsequent columns, we augment the regression with different sets of fixed effects, which eliminate the coefficients on $Treat_{jms}$ and $Post_{jst}$. The estimated coefficient on the interaction term becomes highly significant and increases in terms of magnitude. Given that the treatment is at the seniority-firm-year level, the specification in Column (4) is our preferred one. Quantitatively, the

[44] One potential concern is that a CEO may improve job opportunities for connected individuals in firms they have worked in or currently work in. To mitigate this, we exclude transitions to firms where the CEO was employed between the *connection spell* and the CEO appointment.

Table 5: CEO Appointment of Former Coworker and Job Mobility (Any Firm Switch)

	Firm Switch				
	(1)	(2)	(3)	(4)	(5)
Treat	-0.002				
	(0.001)				
Post	-0.010***	-0.016***	-0.019***		
	(0.001)	(0.001)	(0.001)		
Treat × Post	0.002	0.002	0.002	0.005***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.012	0.139	0.140	0.166	0.197
Observations	22,777,381	22,777,381	22,777,381	22,777,381	16,139,755
Pre-Treatment Control Mean	0.094	0.094	0.094	0.094	0.095
Year fixed effects	✓	✓	✓		
Individual fixed effects		✓	✓	✓	✓
Firm-Seniority fixed effects			✓		
Firm-Seniority-Year fixed effects				✓	✓
MSA-Naics4-Year fixed effects					✓

Notes: The dependent variable in all regressions is a dummy equal to one in the last year before an individual switches firms. *Treat* is an indicator for having worked alongside a future CEO. *Post* is an indicator for periods following the CEO appointment. The fixed effects and standard errors refer to the position the individual worked in alongside the future CEO. Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

probability of switching firms increases by about 0.5 percentage points, amounting to a 5% increase compared to the baseline.

One challenge to our identification strategy consists of potential latent differences between individuals working alongside a future CEO and their respective control groups; for instance, the former may work at headquarters while the latter are based in regional offices. The environment in the treatment group may be more competitive and ambitious, or it may offer better outside options due to the clustering of similar industries nearby. While we do not observe any baseline differences across the two groups in Column (1), we explicitly address this issue by including fixed effects at the MSA-NAICS-4-year level, effectively controlling for any time-varying differences across narrow industries and geographic locations in the level of job mobility. The results are shown in Column (5). While the estimated coefficient slightly decreases in size, this change is neither statistically nor economically significant.

We repeat the analysis for switches across NAICS-4 industries, with the results included in Table A13. While naturally smaller in absolute size, the signs and relative magnitudes are closely in line with the previous results. For instance, the estimate from Column (4) suggests a 7% increase in mobility across industries compared to the baseline.

Moving beyond the overall increase in worker mobility in response to the information shock, we turn to examining the underlying dynamics. To this end, we further differentiate the main outcome based on whether an individual moved to a more senior position, a less senior position, or remained at the same seniority level. The results show that the rise in overall mobility is driven entirely by an increase in the frequency of downward transitions across firms (Table 6), while upward and lateral transitions remain practically unaffected (Tables A14 and A15).

Next, we assess whether the transitions between firms in response to the information shock are accompanied by changes in job categories, distinguishing between seven functional areas.[45] The estimates in Tables A16 and A17 indicate that the increase in job mobility is mainly due to a higher probability of switching across job categories. Even though the coefficients from our preferred specification are similar in both cases, the relative increase in cross-category switches is nearly twice as large, once taking the baseline differences into account. These dynamics are potentially self-reinforcing, as individuals with broader experience tend to be more willing to move across positions (Cappelli and Hamori, 2014).

In sum, these findings support the idea that workers emulate future CEOs' employment trajectories. While upward or lateral moves may be motivated by financial incentives, the greater prevalence of downward transitions suggests that employees are seeking to acquire a broader range of generalist skills across firms and functional areas—–skills that are highly valued for future CEO roles.

As a first robustness check, we modify our preferred specification to obtain event-study estimates, presented in Figure A24. The estimated coefficients are generally small and insignificant during the pre-treatment periods, followed by a gradual increase in the post-treatment periods for overall and downward switches. In contrast, we observe no discernible response for upward or lateral switches. We also show the results from a placebo test, where we focus on individuals who left the initial firm between one and five years before the prospective CEO was hired at that firm. The estimates, included in Table A18, are close to zero and insignificant across the board.

To bolster the validity of our mechanism, we provide a battery of consistency checks, focusing particularly on downward mobility. As our argument hinges on network connections, we conjecture that the response in job mobility should be more pronounced among those who have closer ties to the future CEO. One potential measure for proximity is shared tenure, i.e., the time spent together at the same seniority level within a firm during their former job. We test this in Table A19 by including an interaction with an indicator equal to one for those whose shared tenure is in the highest quartile. The estimated coefficients on the triple interaction are large and significant, suggesting that this group reacts more strongly to the information shock. Figure A25 shows the coefficients on the marginal effect for downward mobility (Column 4 of Table A19) separately for all quartiles of shared tenure, revealing a strong gradient in the response across the entire distribution.

In a similar vein, we hypothesize that the information shock spills over to individuals in other seniority levels at the initial firm. To check this, Tables A20 and A21 focus on individuals in the two levels above and below the future CEO, respectively. We find that employees who worked just above the seniority level of the future CEO exhibit a similar reaction to the treatment as those

[45] The job categories are Admin, Engineering, Finance, Marketing, Operations, Sales, and Science.

Table 6: CEO Appointment of Former Coworker and Job Mobility (Downward Firm Switch)

	Firm and Downward Switch				
	(1)	(2)	(3)	(4)	(5)
Treat	-0.005***				
	(0.001)				
Post	-0.010***	-0.012***	-0.013***		
	(0.001)	(0.001)	(0.001)		
Treat × Post	0.003***	0.004***	0.004***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.005	0.090	0.090	0.111	0.144
Observations	22,777,381	22,777,381	22,777,381	22,777,381	16,139,755
Pre-Treatment Control Mean	0.041	0.041	0.041	0.041	0.041
Year fixed effects	✓	✓	✓		
Individual fixed effects		✓	✓	✓	✓
Firm-Seniority fixed effects			✓		
Firm-Seniority-Year fixed effects				✓	✓
MSA-Naics4-Year fixed effects					✓

Notes: The dependent variable in all regressions is a dummy equal to one in the last year before an individual switches firm and transitions to a lower seniority level. *Treat* is an indicator for having worked alongside a future CEO. *Post* is an indicator for periods following the CEO appointment. The fixed effects and standard errors refer to the position the individual worked in alongside the future CEO. Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

who worked at the same seniority level as the future CEO, whereas the response in seniority levels below the CEOs is more muted.

We also examine whether the response to the information treatment has become stronger over time. In Table A22, we test for time variation in the treatment effect by interacting the variable of interest with indicators for 5-year bins, excluding the final two bins to ensure a balanced 10-year post-period. The results indicate a structural break during the period 2000 to 2004, which is omitted as a baseline. In the early 1990s, treated individuals reacted to the information shock by increasing their lateral job mobility. During the late 2000s and early 2010s, the response shifted toward downward job mobility, further prolonging the career trajectory of prospective CEOs. Given the increasing coefficients on downward mobility after 2000, this result speaks against a one-off shock but in favor of a gradual increase in the weight attributed to generalist human capital.

Next, we consider heterogeneity with respect to the future CEOs' job mobility between leaving the firm and being promoted to CEO. In Table A23, we build on the idea that the information shock is stronger for those who have seen their former colleague transition across a higher number of positions. To evaluate this hypothesis, we introduce an interaction term with an indicator equal to one if the number of CEO transitions is in the highest quartile. In line with our expectations, the estimated coefficients on the triple interactions are positive for both overall and downward transitions. Moreover, we test for heterogeneity depending on the direction of the CEO switch in terms of seniority. Assuming individuals imitate successful career paths, one would anticipate a higher probability of upward, lateral, or downward switches after having witnessed a former coworker leaving in the respective direction (the omitted category is upward, i.e., a future CEO leaving the company for a more senior position). The results shown in Table A24 point in this direction, showing a significant coefficient for downward moves in Column (4), the category of greatest interest to us.

In addition to CEOs' career paths, we hypothesize that the treated individual's own characteristics and career considerations will play a role in the response of job mobility. Downward and industry switches should be more prevalent responses among individuals working in smaller firms where it is harder to acquire generalist skills, possibly due to the limited scope of the firm's operations. We scrutinize this idea by including interactions with size quartiles of a worker's current firm, with results shown in Table A25 and Figure A26. As hypothesized, we find that the positive response to the information shock is concentrated among individuals working in smaller firms. This result complements Lazear (2009), who argues that quits should be less common among more idiosyncratic, i.e., smaller, firms, as the market for the skills of their employees is thinner. Importantly, the increase in career mobility is not primarily driven by switches to larger firms. To demonstrate this, we distinguish downward moves by the size of the destination firm. The results in Table A26 reveal that the rise in turnover is driven by switches to smaller firms, both in absolute terms and compared to the current employer.[46]

As a direct implication of the higher likelihood of moving to less senior positions, we anticipate that individuals forgo income in the medium run in order to improve their long-term career prospects. To test this hypothesis, we repeat the analysis with the growth rate of imputed salary as the dependent variable. The results included in Table A27 are in line with our expectations, indicating a reduction in salary growth of around 11% relative to the counterfactual. As before, this result is robust to adding fixed effects at the MSA-NAICS-4-year level, suggesting that we can rule out differences in local labor market conditions as the driver of these results.

Taken together, these estimates support the hypothesis that the observed trends are partly influenced by an increase in generalist skills on the labor supply side. They provide evidence in favor of the idea that positive information about the returns to job mobility among connected individuals increases employees' probability of switching across firms with the intention of gathering generalist skills across a wide range of functional areas. Consequently, the career paths of prospective CEOs become longer, leading to higher age at CEO appointment.

5.3 Decomposing Variation in the Aging Patterns

In this section, we decompose the aging trend into a sectoral and a geographical dimension. Our results in Section 5.1 suggest that sectoral shocks, specifically shifts in uncertainty and complexity

[46] This does not exclude the possibility that ambitious and successful individuals are generally willing to trade off working in a larger firm with a lower seniority level. In Figure A27, we focus on firm switches of future CEOs and regress the differences in firm size against differences in seniority. We find that such a trade-off indeed exists and that it has become stronger over time.

in the economic environment, have contributed to higher demand for generalist skills. Yet, the implications of these shocks on CEO appointments are heterogeneous across space due to frictions in the availability of generalist skills. As such, one can interpret sectoral variation over time as primarily reflecting changes in the demand for generalist skills, while variation across space tends to capture changes in the supply thereof (in line with our identifying variation in Section 5.2).

To quantify the role of these two dimensions, we assess the explanatory power of different combinations of fixed effects for CEO age at appointment. We consider a CEO appointment in firm j, MSA m, industry i and year t, and estimate a series of regressions to obtain the following coefficients of determination:

$$R_i^2: \qquad Age_{jt} = \phi_i \times (\delta_t + X_{jt}) + \epsilon_{jt} \tag{4}$$

$$R_m^2: \qquad Age_{jt} = \gamma_m \times (\delta_t + X_{jt}) + \epsilon_{jt} \tag{5}$$

$$R_{i+m}^2: \qquad Age_{jt} = (\phi_i + \gamma_m) \times (\delta_t + X_{jt}) + \epsilon_{jt} \tag{6}$$

$$R_{i\times m}^2: \qquad Age_{jt} = \phi_i \times \gamma_m \times (\delta_t + X_{jt}) + \epsilon_{jt}. \tag{7}$$

As before, Age_{jt} denotes CEO age at appointment. The fixed effects ϕ_i and γ_m are at the NAICS-4 and MSA level, respectively, and interacted with year fixed effects, δ_t, and a vector of control variables, X_{jt}, which includes the number of employees, firm age (both in terms of their natural logarithm) and average age of other executives. As we add all lower-level interactions, we estimate to what extent sectoral and geographical factors can explain variation in CEO age at appointment, both differentially across years and firm-level characteristics.

We then use the estimated R^2s to calculate the contribution of each dimension to $R_{i\times m}^2$, which is generated by the full model. In doing so, the key complication is that $R_i^2 + R_m^2 \neq R_{i+m}^2$ if the regressors are non-orthogonal. We address this by calculating Shapley values, which provide the unique decomposition of $R_{i\times m}^2$ that is both additive and symmetric, i.e., it is invariant to the order in which regressors are added to the model (Grömping, 2015; Sharapov et al., 2021). Due to the nested fixed effects structure, the analytical expressions for the three components simplify as follows:

$$\text{Sectoral contribution} = \frac{1}{2}(R_i^2 + R_{i+m}^2 - R_m^2) \tag{8}$$

$$\text{Geographical contribution} = \frac{1}{2}(R_m^2 + R_{i+m}^2 - R_i^2) \tag{9}$$

$$\text{Interaction} = R_{i\times m}^2 - R_{i+m}^2. \tag{10}$$

In the final step, we rescale the contributions by $R_{i\times m}^2$ to represent the share of the total explained variance that we can trace back to one of the factors.

Table 7 shows the results. In the first row, we focus on interactions with year fixed effects. The estimated $R_{i\times m}^2$ is at 36%, of which approximately 38% and 28% can be attributed to sectoral and geographical factors, respectively, while the interaction term accounts for the remaining one-third of the explained variance. In the subsequent rows, we successively introduce additional interactions

Table 7: Decomposition of CEO Aging Trend (in %)

Independent Variables	Sectoral	Geographical	Interaction	$R^2_{i\times m}$
$(\phi_i + \gamma_m) \times$ Year	38.1	28.2	33.7	36.2
	(0.9)	(0.9)	(0.9)	(0.9)
+ $(\phi_i + \gamma_m) \times$ Log(Employment)	36.5	25.7	37.8	44.6
	(0.8)	(0.7)	(0.9)	(0.8)
+ $(\phi_i + \gamma_m) \times$ Log(Firm Age)	35.4	25.6	39.0	49.4
	(0.9)	(0.8)	(1.0)	(0.9)
+ $(\phi_i + \gamma_m) \times$ Executive Age	37.0	28.4	34.6	56.7
	(0.8)	(0.7)	(0.9)	(0.8)

Notes: Shows the estimated contributions (in %) of sectoral and geographical factors, and their interaction to the CEO aging trend as described in Equations 8, 9, and 10. $R^2_{i\times m}$ denotes the R^2 obtained from estimating Equation (7). The first row shows the results obtained from interacting ϕ_i, γ_m, and $\phi_i \times \gamma_m$ with δ_t. The following rows add further interactions with the natural logarithm of both the number of employees and firm age, as well as average age of other executives (obtained from the employment history data). Standard errors obtained from bootstrapping (100 replications) contained in brackets.

with the number of employees, firm age, and average executive age. While we are now able to explain 57% of the variation in age, the relative contributions of the two dimensions remain remarkably stable across specifications. We also report bootstrapped standard errors, which confirm that the components are statistically significantly different from one another.[47]

Taken together, the three components can be interpreted as capturing distinct forces behind the rising CEO age at appointment. Given our results from Section 5.1, the sectoral dimension maps most closely to demand-side factors that increase the value of a diverse set of labor market experiences. Holding the supply of generalist candidates constant, such demand-side factors, which include higher uncertainty and greater business diversification, jointly account for approximately 37% of the explained variation in CEO age. Analogously, the geographic component, as captured by the local supply of generalists across metro areas, explains around 28% of the variation. This availability is shaped by factors such as labor market thickness, the responsiveness of prospective executives to changes in firm-level demand, and the presence of executive training pipelines.[48] The third term reflects the degree to which these two forces interact with each other, in particular the extent to which the effects of increases in demand depend on the local supply of generalist skills. For instance, firms in sectors experiencing a surge in the demand for generalists can only adjust

[47] One limitation of this approach is that it does not account for general demographic changes, which are absorbed by both the time-varying sectoral and geographical variation. To gauge the magnitude of this concern, we repeat the exercise using CEO age after residualizing for year fixed effects. Even with this overly conservative adjustment, our preferred specification attributes 35.8% and 26.4% to sectoral and geographical factors, respectively ($R^2 = 54.6\%$). As CEOs at appointment have aged more rapidly than the population at large, these estimates can be interpreted as lower bounds.

[48] In our sample, about 56% of CEO appointments occur within the same metro area. Yonker (2017) reports that firms are over five times more likely to appoint a local CEO than predicted if geography did not matter in the matching process. This pattern persists when focusing on external appointments from other firms or industries. After considering several competing explanations, he argues that CEOs' geographic preferences are the most plausible driver of the prevalence of local hiring. Amore et al. (2022) complement this view by documenting that closer physical proximity of CEOs contributes positively to the working environment within firms.

fully if they are located in labor markets in which these skills are available. The contribution of 35% highlights that such frictions or complementarities are sizable.

6 Conclusion

This paper contributes to our understanding of the evolving market for corporate leadership by documenting and explaining the substantial increase in CEO age upon appointment over the past two and a half decades. Our findings reveal that this trend reflects fundamental changes in how executives build careers and how firms select their leaders. The rise in CEO age is primarily driven by longer external career paths prior to appointment, with prospective CEOs accumulating increasingly diverse experiences across positions, firms, and sectors.

Using plausibly exogenous variation in access to strategy consulting firms, we demonstrate that demand for generalist skills in response to greater industry-level uncertainty and complexity has causally contributed to the appointment of older CEOs. Simultaneously, executives strategically respond to these evolving skill requirements by increasing their job mobility through professional networks, on average at the cost of reduced short-term compensation.

This mechanism explains distinct CEO hiring patterns by firm size. CEOs in large firms are predominantly promoted internally (e.g., Cziraki and Jenter, 2021) and have experienced a decline in executive mobility since 2000 (Barry et al., 2025). In smaller firms, by contrast, the majority of CEOs are appointed externally, typically following career paths that involve an increasing number of transitions across other firms. The rising demand for generalist skills rationalizes these patterns: large firms can cultivate generalists internally through diverse assignments across divisions and functions, while smaller firms tend to recruit executives who accumulated generalist experience externally. Consequently, the lengthening of external career paths translates into older CEO appointments primarily at smaller firms.

The implications of this trend are substantial, given that older CEOs tend to manage firms with slower growth rates and less radical innovation. While these patterns might appear concerning for long-term economic dynamism, they may represent a rational response to changing business environments characterized by heightened uncertainty and complexity. Understanding the underlying mechanisms driving this transformation provides important insights into evolving corporate governance and the firm-level origins of aggregate fluctuations.

More broadly, the shift toward generalist human capital reflects the growing demand for skills that enable coordination, adaptation, and decision-making under uncertainty. While central to firm organization (Garicano, 2000), these skills are difficult to codify and automate. As technology, including AI, increasingly substitutes routine tasks, it may disrupt the pathways through which expertise has traditionally been acquired, while simultaneously increasing the value of experienced decision-makers who can effectively leverage these technologies (Garicano and Rayo, 2025; Garicano et al., 2026). The rising importance of generalist human capital thus reflects not only its relative resilience to automation, but also suggests that the patterns we document may prove persistent.

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Online Appendix for

"AGING AT THE VERY TOP"

April 9, 2026

Valentin Kecht Alessandro Lizzeri Farzad Saidi

Contents

A Model Appendix

A.1 Overview

We formalize the analysis underlying the model section. Job slots are indexed by a scalar productivity s; in the CEO application $s = z$, but the analysis extends to any scalar slot index generated by a hierarchical firm structure. Under transferable utility and a multiplicative surplus, equilibrium matching is positively assortative in slot productivity and worker score, so age patterns across the productivity distribution reduce to the distribution of worker age conditional on score. The analysis delivers three results.

1. **Age and slot productivity at fixed α (Theorem 1).** Higher score tails contain stochastically older workers; under positive assortative matching (PAM), more productive slots are filled by stochastically older workers.

2. **Within-tail age–ability selection (Theorem 2).** Selection into a score tail induces a weakly (strictly under mild regularity) negative age–ability relationship.

3. **Comparative statics in α at fixed selectivity (Theorem 3).** Holding the selected fraction fixed, raising α shifts the tail age distribution upward in first-order stochastic dominance.

A parametric example with exponential ability illustrates how the key condition for the third result reduces to monotonicity of the age-output profile $y(\cdot)$.

A.2 Environment, Surplus, and Equilibrium Sorting

Slots have productivity $S \sim G_S$ on $[\underline{s}, \bar{s}]$ with $\underline{s} > 0$ (continuous CDF). Workers are characterized by ability A and age T. Match surplus is

$$\pi(s, a, t; \alpha) = s \cdot \phi(a, t; \alpha), \tag{11}$$

where the worker score is

$$\phi(a, t; \alpha) = (1 - \alpha)\big[a + h(t)\big] + \alpha\, y(t), \qquad \alpha \in [0, 1). \tag{12}$$

The restriction $\alpha < 1$ ensures ability enters with positive weight. Writing $\Phi_\alpha := \phi(A, T; \alpha)$, it is convenient to decompose the score as

$$\Phi_\alpha = (1 - \alpha)A + g_\alpha(T), \qquad g_\alpha(t) := (1 - \alpha)h(t) + \alpha y(t). \tag{13}$$

We maintain the following assumptions throughout.

Assumption 1.

(a) *(Continuous score.)* For each α, Φ_α has a continuous distribution.

(b) *(Independence.)* $A \perp T$ in the population.

(c) *(Log-concave ability.)* A has a log-concave density f_A.

(d) *(Monotone composite age component.)* $g_\alpha(\cdot)$ is weakly increasing on $[\underline{t}, \bar{t}]$.

Remark 2 (On Assumption 1d). The composite term $g_\alpha = (1-\alpha)h + \alpha y$ can be increasing even when h is single-peaked, provided $\alpha y'(t) \geq -(1-\alpha)h'(t)$ for all t, which is satisfied when α is large enough relative to the rate of decline of h, or y' is sufficiently steep.

Remark 3 (Positive assortative matching). Under transferable utility, stable matchings maximize total surplus. Because $(s, \varphi) \mapsto s\varphi$ has strictly increasing differences on $\mathbb{R}^2_+$, equilibrium matching is positively assortative in (S, Φ_α): higher-productivity slots are filled by higher-score workers. Assumption 1a ensures score cutoffs at fixed tail fractions are unique.

A.3 Fixed-α Tail Results

Fix α and write $\Phi := \Phi_\alpha$. For a tail fraction $\theta \in (0,1)$, let $\kappa(\theta)$ denote the unique cutoff with $\mathbb{P}(\Phi \geq \kappa(\theta)) = \theta$, and write $C(\kappa) := \{\Phi \geq \kappa\}$.

Age increases stochastically with score

Under Assumption 1, the joint density of (Φ_α, T) is totally positive of order two (TP2). To see this, the change of variables $(a, t) \mapsto (x, t)$ with $x = (1-\alpha)a + g_\alpha(t)$ yields

$$f_{\Phi_\alpha,T}(x,t) = \frac{f_T(t)}{1-\alpha} f_A\left(\frac{x - g_\alpha(t)}{1-\alpha}\right). \tag{14}$$

Log-concavity of f_A implies the kernel $f_A(u-v)$ is TP2 in (u,v) (Karlin, 1968); monotonicity of g_α preserves TP2 under the change of variables; and TP2 of $f_{\Phi_\alpha,T}$ implies that T is stochastically increasing in Φ_α—i.e. $\mathbb{P}(T > t \mid \Phi_\alpha = x)$ is nondecreasing in x for every t (Shaked and Shanthikumar, 2007, Theorem 1.C.1). We denote this property $\mathrm{SI}(T \mid \Phi_\alpha)$.

Theorem 1 (Higher score tails select older workers; more productive slots filled by older workers)**.** *Under Assumption 1,* $\mathrm{SI}(T \mid \Phi)$ *holds. Consequently:*

(i) (Tail selectivity.) *If $\kappa_2 > \kappa_1$, then $T \mid \{\Phi \geq \kappa_2\} \geq_{st} T \mid \{\Phi \geq \kappa_1\}$. Equivalently, for $0 < \theta_2 < \theta_1 < 1$, $T \mid C(\kappa(\theta_2)) \geq_{st} T \mid C(\kappa(\theta_1))$.*

(ii) (Slot productivity.) *Under PAM, the age distribution of the assigned worker is stochastically increasing in slot productivity. In particular, CEOs at larger firms are stochastically older.*

Proof. $\mathrm{SI}(T \mid \Phi)$ follows from the TP2 argument above.

Part (i). Fix t and let $q_t(x) := \mathbb{P}(T > t \mid \Phi = x)$, nondecreasing by SI. For $\kappa_2 > \kappa_1$, $\Phi \mid \{\Phi \geq \kappa_2\}$ FOSD-dominates $\Phi \mid \{\Phi \geq \kappa_1\}$, so $\mathbb{E}[q_t(\Phi) \mid \Phi \geq \kappa_2] \geq \mathbb{E}[q_t(\Phi) \mid \Phi \geq \kappa_1]$, i.e. $\mathbb{P}(T > t \mid \Phi \geq \kappa_2) \geq \mathbb{P}(T > t \mid \Phi \geq \kappa_1)$ for all t.

Part (ii). Under PAM with continuous distributions, the equilibrium assignment is an increasing map $s \mapsto \varphi(s)$ from slot productivity to worker score. The conditional age distribution at slot s is $T \mid \Phi = \varphi(s)$, which is stochastically increasing in s by SI and monotonicity of φ. □

Selection-induced age–ability correlation within a score tail

Membership in $C(\kappa) = \{\Phi \geq \kappa\}$ can be written as an age-dependent ability truncation:

$$C(\kappa) = \{A \geq c_\kappa(T)\}, \qquad c_\kappa(t) := \frac{\kappa - g_\alpha(t)}{1-\alpha}. \tag{15}$$

By Assumption 1d, $c_\kappa(\cdot)$ is weakly decreasing: older workers face a (weakly) lower ability threshold to enter the same tail.

Theorem 2 (Selection induces a negative age–ability relationship within a top tail)**.** *Under Assumption 1, for any cutoff κ with $\mathbb{P}(C(\kappa)) > 0$:*

$$\operatorname{Cov}(A, T \mid C(\kappa)) \leq 0.$$

If moreover g_α is strictly increasing on a set of positive $T \mid C(\kappa)$-measure and the truncated-mean $m(x) := \mathbb{E}[A \mid A \geq x]$ is strictly increasing on the essential range of $c_\kappa(T)$ under $T \mid C(\kappa)$, then the covariance is strictly negative, and if additionally $\operatorname{Var}(A \mid C(\kappa)) > 0$ *then* $\operatorname{Corr}(A, T \mid C(\kappa)) < 0$*.*

Proof. For any t with $\mathbb{P}(C \mid T = t) > 0$, independence gives $\mathbb{E}[A \mid T = t, C] = m(c_\kappa(t))$. Hence $\operatorname{Cov}(A, T \mid C) = \operatorname{Cov}(m(c_\kappa(T)), T \mid C)$. Since $m(\cdot)$ is weakly increasing[49] and $c_\kappa(\cdot)$ is weakly decreasing, the composite $U := m \circ c_\kappa$ is weakly decreasing. For $\widetilde{T}$ an independent copy of $T \mid C$,

$$2\operatorname{Cov}(U(T), T \mid C) = \mathbb{E}\big[(U(T) - U(\widetilde{T}))(T - \widetilde{T}) \mid C\big] \leq 0,$$

since the factors have opposite signs. Strict inequality follows under the additional conditions. □

Remark 4 (Intuition). To clear a fixed score cutoff, an older worker can qualify with lower ability because age raises $g_\alpha(t)$. Hence within a high-score tail, older workers tend to have lower ability than younger workers generating a negative relationship that is absent in the overall population.

A.4 Comparative Statics in α

Fix $\theta \in (0,1)$ and $\alpha_1 < \alpha_2$. For each α_i, let $\kappa_i := \kappa_{\alpha_i}(\theta)$ be the unique cutoff with $\mathbb{P}(\Phi_{\alpha_i} \geq \kappa_i) = \theta$, and define

$$C_i := \{\Phi_{\alpha_i} \geq \kappa_i\} = \{A \geq c_i(T)\}, \qquad c_i(t) := \frac{\kappa_i - g_{\alpha_i}(t)}{1-\alpha_i}. \tag{16}$$

By Assumption 1d each $c_i(\cdot)$ is weakly decreasing (with slope $-g'_{\alpha_i}(t)/(1-\alpha_i) \leq 0$).

[49] $m'(x) = h_A(x)[m(x) - x] \geq 0$ since $m(x) \geq x$ and $h_A \geq 0$; strict when f_A is strictly positive near x.

Remark 5 (Mapping to the CEO application). Each firm's rank in the slot-productivity distribution G_S is independent of α, so the tail fraction θ corresponding to a given firm is fixed across economies. Theorem 3 therefore compares CEO age distributions at a given firm-size quantile across environments with different α.

Cutoff schedules across α

A direct calculation yields

$$c_2(t) - c_1(t) = \underbrace{\left(\frac{\kappa_2}{1-\alpha_2} - \frac{\kappa_1}{1-\alpha_1}\right)}_{\text{constant in } t} - \underbrace{\left(\frac{\alpha_2}{1-\alpha_2} - \frac{\alpha_1}{1-\alpha_1}\right)}_{>0} \cdot y(t). \tag{17}$$

If $y(\cdot)$ is weakly increasing, then $c_2(t) - c_1(t)$ is weakly decreasing in t: raising α relatively lowers the ability threshold for older workers. Because θ is held fixed, the schedules generically cross—a uniform ordering $c_2 \le c_1$ would typically violate $\mathbb{P}(C_1) = \mathbb{P}(C_2) = \theta$.

By Bayes' rule and independence, the age density conditional on belonging to the top-θ tail is

$$f_{T|C_i}(t) \propto f_T(t)\, \bar{F}_A(c_i(t)), \tag{18}$$

so the likelihood ratio of the two tail densities satisfies $f_{T|C_2}(t)/f_{T|C_1}(t) \propto \bar{F}_A(c_2(t))/\bar{F}_A(c_1(t))$.

Main comparative-statics result

Assumption 2 (Tail likelihood-ratio monotonicity (TLR))**.** The ratio $t \mapsto \bar{F}_A(c_2(t))/\bar{F}_A(c_1(t))$ is weakly increasing on $[\underline{t}, \bar{t}]$.

Theorem 3 (Greater weight on experience shifts the selected age distribution upward)**.** *Fix $\theta \in (0,1)$ and $\alpha_1 < \alpha_2$. Under Assumptions 1b, 11a, and 2, increasing the weight on experience shifts selection toward older workers. Formally,*

$$T \mid C_2 \ \ge_{st} \ T \mid C_1.$$

Proof. By (18), the likelihood ratio $f_{T|C_2}/f_{T|C_1}$ is proportional to $\bar{F}_A(c_2(t))/\bar{F}_A(c_1(t))$, which is nondecreasing by Assumption 2. MLR dominance implies FOSD (Whitt, 1982). □

Sufficient conditions for TLR

Exponential ability. A revealing example is one with an exponential distribution of ability If $\bar{F}_A(x) = e^{-\lambda x}$ on the relevant cutoff range, then $\bar{F}_A(c_2(t))/\bar{F}_A(c_1(t)) = \exp\{-\lambda(c_2(t) - c_1(t))\}$. When $y(\cdot)$ is weakly increasing, $c_2(t) - c_1(t)$ is weakly decreasing by (17), so the ratio is weakly increasing—TLR holds. The exponential case is especially transparent because the constant hazard rate means selection probabilities depend only on cutoff *differences*, eliminating any dependence on levels: monotonicity of y is both necessary and sufficient.

General hazard-rate condition. For non-exponential ability, differentiating the log of the likelihood ratio gives

$$\frac{d}{dt} \log \frac{\bar{F}_A(c_2(t))}{\bar{F}_A(c_1(t))} = h_A(c_2(t)) \cdot \frac{g'_{\alpha_2}(t)}{1-\alpha_2} - h_A(c_1(t)) \cdot \frac{g'_{\alpha_1}(t)}{1-\alpha_1},$$

where $h_A(x) := f_A(x)/\bar{F}_A(x)$ is the ability hazard rate. TLR holds whenever this expression is nonnegative for all t. Since $g'_\alpha(t)/(1-\alpha) = h'(t) + [\alpha/(1-\alpha)]y'(t)$ is increasing in α when $y'(t) \geq 0$, the slope term favors TLR; whether this dominates depends on how the hazard varies across the two endogenous cutoff levels $c_1(t)$ and $c_2(t)$.

A.5 Reshuffling Pressure from Changes in α

The model is static but implies how much the frictionless target ranking changes when α rises. For worker $w = (a,t)$, define her upper-tail rank under α by $q_\alpha(w) := \mu\{w' : \Phi_\alpha(w') \geq \Phi_\alpha(w)\}$, where μ is the population measure. Let $S_{\alpha_1,\theta} := \{w : q_{\alpha_1}(w) \leq \theta\}$ be the baseline top-θ workers. Cumulative reshuffling pressure is

$$V_\theta(\alpha_1, \alpha_2) := \int_{S_{\alpha_1,\theta}} TV_{[\alpha_1,\alpha_2]}(q_\cdot(w))\, d\mu(w), \tag{19}$$

where TV denotes total variation. Using cumulative rather than net rank change ensures intermediate movements do not cancel.

Proposition 1 (Larger α-changes generate more reshuffling pressure)**.** *For fixed θ and α_1, the map $\alpha_2 \mapsto V_\theta(\alpha_1, \alpha_2)$ is weakly increasing on $[\alpha_1, 1)$.*

Proof. For each pair (w, w'), $\Phi_\alpha(w') - \Phi_\alpha(w)$ is affine in α, so $\mathbf{1}\{\Phi_\alpha(w') \geq \Phi_\alpha(w)\}$ changes sign at most once, bounding $TV_{[\alpha_1,\alpha_2]}(q_\cdot(w)) \leq 1$ and ensuring (19) is well-defined. Monotonicity follows because total variation is monotone in the interval: $[\alpha_1, \alpha_2] \subseteq [\alpha_1, \alpha_2']$ implies $TV_{[\alpha_1,\alpha_2]}(q_\cdot(w)) \leq TV_{[\alpha_1,\alpha_2']}(q_\cdot(w))$ for every w; integrating over $S_{\alpha_1,\theta}$ gives the result. $\square$

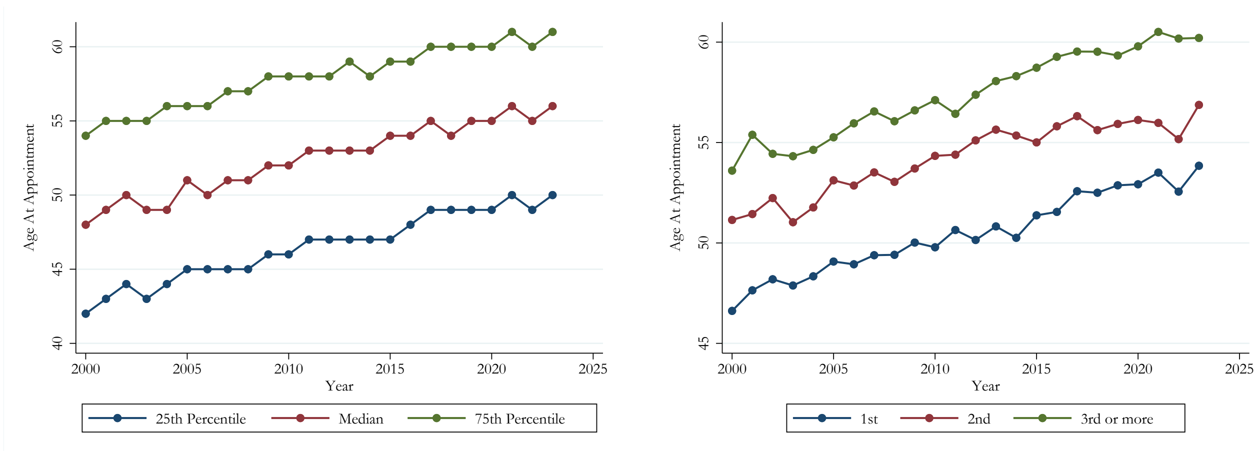
Remark 6. This measures *reshuffling pressure*, not realized turnover: it captures how extensively the frictionless assignment must be reorganized when the importance of experience rises. Larger changes in α require more extensive re-ranking of initially top-ranked workers.

B Additional Figures

Appendix Figure A1: CEO Age at Appointment

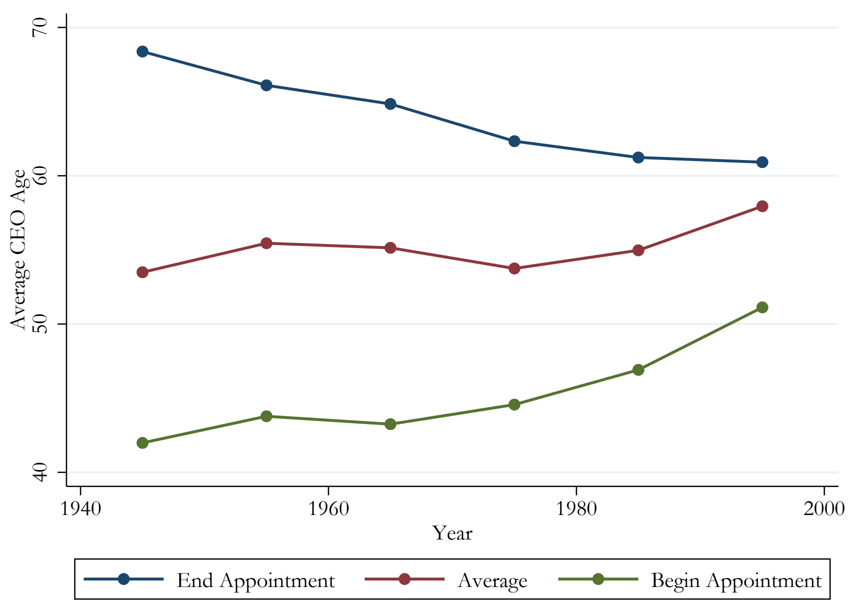
(a) Age Distribution

(b) Average CEO Age by Order of Appointment



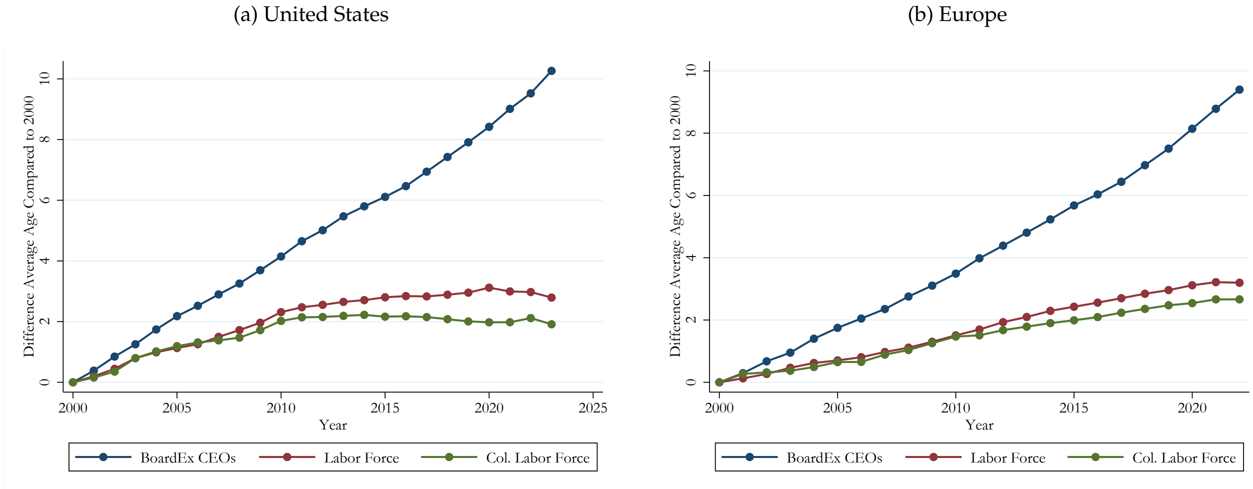
Notes: The figure shows CEO age at appointment over time. While panel (a) illustrates the age distribution by plotting the quartiles of CEO age, panel (b) shows average CEO by order of appointment, distinguishing between first, second, and third or higher appointments.

Appendix Figure A2: Long-Run CEO Age Patterns



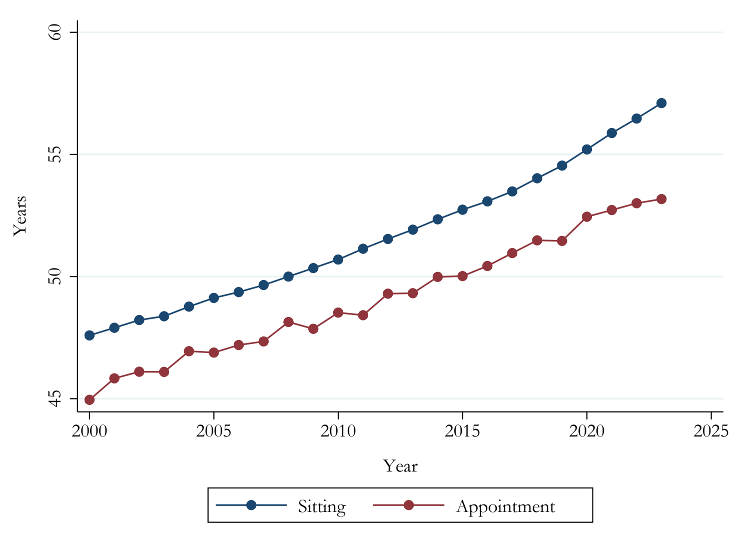
Notes: The figure plots long-run developments in average age as well as age at the beginning and the end of the appointment of American executives, obtained from the *Great American Business Leaders of the 20th Century database* (https://www.hbs.edu/leadership/20th-century-leaders). We show aggregates by decade to reduce noise.

Appendix Figure A3: Change in Average Age Since 2000 for CEOs vs. Labor Force



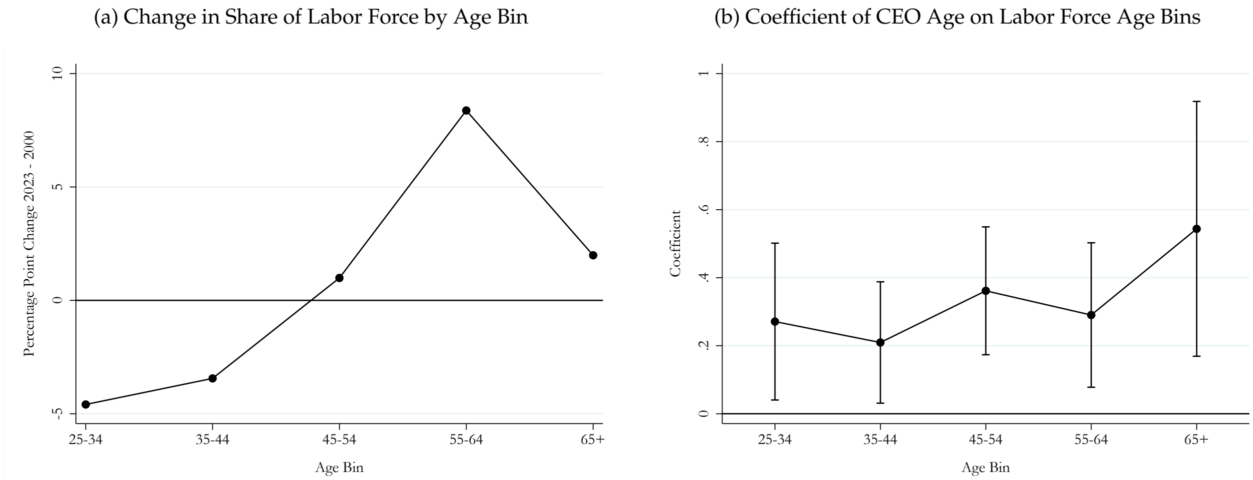
Notes: The figure compares the average age of sitting CEOs from BoardEx with that of the overall and the college-educated labor force, calculated from survey data. Panel (a) uses data from the *Current Population Survey*, showing the average age of all respondents in the labor force, calculated using ASEC weights. We define individuals holding at least a bachelor's degree as college-educated. The data have been obtained via *IPUMS* (Flood et al., 2024). Panel (b) uses data from the *European Labour Force Survey*. We compute average labor force age at the country level and then aggregate across countries, weighting by the number of BoardEx CEOs in each country-year cell. The countries included are Austria, Belgium, Switzerland, Cyprus, Germany, Denmark, Estonia, Greece, Spain, Finland, France, Hungary, Italy, Lithuania, Luxembourg, Norway, Poland, Portugal, and Sweden. We define individuals with some tertiary education as college-educated (ISCED-level 5 or above).

Appendix Figure A4: Average CEO Age Over Time—Europe



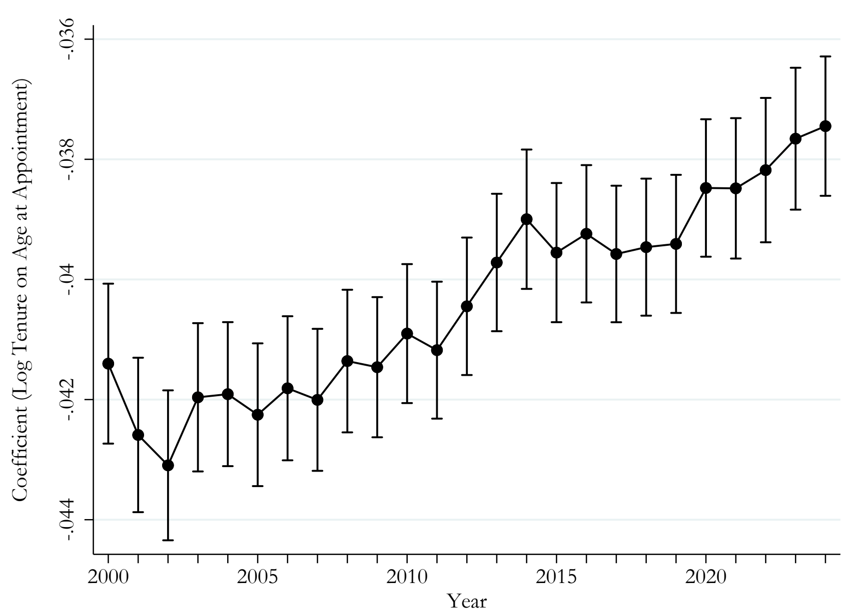
Notes: The plot shows the average age of CEOs in Europe over time, separately for sitting CEOs and CEOs at appointment. The countries included are Austria, Belgium, Switzerland, Cyprus, Germany, Denmark, Estonia, Greece, Spain, Finland, France, Hungary, Italy, Lithuania, Luxembourg, Norway, Poland, Portugal, and Sweden.

Appendix Figure A5: Estimating the Contribution of Labor Force Aging to CEO Age Increase



Notes: The figure shows results used to quantify the contribution of labor force aging to the CEO age increase. Panel (a) shows the average percentage point change in the share of the work force by 10-year age bin between 2000 and 2023, using data from the ILO (*Labour force by sex and age (thousands)*, available here). The countries included are Austria, Belgium, Switzerland, Cyprus, Germany, Denmark, Estonia, Greece, Spain, Finland, France, Hungary, Italy, Lithuania, Luxembourg, Norway, Poland, Portugal, Sweden, and the United States. Panel (b) shows coefficients obtained from regressing average CEO age by year and country on the share of the labor force by 10-year age bin, with individuals 15–24 as the omitted category. The regression controls for country and year fixed effects. Point estimates are plotted alongside 95% confidence intervals, based on robust standard errors.

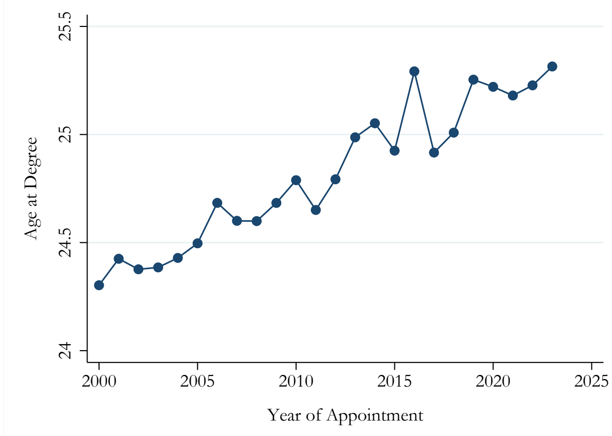
Appendix Figure A6: Time-Varying Correlation of CEO Tenure and Age at Appointment



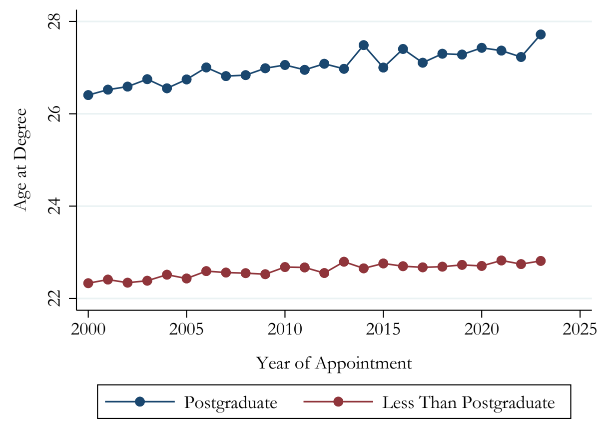
Notes: Shows the time-varying correlation of CEO tenure with age at appointment. The data are at the CEO-year level. The coefficients are obtained from regressions of the natural logarithm of tenure on year dummies, both alone and interacted with CEO age at appointment. Point estimates are plotted alongside 95% confidence intervals, based on standard errors clustered at the firm level.

Appendix Figure A7: CEO Education By Year of Appointment

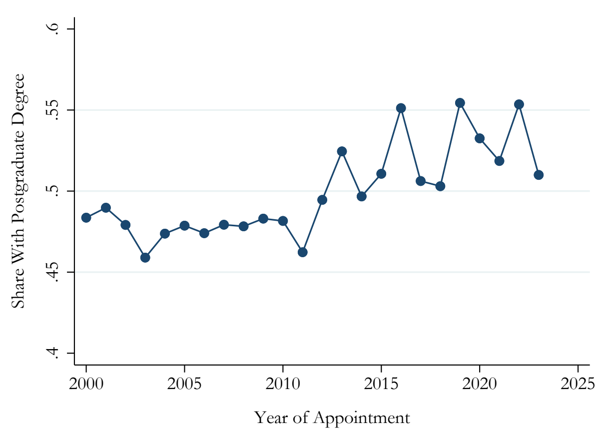
(a) Average Age at Highest Full-Time Degree



(b) Age at Highest Degree By Degree Type

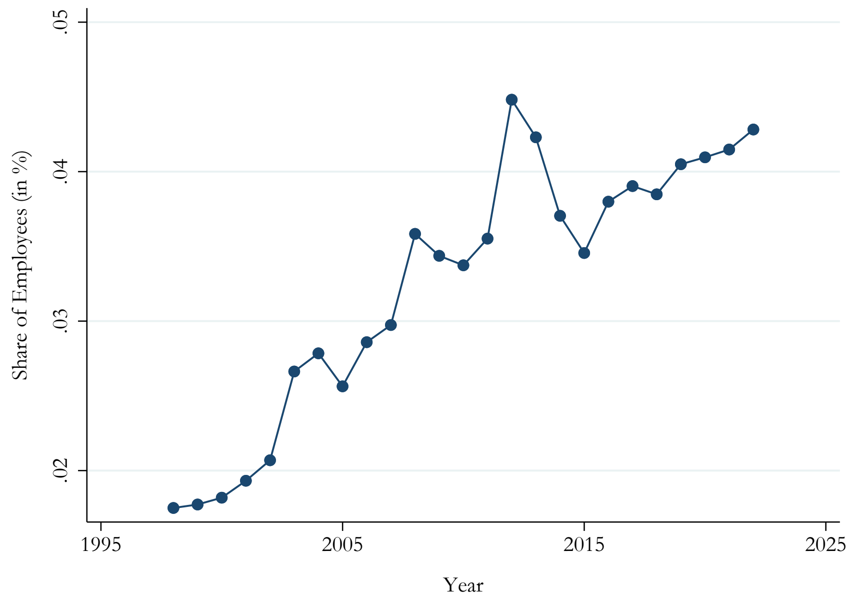


(c) Share of CEOs with Postgraduate Degree



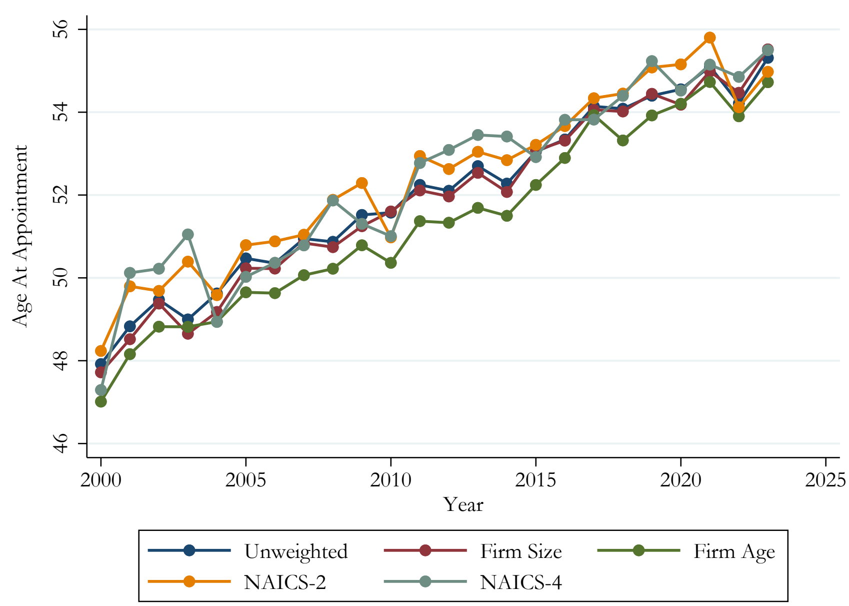
Notes: Shows CEO education by year of appointment, focusing on full-time degrees obtained after at most 5 years post labor market entry. The data are from BoardEx. Panel (a) plots average age at the highest full-time degree. Panel (b) shows average age at the highest full-time degree, distinguishing between postgraduate and less than postgraduate degrees. Panel (c) plots the share of CEOs with a postgraduate degree.

Appendix Figure A8: Employment Share of "Professional and Management Development Training"



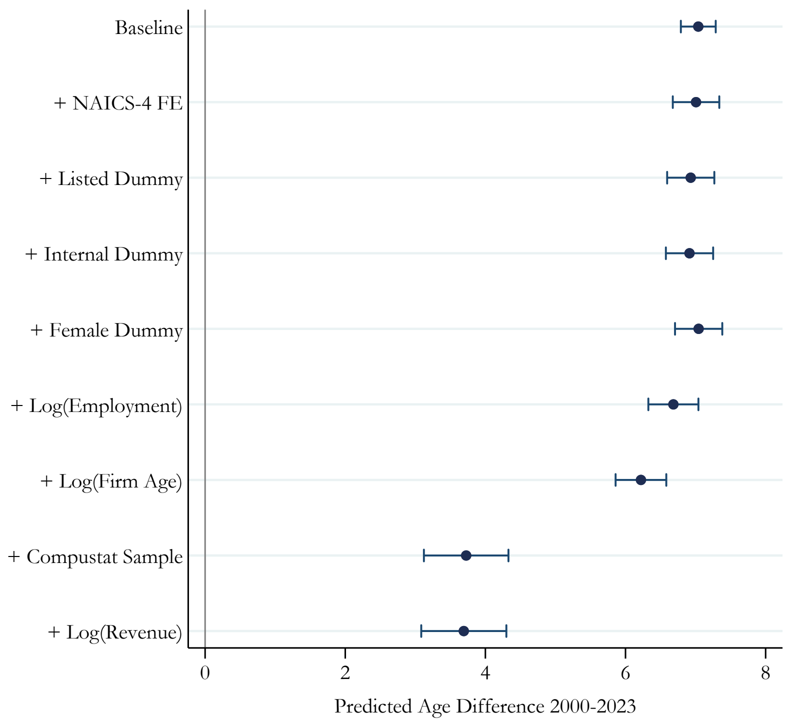
Notes: Shows the number of employees employed in the NAICS sector "611430: Professional and Management Development Training", divided by the overall number of employees in the economy. The data are obtained from the US flat files of County Business Patterns.

Appendix Figure A9: CEO Age at Appointment—Robustness to Population Reweighting



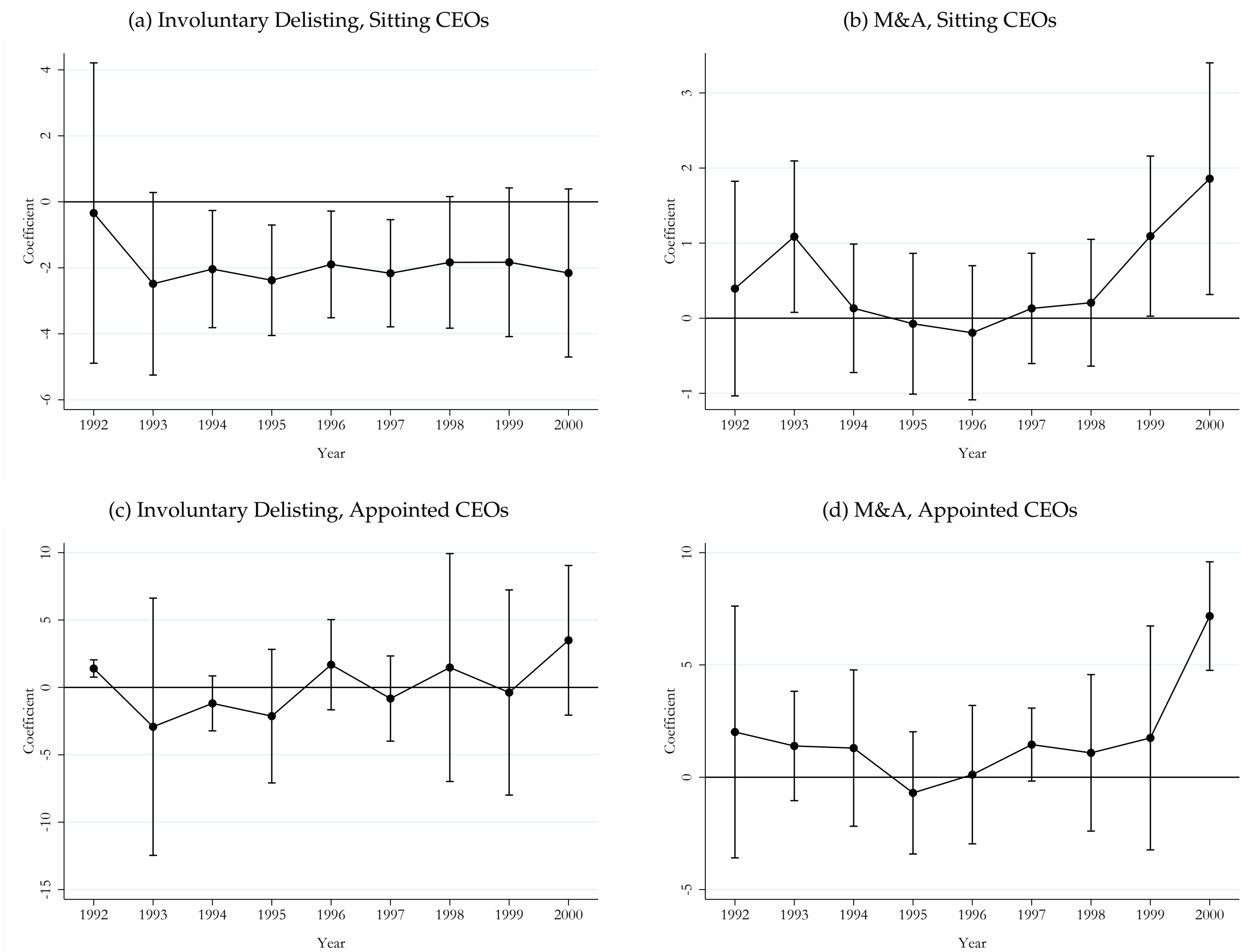
Notes: The figure shows CEO age at appointment over time. The blue line plots the unweighted average, whereas the other lines compare our sample to the Business Dynamics Statistics (BDS) and reweight CEO age at appointment by the inverse frequency of firms in each category (firm size, firm age, NAICS-2 or NAICS-4 industries) relative to the population in the respective year. The BDS data have been drawn from the US Census Bureau (available here). Firm size (file *BDSFSIZE*) is binned to the following categories: at least 1, 20, 100, 500, 1000, 2500, 5000, and 10000 employees. Firm age (file *BDSFAGE*) is binned to the following categories: at least 1, 6, 11, 16, and 21 years. Sectoral counts at the NAICS-2 and NAICS-4 level have been obtained from file *BDSNAICS*.

Appendix Figure A10: CEO Age at Appointment—Predicted Age Difference 2000–2023 Conditional on Controls



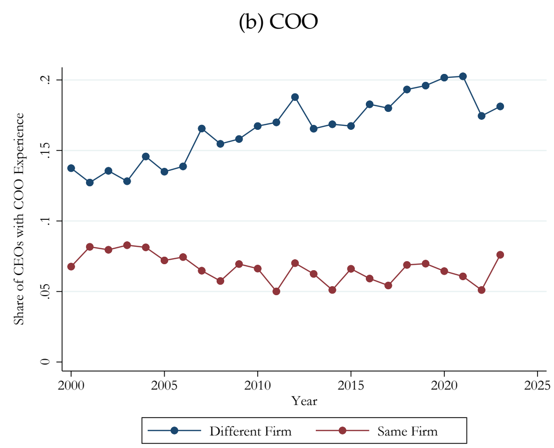
Notes: The figure shows coefficients obtained from regressing CEO age at appointment on a linear time trend (normalized to range between 0 and 1 from 2000 to 2023). While the baseline specification includes no controls, we then consecutively control for NAICS-4 fixed effects, dummies for whether a firm is listed, or whether the CEO is promoted internally or is female, and the natural logarithm of employment and firm age (both derived from employment biographies). We then restrict the sample to the set of firms contained in Compustat. Finally, we control for the natural logarithm of revenue. Point estimates are plotted alongside 95% confidence intervals, based on standard errors clustered at the firm level.

Appendix Figure A11: CEO Age of Firms Delisted 1997–2002—Differential Effects



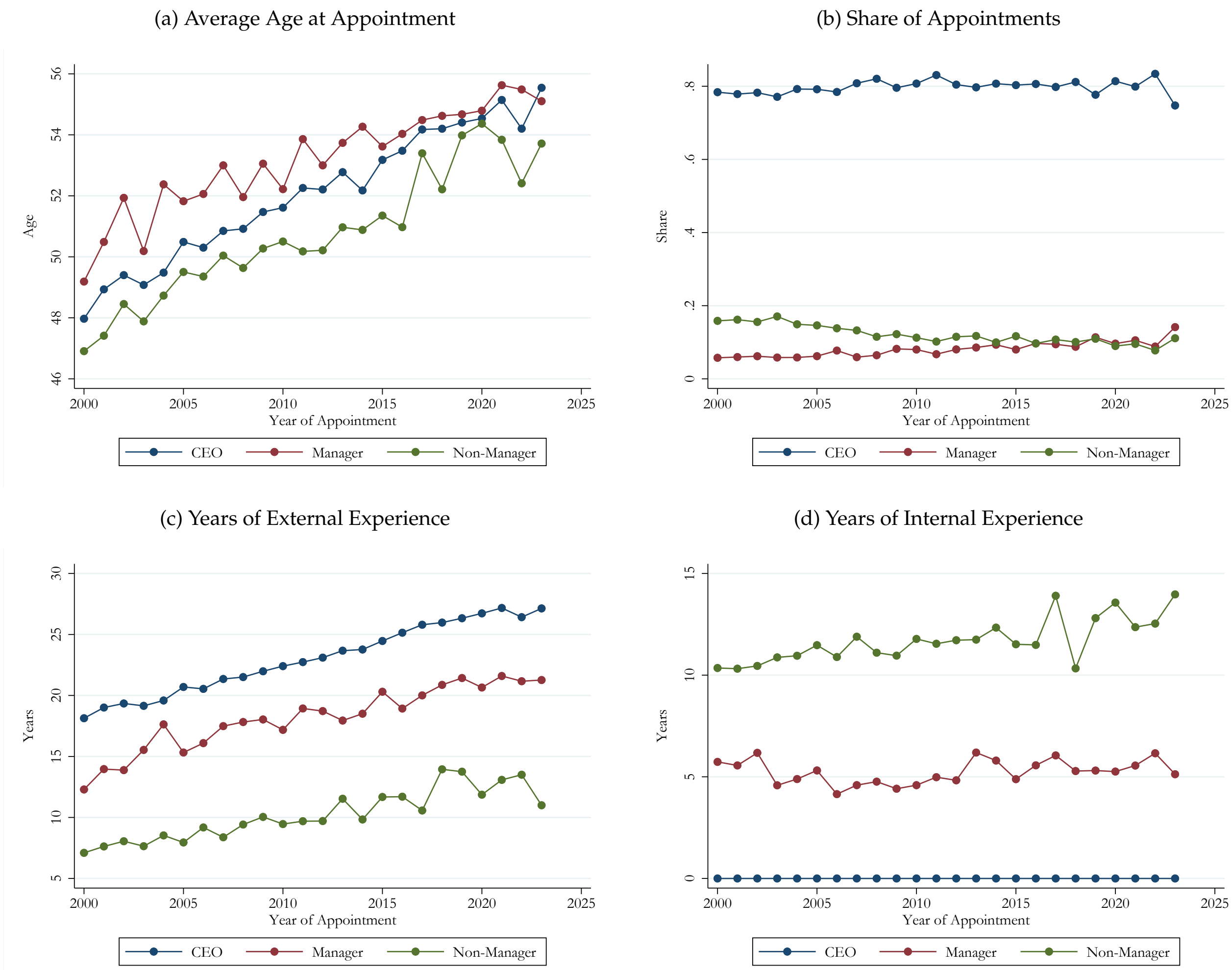
Notes: Shows coefficients from regressions of CEO age on year fixed effects interacted with indicators for different types of delistings (involuntary delistings in panels (a) and (c) and delistings due to M&A activity in panels (b) and (d)). The CEO data are from Execucomp and cover the S&P1500 during 1992 and 2000. The data have been combined with information on delistings during 1997 and 2002, obtained from CRSP. We follow the literature (e.g. Bharath and Dittmar, 2010) in our definition of involuntary delistings due to bankruptcy or liquidation (DLSTCD codes $\geq$ 400 excluding 570 and 573) and mergers and acquisitions (DLSTCD codes 200-399 excluding 332). All regressions include NAICS-4-year fixed effects and control for the natural logarithm of firm age, employment, and revenue, obtained from Compustat. Point estimates are plotted alongside 95% confidence intervals, based on standard errors clustered at the NAICS-4 level.

Appendix Figure A12: Share of CEO Appointments with Experience as CFO or COO Over Time



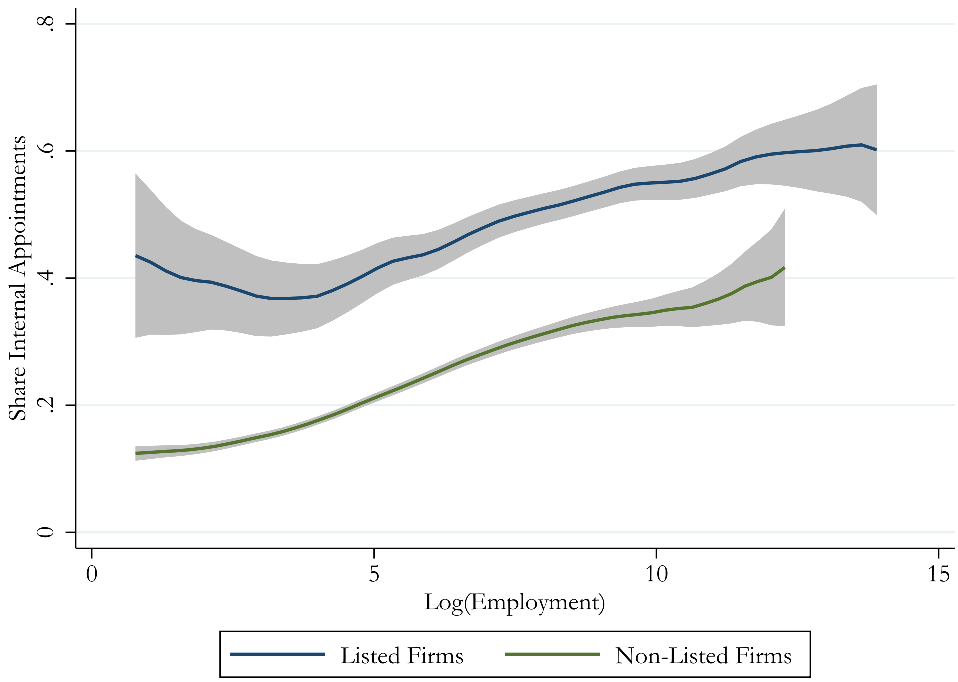
Notes: This figure shows the share of appointed CEOs who previously worked as CFO (Panel a) or COO (Panel b), distinguishing between those who served in this role at the same firm or a different firm from the one that promoted them to CEO. CFOs are identified by role names containing any of the following keywords: "CFO", "Chief Financial Officer", "General Manager - Finance", and "Head of Finance", "Director - Finance". For COOs, the corresponding keywords are "COO", "Chief Operations Officer", "General Manager - Operations", "Head of Operations", and "Director - Operations".

Appendix Figure A13: CEO Appointments by Seniority of First Position in Firm



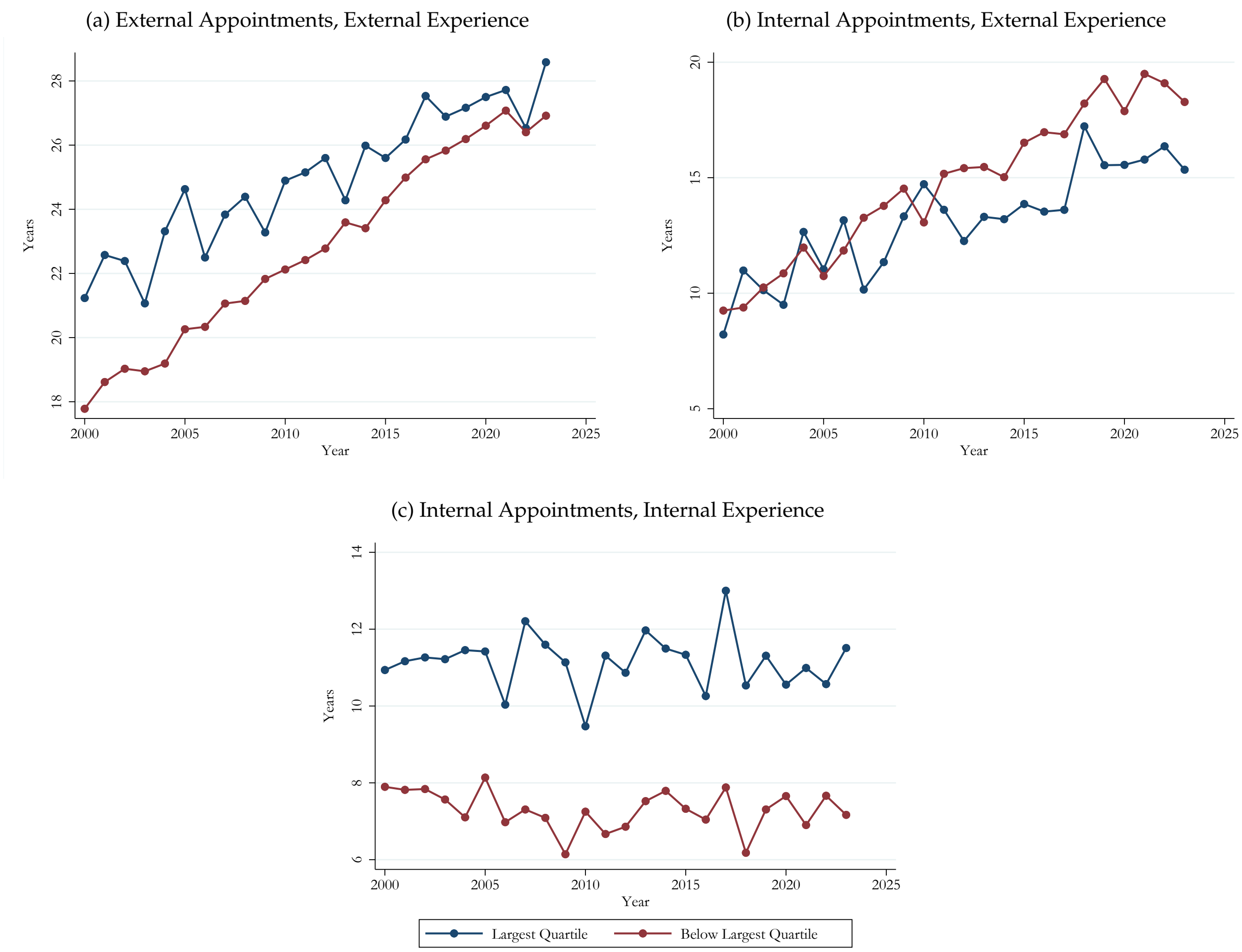
Notes: The figure plots descriptives on CEO appointments over time, stratified by the seniority of their first position in the firm. Panel (a) displays the average age at appointment, while Panel (b) shows the share of appointments for each group. Panels (c) and (d) present the average years of external and internal experience, respectively.

Appendix Figure A14: Share of Internal Appointments by Firm Size and Listing Status



Notes: Plots the share of internal appointments against firm size measured by the natural logarithm of employment (obtained from employment histories). The data are smoothed with a local polynomial with Epanechnikov kernel and bandwidths of 0.91 and 0.78, respectively, which have been obtained via optimal bandwidth selection. Point estimates are shown alongside 95% confidence intervals.

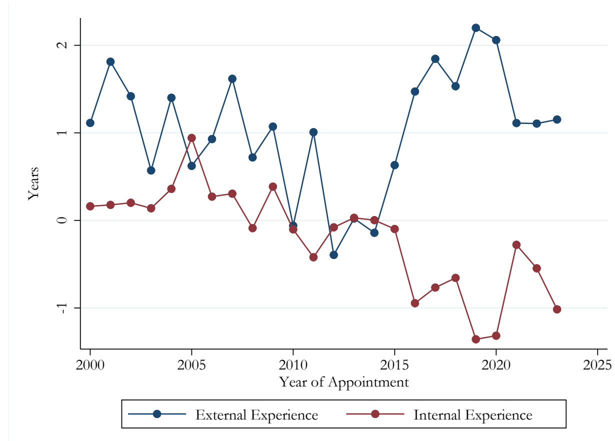
Appendix Figure A15: Years of External vs. Internal Experience by Firm Size



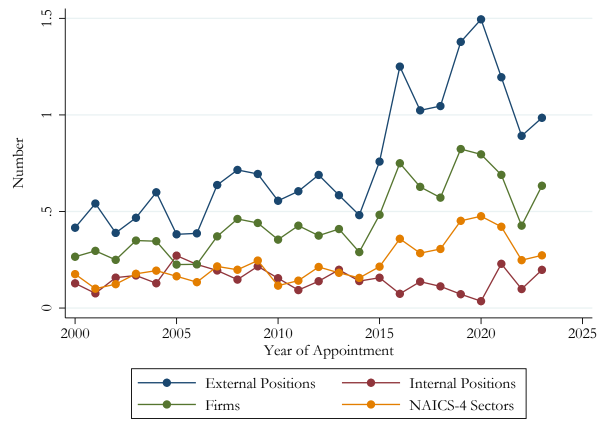
Notes: The figure plots years of experience, separately for those in the largest firm quartile and for those in the other three quartiles. Panel (a) shows years of external experience for externally appointed CEOs, panel (b) shows years of external experience for internally appointed CEOs, and panel (c) shows years of internal experience for internally appointed CEOs.

Appendix Figure A16: Work Experience At First Appointment to Most Senior Position: CEOs vs. Non-CEO Executives

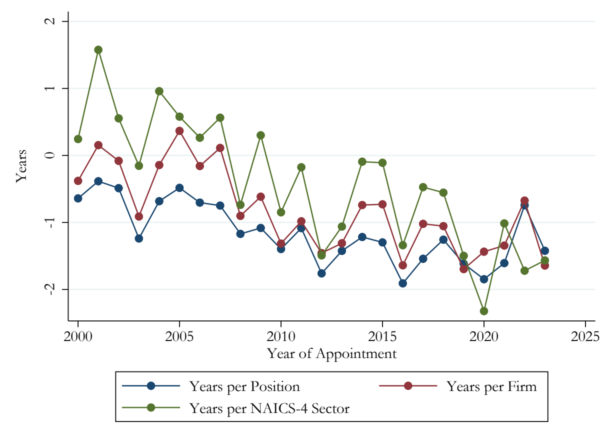
(a) Years of External vs. Internal Work Experience



(b) Average Number of Positions, Firms and Sectors



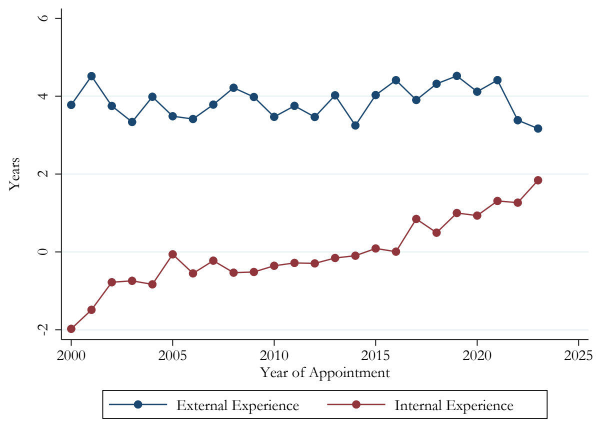
(c) Years per Position and Firm



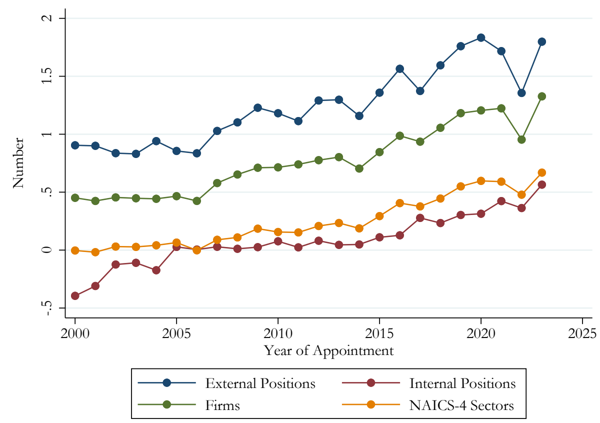
Notes: The figure plots work experience of CEOs compared to non-CEO executives over time, computed as the CEO average minus the non-CEO executive average in each year. The groups are defined based on the most senior position reached by the individual throughout the sample, focusing on the first appointment. Panel (a) plots the average external and internal work experience prior to appointment. Panel (b) shows the average number of positions (separately for external and internal positions) as well as the number of firms and sectors the executive worked in. Panel (c) shows the average number of years per position, firm, and NAICS-4 industries.

Appendix Figure A17: Work Experience At First Appointment to Most Senior Position: CEOs vs. Non-Executive Managers

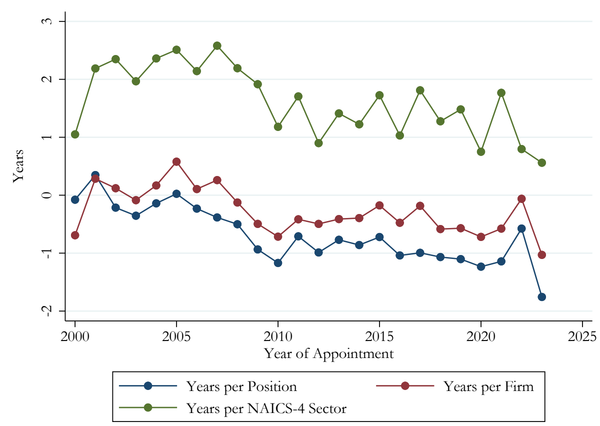
(a) Years of External vs. Internal Work Experience



(b) Average Number of Positions, Firms and Sectors

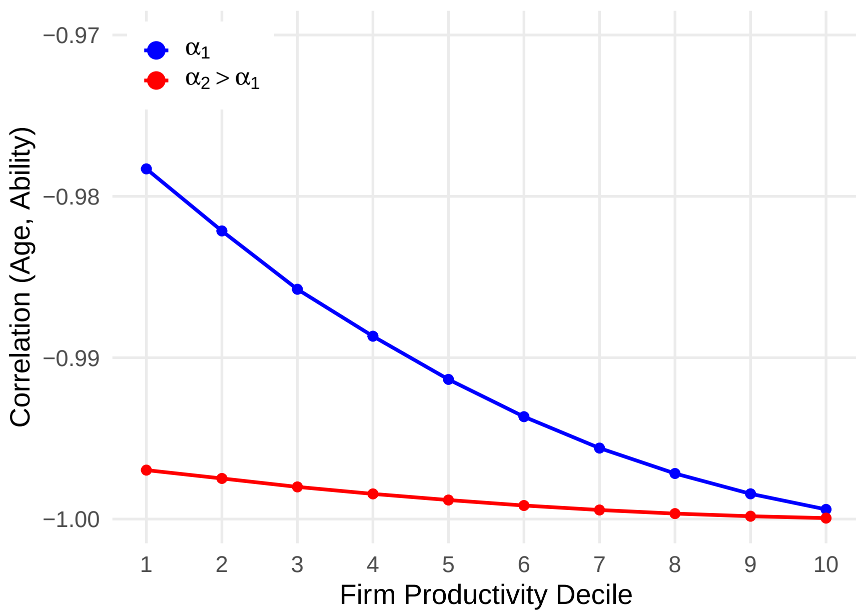


(c) Years per Position and Firm



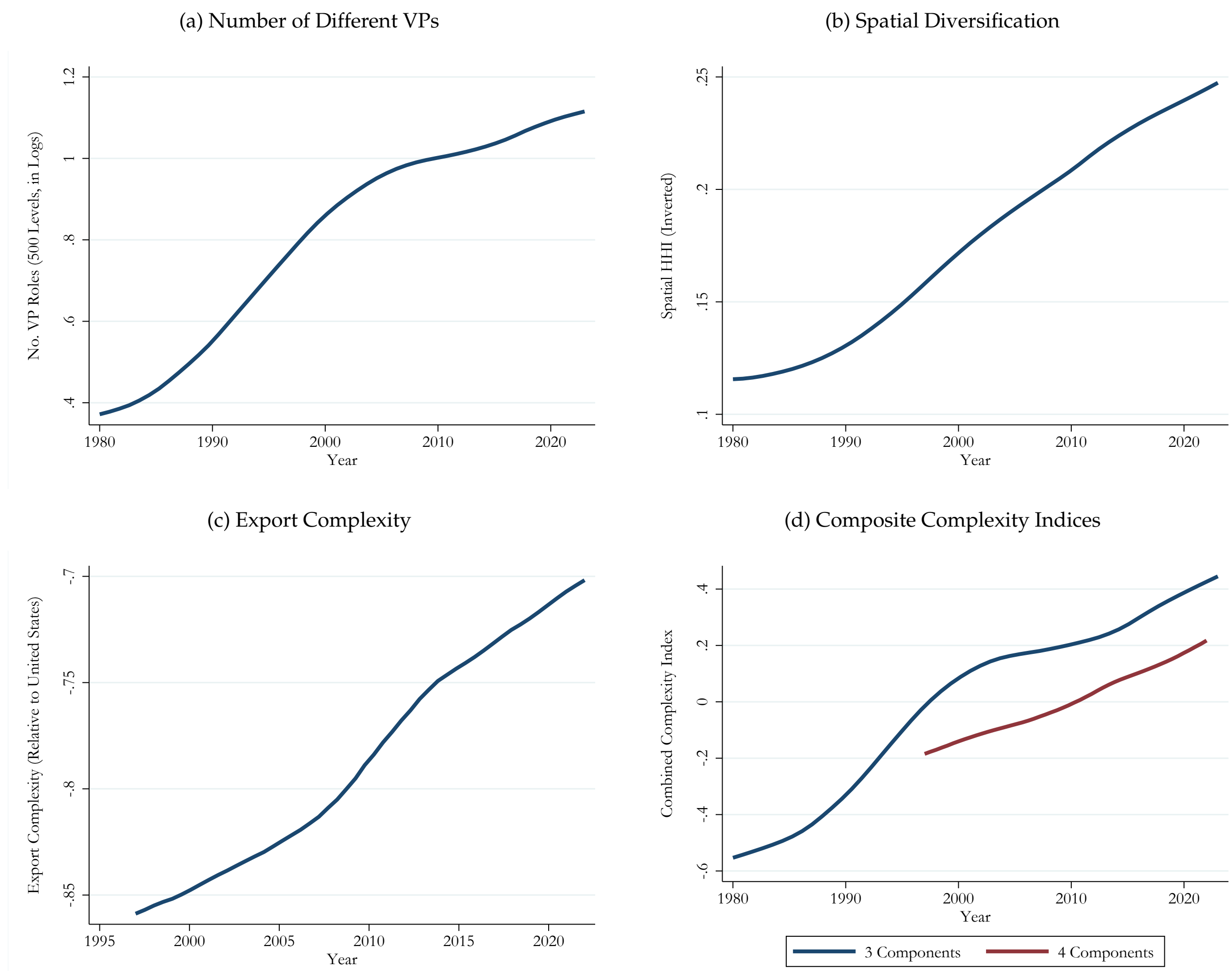
Notes: The figure plots work experience of CEOs compared to non-executive managers over time, computed as the CEO average minus the non-executive manager average in each year. The groups are defined based on the most senior position reached by the individual throughout the sample, focusing on the first appointment. Panel (a) plots the average external and internal work experience prior to appointment. Panel (b) shows the average number of positions (separately for external and internal positions) as well as the number of firms and sectors the executive CEO worked in. Panel (c) shows the average number of years per position, firm, and NAICS-4 industry.

Appendix Figure A18: Illustrative Correlation of Age and Ability at the Top Position by Firm Productivity



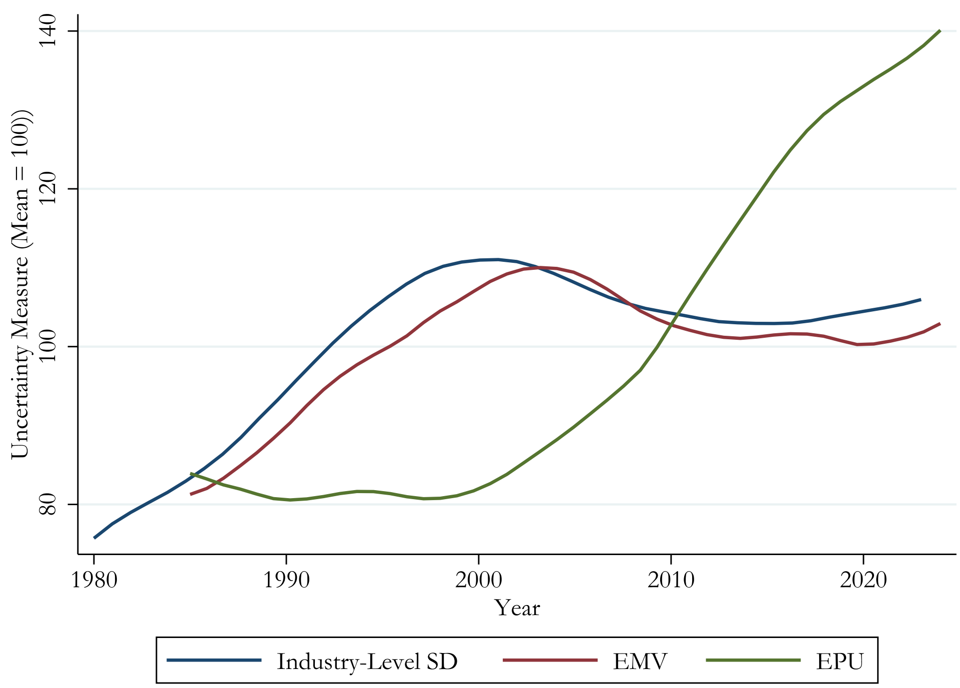
Notes: The figure plots the correlation of age and ability across firm productivity deciles for two values of α: $\alpha_1 = 0.4$ (blue line) and $\alpha_2 = 0.8$ (red line) and an illustrative parametrization. We simulate 100,000 workers with ability $a \sim U(0, 200)$ and age $t \sim U(0, 50)$. Skills are defined as $h(t) = -0.04t(t - 50)$ and $y(t) = -0.1t(t - 150)$. On the firm side, we draw 1,000 firms with productivity $z \sim U(0, 1)$, capacity $m = 100$, and hierarchical decay parameter $\beta = 0.08$. Within each firm, the CEO corresponds to the top slot ($k = 1$). We exploit the assortative matching implied by the model and compute the correlation of a and t within each firm productivity decile. The simulation is repeated 500 times, and results are averaged across all replications.

Appendix Figure A19: Complexity Measures Over Time



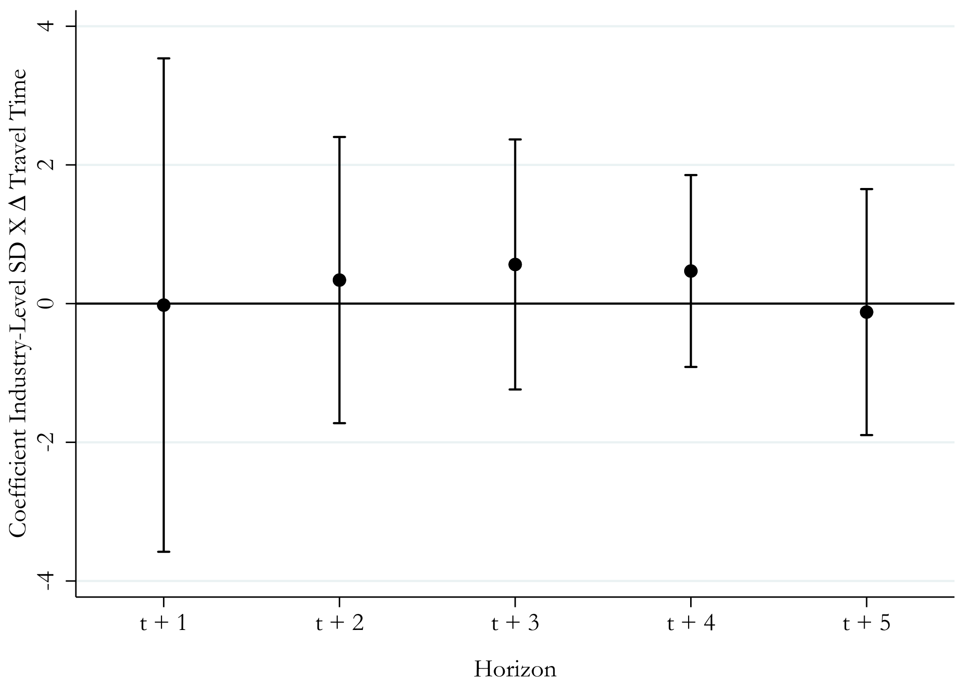
Notes: This figure shows different measures of sectoral complexity over time, smoothed using a local polynomial. Panel (a) plots the average number of distinct VPs per firm, taking the median at the NAICS-4 level and the natural logarithm thereof. Panel (b) shows the average HHI of employees across offices, where an office is defined as having at least five employees in a given MSA-year. We take the median at the NAICS-4 level. For exposition, we plot the inverse of the measure so that higher values correspond to greater diversification. Panel (c) shows average export complexity, defined as the economic complexity of trade partners weighted by the NAICS-4 industry-specific share of exports to that country. We express this as the distance from the complexity frontier by subtracting the average complexity of the US economy from the EECI. Panel (d) shows composite indices of complexity, constructed by standardizing all variables to mean zero and a standard deviation of one (if necessary), and summing across components. The 3-component index includes the industry-level standard deviation of revenue growth (the uncertainty measure used in the main analysis) together with the measures from Panels (a) and (b); the 4-component index additionally uses the export complexity measure from Panel (c).

Appendix Figure A20: Uncertainty Indices Over Time



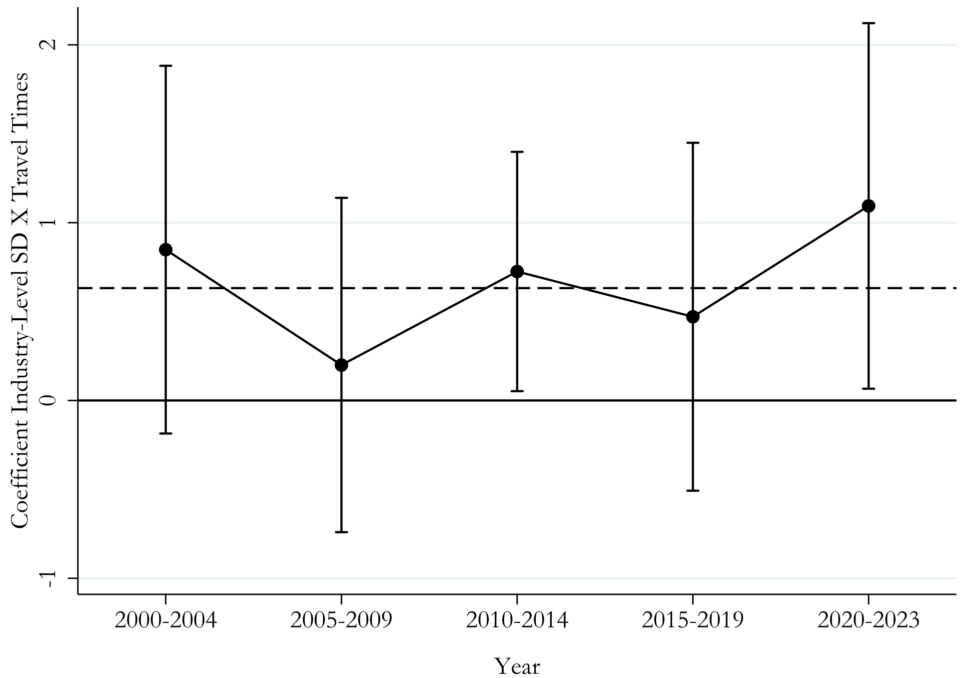
Notes: The figure plots different measures of aggregate uncertainty over time. *Industry-Level SD* is the cross-sectional (NAICS-4-level) standard deviation of revenue growth rate (obtained from Compustat), which we aggregate by weighting with revenue. *EMV* is a newspaper-based Equity Market Volatility index constructed in Baker et al. (2019). *EPU* is the Economic-Policy Uncertainty index for the US, obtained from Baker et al. (2016). We annualize the variables by computing their arithmetic means and normalize them by adjusting their average over the sample window to 100. The data are smoothed with a local polynomial with Epanechnikov kernel and bandwidths of 3.78, 5.26, and 5.08, respectively, which have been obtained via optimal bandwidth selection.

Appendix Figure A21: MBB Availability, Uncertainty and CEO Age—Placebo Test



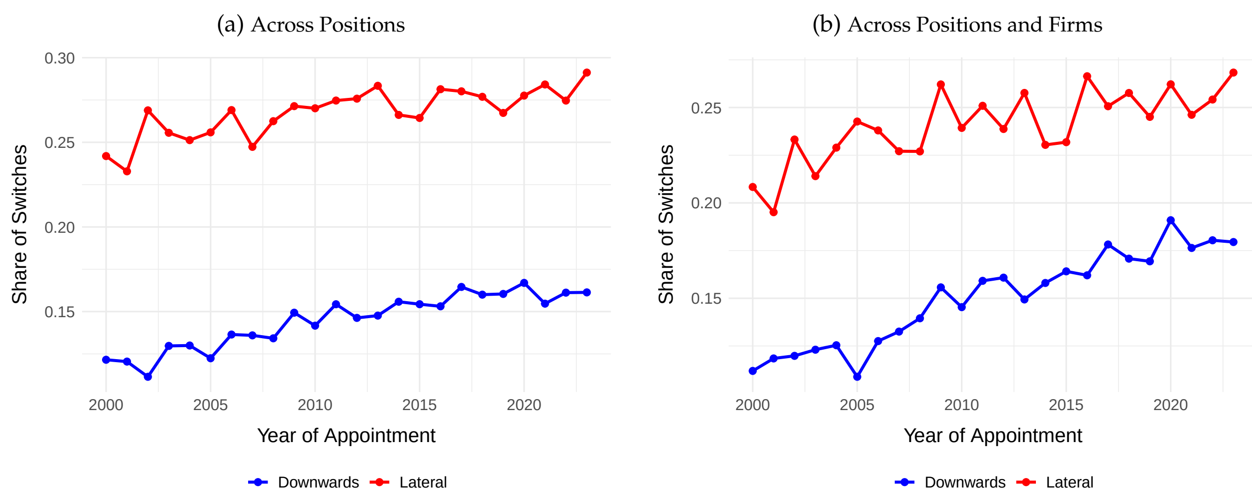
Notes: The plot shows coefficients from estimating the specification from Table 1, Column (4), while replacing *Travel Time*$_{mt}$ with Δ*Travel Time*$_{m\,\tau-t}$, $\tau = \{1 \ldots 5\}$. Point estimates are plotted alongside 95% confidence intervals, based on standard errors double-clustered at the NAICS-4 industry and MSA level.

Appendix Figure A22: MBB Availability, Uncertainty and CEO Age—Time-Varying Estimates



Notes: The plot shows coefficients from time-varying estimates, obtained by augmenting the specification from Table 1, Column (4) with interactions for 5-year bins. Uncertainty, calculated as the cross-sectional standard deviation of the symmetric growth rate of firm revenue within a firm's NAICS-4 industry, is standardized within each 5-year bin to mean zero and standard deviation one. Point estimates are plotted alongside 95% confidence intervals, based on standard errors double-clustered at the NAICS-4 industry and MSA level. The dashed horizontal line shows the point estimate from the baseline regression.

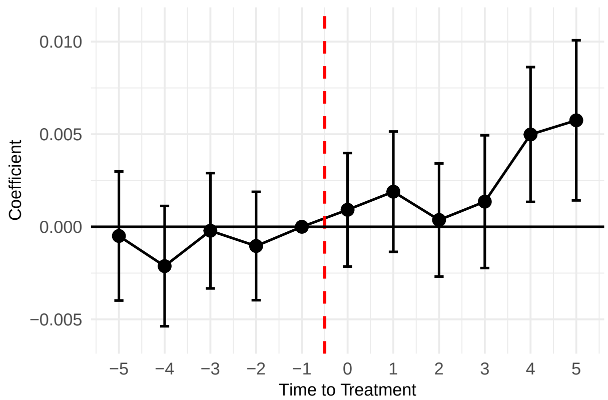
Appendix Figure A23: Share of Downward/Lateral Switches of CEOs Prior to Appointment



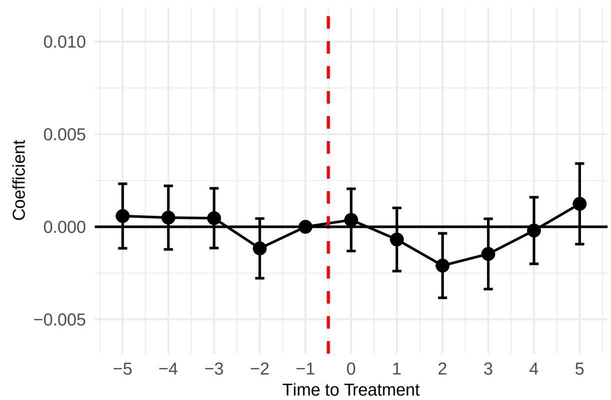
Notes: The plot shows the share of downward/lateral switches of CEOs prior to appointment by year of appointment, calculated as the ratio between the number of downward or lateral switches over the number of total switches. Panel (a) includes all switches across positions, panel (b) focuses on those across positions and firms. Switches are identified from a panel constructed from employment biographies from Revelio Labs, prioritizing more senior positions and those that started earlier in the case of overlapping spells.

Appendix Figure A24: CEO Appointment of Former Coworker and Job Mobility—Event Study

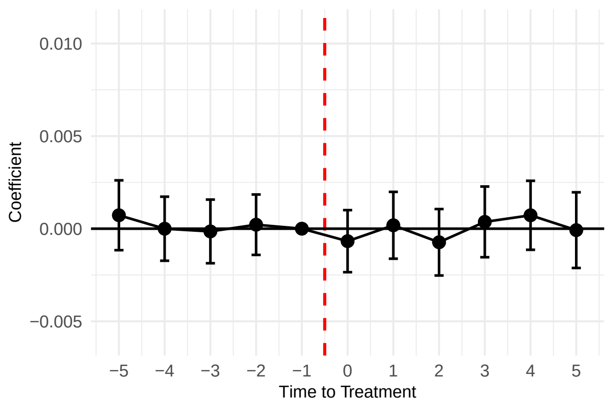
(a) Any Firm Switch



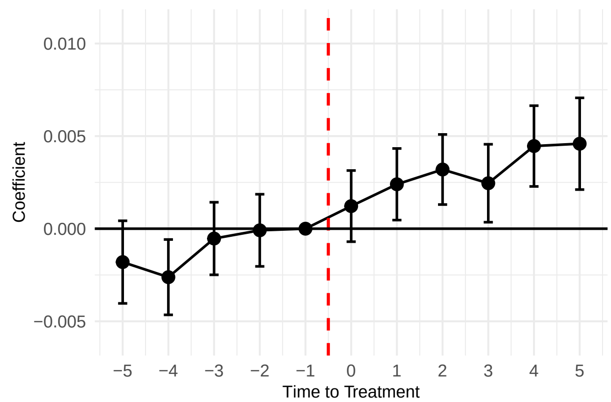
(b) Upward Firm Switch



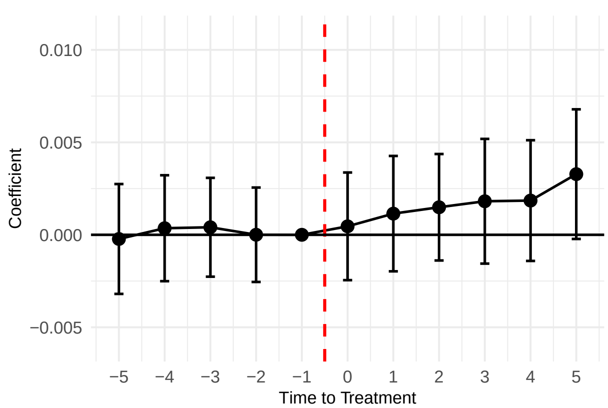
(c) Lateral Firm Switch



(d) Downward Firm Switch

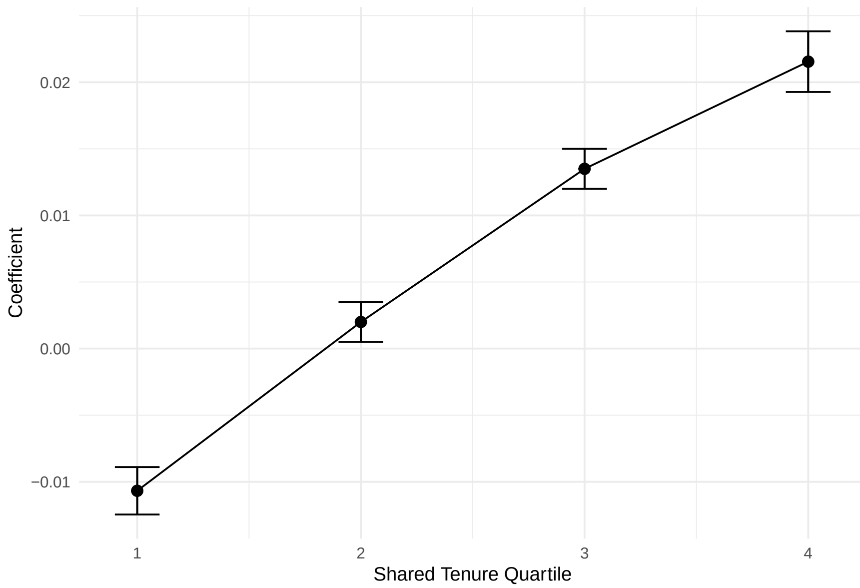


(e) Any Sector Switch



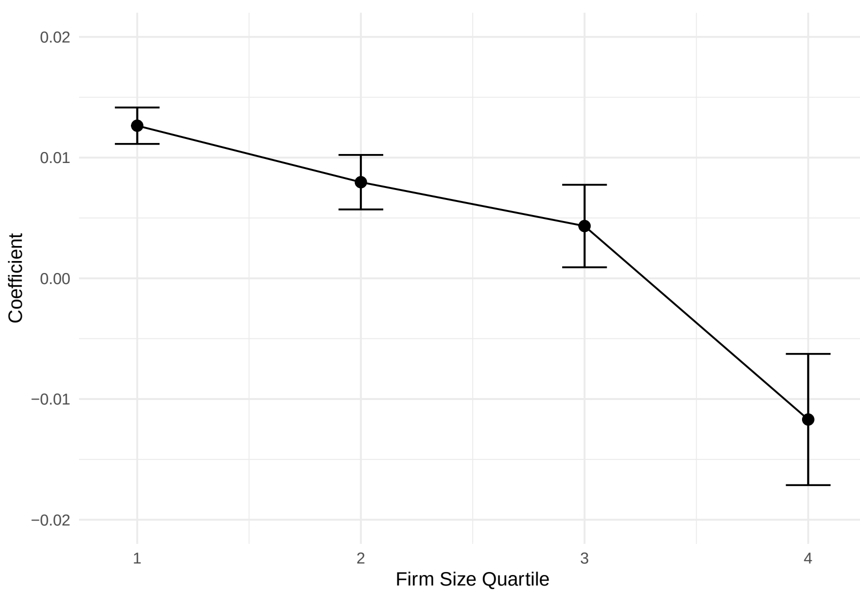
Notes: The figure shows event-study estimates, obtained by estimating the specification in Column (4) from Table 5 (Panel a), Table 6 (Panel b), Table A14 (Panel c), Table A15 (Panel d), and Table A13 (Panel e), respectively, replacing *Post* by indicators for the number of years until treatment. The endpoints are binned at $t = -6$ and $t = 6$, while $t = -1$ is omitted as the reference category. Point estimates are shown alongside 95% confidence intervals, which are obtained from standard errors clustered at the firm level.

Appendix Figure A25: Heterogeneity for Downward Mobility Response by Quartile of Shared Tenure



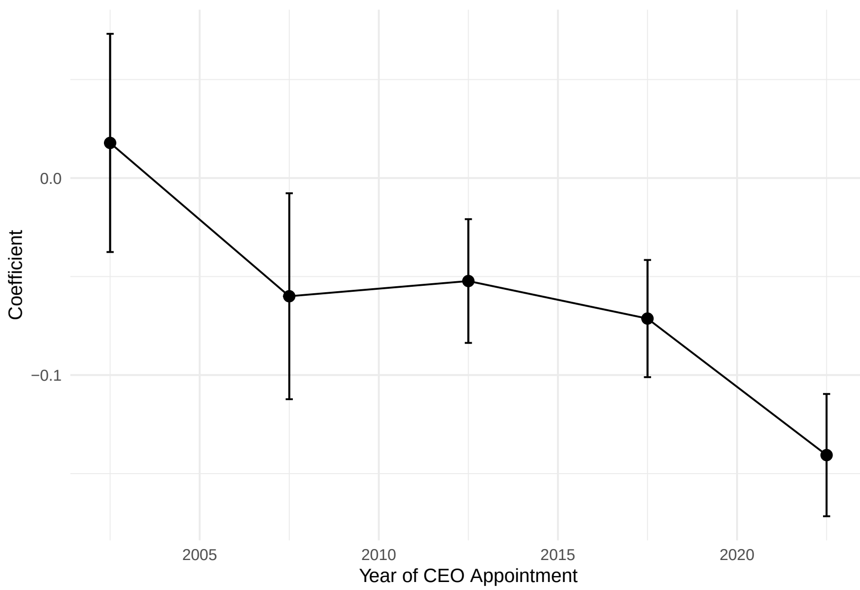
Notes: The specification equals Column (4) from Table A19 and shows the point estimates for the coefficients on $Treat \times Post \times Quartile = k \; \forall \, k = 1, 2, 3, 4$ alongside 95% confidence intervals, which are obtained from errors clustered at the firm level.

Appendix Figure A26: Heterogeneity for Downward Mobility Response by Size Quartile of Current Firm



Notes: The specification equals Column (4) from Table A25. Shows the point estimates for the coefficients on $Treat \times Post \times Quartile = k \; \forall \, k = 1, 2, 3, 4$ alongside 95% confidence intervals, which are obtained from standard errors clustered at the firm level.

Appendix Figure A27: Time-Varying Correlation of Firm Size and Seniority Differences from CEO Employment Histories



Notes: Plots the time-varying correlation of differences in firm employment and differences in seniority levels for job switches, using data from CEO employment histories. The coefficients are obtained from regressions of first differences of the natural logarithm of firm employment on 5-year bins for year of appointment, both alone and interacted with first differences in seniority. Point estimates are plotted alongside 95% confidence intervals, which are obtained from standard errors clustered at the CEO level.

C Additional Tables

Appendix Table A1: Summary Statistics—Descriptives and Demand-Side Results

	Mean	SD	P25	P50	P75	N
Panel A: Descriptives						
CEO Age at Appointment	51.89	9.11	46.00	52.00	58.00	50,510
Internal Appointment	0.20	0.40	0.00	0.00	0.00	50,510
Internal Appointment, Firm Entry Manager	0.10	0.30	0.00	0.00	0.00	50,510
Years of External Experience	21.12	10.76	14.00	21.00	29.00	50,510
Years of Internal Experience	1.67	5.15	0.00	0.00	0.00	50,510
Number External Positions	4.86	3.01	3.00	5.00	7.00	50,510
Number Internal Positions	0.41	1.11	0.00	0.00	0.00	50,510
Number of Firms	3.91	2.21	2.00	4.00	5.00	50,510
Number of NAICS-4 Sectors	1.47	1.20	1.00	1.00	2.00	50,510
Panel B: Demand Side, Baseline						
CEO Age	53.18	8.58	48.00	53.00	59.00	15,679
Age Firm Entry	47.25	10.92	41.00	48.00	55.00	15,679
Internal Experience	5.93	9.10	0.00	1.00	8.00	15,679
Travel Time to Closest Office	1.17	0.40	0.94	1.13	1.25	15,679
Employment, Revelio Labs	4212.22	20782.49	44.17	266.82	1649.44	15,679
Firm Age, Revelio Labs	27.82	17.83	12.00	26.00	42.00	15,679
Panel C: Demand Side, External Validity						
No. VP Roles (50 Levels)	7.08	7.12	2.00	5.00	10.00	11,033
No. VP Roles (150 Levels)	9.64	12.42	2.00	5.00	12.00	11,033
No. VP Roles (300 Levels)	11.01	16.68	2.00	5.00	13.00	11,033
No. VP Roles (500 Levels)	12.09	20.99	2.00	6.00	14.00	11,033
No. VP Roles (1000 Levels)	13.85	29.74	2.00	6.00	15.00	11,033
No. VPs	43.77	573.95	2.00	6.00	19.00	11,033
Spatial HHI	0.58	0.34	0.27	0.54	1.00	11,279
Spatial HHI (Office = 10 Individuals)	0.61	0.35	0.29	0.58	1.00	9,907
Share Employees Non-HQ	0.40	0.34	0.00	0.37	0.69	11,279
No. Offices	11.30	24.67	1.00	2.00	8.00	14,609
Export-Related Economic Complexity Index	-0.12	1.15	-0.85	0.06	0.71	6,070
Import-Related Economic Complexity Index	-0.12	1.05	-0.41	0.14	0.58	6,070
No. Export Countries	96.14	16.20	98.00	102.00	104.00	6,070
No. Import Countries	77.64	18.27	72.00	82.00	90.00	6,070
Panel D: MBB Experience vs. Age						
MBB Inflows	0.01	0.05	0.00	0.00	0.00	18,115
MBB Experience	0.05	0.23	0.00	0.00	0.00	18,115

Notes: Shows summary statistics for the results in Section 3 and 5.1.

Appendix Table A2: CEO Age and Industry-Level Market Concentration

	CEO Age					
	(1)	(2)	(3)	(4)	(5)	(6)
4-firm concentration ratio	-1.158					
	(0.888)					
8-firm concentration ratio		-1.058				
		(0.865)				
20-firm concentration ratio			-1.096			
			(0.920)			
HHI-Floor Sales				-7.883		
				(4.952)		
HHI-Floor Employment					-4.500	
					(6.379)	
HHI-Floor Payroll						-4.605
						(5.924)
R^2	0.119	0.119	0.119	0.119	0.131	0.131
Observations	45,370	45,370	45,370	45,326	33,092	33,092
Year fixed effects	✓	✓	✓	✓	✓	✓
Naics4 fixed effects	✓	✓	✓	✓	✓	✓

Notes: Shows results from regressing CEO age at appointment on different measures of market concentration at the NAICS4-level, using data from the most recent wave of the Economic Census (1997, 2002, 2007, 2012, and 2017). Data from the Economic Census have been obtained from here for years up to 2012 and via the United States Census Bureau for 2017. In Columns (1), (2), and (3), the concentration measures are the combined percentage of the total industry sales accounted for by the largest 4, 8, and 20 firms in the industry, respectively. Columns (4), (5), and (6) use the HHI-floor based on sales, employment, and payroll, respectively. The HHI-floor is a lower-bound estimate of the Herfindahl–Hirschman Index (HHI), constructed from concentration ratios, as described in Keil (2017). All regressions control for NAICS-4 and year fixed effects as well as the natural logarithm of employment and firm age, both obtained from the employment history data. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A3: Share of Appointments by Firm Size and Listing Status

Panel A: By Firm Size Quintile					
	Q5	Q4	Q3	Q2	Q1
External	0.60	0.71	0.79	0.83	0.87
Internal	0.40	0.29	0.21	0.17	0.13
Manager	0.19	0.14	0.11	0.09	0.07
Non-Manager	0.21	0.15	0.10	0.08	0.06
Panel B: By Listing Status					
	S&P500	S&P400	S&P600	Other Listed	Private
External	0.44	0.49	0.55	0.71	0.85
Internal	0.56	0.51	0.45	0.29	0.15
Manager	0.30	0.30	0.29	0.19	0.06
Non-Manager	0.26	0.21	0.16	0.10	0.09

Notes: The table includes the share of appointments by seniority at firm entry against firm size quintile by employment (Panel a) and listing status (Panel b).

Appendix Table A4: CEO Age and College Selectivity

	CEO Age					
	(1)	(2)	(3)	(4)	(5)	(6)
College Selectivity	-2.200***	-2.406***	-1.890***	-2.020***	-9.904***	-10.812***
	(0.212)	(0.231)	(0.157)	(0.175)	(0.722)	(0.825)
R^2	0.252	0.347	0.253	0.348	0.265	0.369
Observations	16,182	15,137	16,182	15,137	13,107	12,113
Controls	✓	✓	✓	✓	✓	✓
Naics4-Year fixed effects	✓	✓	✓	✓	✓	✓
MSA-Year fixed effects		✓		✓		✓
Selectivity Measure	Ivy Plus		Highly Selective		Ln(SAT 2001)	

Notes: Regresses CEO age on different measures of school selectivity. We focus on a CEO's first postsecondary degree, identified either by the stated degree name or, if missing, by the first degree recorded in BoardEx. We exclude first postsecondary degrees obtained from institutions outside of the US. *Ivy Plus* is an indicator taken from Chetty et al. (2020), comprising Brown, Columbia, Cornell, Dartmouth, Duke, Harvard, MIT, Princeton, Stanford, Chicago, UPenn, and Yale. *Selective* is an indicator for institutions classified as highly selective in Barron's Selectivity Index (in 1982, 1992, and 2002 in order to avoid selection issues over time). *Ln(SAT)* is the natural logarithm of the institution's average SAT admission score in 2001, taken from Chetty et al. (2020). Controls include the natural logarithm of employment and firm age. Standard errors are clustered at the firm level.

Appendix Table A5: Variation in MBB Availability and Employees Inflows from MBB

	Inflows from MBB			
	(1)	(2)	(3)	(4)
Δ(Travel Time)	-0.071***	-0.067**	-0.072***	-0.076**
	(0.026)	(0.026)	(0.027)	(0.034)
Lag(Inflows from MBB)		0.281***		
		(0.041)		
R^2	0.472	0.523	0.479	0.501
Observations	707,068	682,272	707,068	707,068
Outcome Mean	0.370	0.377	0.399	0.498
Naics4-Year fixed effects	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓
Time Between Spells	1 Month	1 Months	3 Months	1 Year

Notes: The dependent variable is the natural logarithm of one plus the number of employees who transition from an MBB firm to the firm of interest (multiplied by 100), constructed from the employment history data. In Columns (1) and (2), we restrict the sample to job-to-job transitions with at most one month between spells; Column (3) relaxes this window to three months, and Column (4) to one year. The main independent variable is the first difference in flight time (in hours) to the nearest MBB office, constructed using MBB office openings combined with flight data from the Bureau of Transportation Statistics. The sample is restricted to MSAs without MBB presence. All regressions control for firm size by including the natural logarithm of employment and firm age (extracted from the employment history data). Standard errors are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A6: MBB Availability, Number of Distinct VPs and CEO Age

	CEO Age				
	(1)	(2)	(3)	(4)	(5)
Travel Time × No. VP Roles (50 Levels)	1.748*				
	(0.905)				
Travel Time × No. VP Roles (150 Levels)		3.281**			
		(1.262)			
Travel Time × No. VP Roles (300 Levels)			5.057***		
			(1.600)		
Travel Time × No. VP Roles (500 Levels)				4.683***	
				(1.549)	
Travel Time × No. VP Roles (1000 Levels)					3.832**
					(1.744)
Travel Time × No. VPs	-1.659***	-2.987***	-4.494***	-4.281***	-3.743**
	(0.610)	(0.984)	(1.377)	(1.401)	(1.623)
R^2	0.364	0.364	0.365	0.365	0.364
Observations	14,933	14,933	14,933	14,933	14,933
MSA-Year fixed effects	✓	✓	✓	✓	✓
Naics4-Year fixed effects	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓

Notes: The dependent variable in all regressions is CEO age upon appointment, obtained from BoardEx. *Travel Time* denotes the flight time (in hours) to the closest office, which we construct from MBB office openings combined with flight data from the Bureau of Transportation Statistics. The variable *No. VP Roles* is defined as the number of distinct roles in which a firm employs vice presidents. *No. VP Roles* is a count variable measuring the number of distinct job roles in which a firm employs vice presidents. We aggregate these measures to the year-specific median within NAICS-4 industries and use their natural logarithm. We identify all vice presidents (VPs) as individuals with job titles including "vp" or "vice president" (case-insensitive), excluding any titles that contain "avp" or "assistant". The job taxonomy assigns activities to job titles by matching descriptions from resumes and online profiles to responsibilities in job postings. It initially classifies 1,500 distinct roles, which are then hierarchically clustered. We utilize this taxonomy at various levels of role granularity (50, 150, 300, 500, and 1000 roles). The sample is restricted to those MSAs without MBB presence. All regressions control for firm size by including the natural logarithm of employment and firm age, both extracted from the employment history data. Standard errors are double-clustered at the NAICS-4 industry and MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A7: MBB Availability, Spatial Diversification and CEO Age

	CEO Age			
	(1)	(2)	(3)	(4)
Travel Time × HHI, Bottom Decile	4.244***			
	(1.262)			
Travel Time × HHI, Bottom Quartile		2.409***		
		(0.723)		
Travel Time × HHI, Bottom Decile (Office = 10 Individuals)			3.784**	
			(1.478)	
Travel Time × Share Employees Non-HQ, Top Decile				2.967**
				(1.269)
Travel Time × No. Offices	-0.568	-0.856**	-0.374	-0.425
	(0.375)	(0.367)	(0.412)	(0.345)
R^2	0.365	0.365	0.368	0.364
Observations	14,195	14,195	12,527	14,185
MSA-Year fixed effects	✓	✓	✓	✓
Naics4-Year fixed effects	✓	✓	✓	✓
Controls	✓	✓	✓	✓

Notes: The dependent variable in all regressions is CEO age upon appointment, obtained from BoardEx. *Travel Time* denotes the flight time (in hours) to the closest office, which we construct from MBB office openings combined with flight data from the Bureau of Transportation Statistics. Spatial diversification is measured as the distribution of employees across offices in the LinkedIn data, which we define as having at least 5 employees in an MSA-year observation. We then construct the following indicators: *HHI, Bottom Decile* and *HHI, Bottom Quartile* for firms in the lowest decile and quartile, respectively; *HHI, Bottom Decile (Office = 10 Individuals)* for firms in the lowest decile, but defining an office as having at least 5 employees in an MSA-year observation; *Share Employees Non-HQ, Top Decile* for firms in the top decile of the share of employees outside of the headquarters. All measures are then aggregated to the NAICS-4-year level by assigning a value of one whenever at least half of the underlying indicators equal one. *No. Offices* denotes the natural logarithm of the median number of offices of each firm within a year and NAICS-4 industry. The sample is restricted to those MSAs without MBB presence. All regressions control for firm size by including the natural logarithm of employment and firm age, both extracted from the employment history data. Standard errors are double-clustered at the NAICS-4 industry and MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A8: MBB Availability, Export-Related Economic Complexity (EECI) and CEO Age

	CEO Age								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Travel Time × ECI, Above Median	2.327***	3.374***					5.648**	17.730***	2.910***
	(0.682)	(0.544)					(2.237)	(3.287)	(0.769)
Travel Time × ECI			1.294**						
			(0.518)						
Travel Time × ECI, Upper Quartile				2.376**					
				(1.045)					
Travel Time × ECI (1999 Weights)					1.922***				
					(0.698)				
Travel Time × ECI, Above Median (1999 Weights)						2.780***			
						(0.908)			
Travel Time × No. Countries Export $\geq$ 1%									-4.328***
									(1.490)
Travel Time × No. Countries Export		-9.049**	-8.759**	-6.873**	-6.262**	-5.460**	-8.078**	-16.638***	
		(3.487)	(3.955)	(3.332)	(2.694)	(2.620)	(3.642)	(5.858)	
R^2	0.406	0.408	0.407	0.407	0.408	0.407	0.407	0.388	0.408
Observations	5,136	5,136	5,136	5,136	5,136	5,136	5,136	2,235	5,136
MSA-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Naics4-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Measure	SITC	SITC	SITC	SITC	SITC	SITC	HS 92	HS 2012	SITC

Notes: The dependent variable in all regressions is CEO age upon appointment, obtained from BoardEx. *Travel Time* denotes the flight time (in hours) to the closest office, which we construct from MBB office openings combined with flight data from the Bureau of Transportation Statistics. The complexity measures are based on the country-level economic complexity index (ECI) from Hidalgo and Hausmann (2009), weighted by the corresponding exports from the United States and the respective country. The complexity data have been obtained from the Atlas of Economic Complexity. Annual data on exports (FAS value) at the NAICS-4 level have been obtained from the United States International Trade Commission. In Column (1), travel time is interacted with an indicator for above-median values of economic complexity. Column (2) additionally controls for the natural logarithm of the number of countries the US exports to. Column (3) uses the EECI in linear terms, standardized to mean zero and a standard deviation of one. Column (4) uses an indicator for the upper quartile of the EECI. Columns (5) and (6) use weights based on exports in 1999. Columns (7) and (8) rely on the EECI derived from HS 92 and HS 12 product codes, respectively. Column (9) controls for the natural logarithm of all countries to which a NAICS-4 industry exports at least 1% of value in a given year. The sample is restricted to those MSAs without MBB presence. All regressions control for firm size by including the natural logarithm of employment and firm age, both extracted from the employment history data. Standard errors are double-clustered at the NAICS-4 industry and MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A9: MBB Availability, Import-Related Economic Complexity (IECI) and CEO Age

	CEO Age								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Travel Time × ECI, Above Median	0.932	1.101					-0.373	1.753	0.696
	(0.838)	(0.701)					(1.254)	(2.524)	(0.767)
Travel Time × ECI			-0.100						
			(0.533)						
Travel Time × ECI, Upper Quartile				-0.086					
				(0.881)					
Travel Time × ECI (1999 Weights)					0.087				
					(0.531)				
Travel Time × ECI, Above Median (1999 Weights)						0.331			
						(0.617)			
Travel Time × No. Countries Import $\geq$ 1%									1.581
									(1.617)
Travel Time × No. Countries Import		-2.355	-1.855	-2.090	-2.307	-2.207	-1.762	-9.675***	
		(2.459)	(2.350)	(2.435)	(2.285)	(2.432)	(2.316)	(3.212)	
R^2	0.405	0.406	0.406	0.406	0.406	0.406	0.406	0.384	0.406
Observations	5,136	5,136	5,136	5,136	5,136	5,136	5,136	2,235	5,136
MSA-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Naics4-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Measure	SITC	SITC	SITC	SITC	SITC	SITC	HS 92	HS 2012	SITC

Notes: The dependent variable in all regressions is CEO age upon appointment, obtained from BoardEx. *Travel Time* denotes the flight time (in hours) to the closest office, which we construct from MBB office openings combined with flight data from the Bureau of Transportation Statistics. The complexity measures are based on the country-level economic complexity index (ECI) from Hidalgo and Hausmann (2009), weighted by the corresponding imports of the United States from the respective country. The complexity data have been obtained from the Atlas of Economic Complexity. Annual data on imports (general customs value) at the NAICS-4 level have been obtained from the United States International Trade Commission. In Column (1), travel time is interacted with an indicator for above-median values of economic complexity. Column (2) additionally controls for the natural logarithm of the number of countries the US exports to. Column (3) uses the IECI in linear terms, standardized to mean zero and a standard deviation of one. Column (4) uses an indicator for the upper quartile of the IECI. Columns (5) and (6) use weights based on exports in 1999. Columns (7) and (8) rely on the IECI derived from HS 92 and HS 12 product codes, respectively. Column (9) controls for the natural logarithm of all countries from which a NAICS-4 industry imports at least 1% of value in a given year. The sample is restricted to those MSAs without MBB presence. All regressions control for firm size by including the natural logarithm of employment and firm age, both extracted from the employment history data. Standard errors are double-clustered at the NAICS-4 industry and MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A10: Substitutability of MBB Experience and Age

	CEO Age					
	(1)	(2)	(3)	(4)	(5)	(6)
MBB Inflows	9.744***	8.332***	7.509***	7.741***	7.882***	3.315
	(2.055)	(1.910)	(2.073)	(1.975)	(2.359)	(5.131)
MBB Experience	-3.040***	-3.529***	-3.190***	-3.447***	-3.367***	-2.494***
	(0.304)	(0.297)	(0.304)	(0.344)	(0.375)	(0.573)
MBB Inflows $\times$ MBB Experience	-9.447***	-7.376**	-9.729***	-8.789**	-9.490**	-17.73*
	(3.337)	(3.102)	(3.373)	(3.540)	(4.093)	(9.455)
R^2	0.086	0.121	0.177	0.296	0.384	0.753
Observations	18,115	18,115	17,844	16,154	15,305	10,454
Controls	✓	✓	✓	✓	✓	✓
Year fixed effects		✓	✓			
NAICS-4 fixed effects			✓			
Naics4-Year fixed effects				✓	✓	✓
MSA-Year fixed effects					✓	✓
Firm fixed effects						✓

Notes: The dependent variable in all regressions is CEO age at appointment among CEOs. *MBB Experience* is a dummy equal to one, if the individual had ever worked in an MBB firm. *MBB Inflows* is defined as the company-level sum of new employees with MBB experience during the previous 10 years, divided by the total number of new managers in a company summed over the previous 10 years. Controls are the natural logarithm of employment and firm age, both obtained from the employment biographies. Standard errors are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A11: Substitutability of MBB Experience and Age—Robustness

	CEO Age			
	(1)	(2)	(3)	(4)
MBB Inflows	1.183***	7.390***	7.222***	13.87***
	(0.275)	(1.901)	(2.531)	(3.478)
MBB Experience	-3.122***	-3.354***	-3.313***	-3.377***
	(0.426)	(0.382)	(0.375)	(0.635)
MBB Inflows $\times$ MBB Experience	-1.512**	-7.630**	-10.36**	-79.99**
	(0.734)	(3.146)	(4.051)	(36.49)
R^2	0.384	0.384	0.384	0.460
Observations	15,305	15,305	15,278	5,897
Controls	✓	✓	✓	✓
Naics4-Year fixed effects	✓	✓	✓	✓
MSA-Year fixed effects	✓	✓	✓	✓
Change Compared to Baseline	Discretized	Seniority ≥ 4	5 Year	Controls

Notes: The dependent variable in all regressions is CEO age at appointment among CEOs. *MBB Experience* is a dummy equal to one, if the individual had ever worked in an MBB firm. *MBB Inflows* is defined as the company-level sum of new employees with MBB experience during the previous 10 years, divided by the total number of new employees in a company summed over the previous 10 years. Controls are the natural logarithm of employment and firm age, both obtained from the employment biographies. We deviate from this setup in the following ways: Column (1) discretizes MBB inflows, assigning a value of 1 to all values in the highest quartile (conditional on being strictly positive); Column (2) normalizes the MBB inflows by dividing by inflows at seniority level 4 or above; (3) restricts inflows to the past 5 years prior to appointment; Column (4) replaces the control variables by the natural logarithm of employment, revenue and firm age, obtained from Compustat. Standard errors are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A12: Summary Statistics—Supply-Side Regressions

	Mean	SD	P25	P50	P75	N
Panel A: Treatment Group						
Male	0.64	0.48	0.00	1.00	1.00	320,522
White	0.78	0.41	1.00	1.00	1.00	321,699
Age	40.41	8.44	35.00	40.00	45.00	304,686
Bachelor	0.44	0.50	0.00	0.00	1.00	264,045
More than Bachelor	0.53	0.50	0.00	1.00	1.00	264,045
Salary (in 1000 USD)	126.05	62.35	85.02	111.97	151.40	321,762
Seniority	4.47	1.26	4.00	5.00	5.00	321,781
Tenure at Firm	8.29	6.94	3.00	6.00	11.00	321,776
External Experience	10.11	8.80	2.00	9.00	16.00	321,700
Panel B: Control Group						
Male	0.65	0.48	0.00	1.00	1.00	1,058,186
White	0.81	0.39	1.00	1.00	1.00	1,061,239
Age	40.15	8.67	34.00	39.00	45.00	1,012,153
Bachelor	0.48	0.50	0.00	0.00	1.00	787,624
More than Bachelor	0.48	0.50	0.00	0.00	1.00	787,624
Salary (in 1000 USD)	114.00	59.60	75.67	100.31	136.18	1,061,264
Seniority	4.33	1.34	4.00	5.00	5.00	1,061,494
Tenure at Firm	8.08	6.87	3.00	6.00	11.00	1,061,478
External Experience	10.06	8.91	2.00	9.00	16.00	1,061,267

Notes: Shows summary statistics for the sample used to study network effects (Section 5.2), separately for the treatment (Panel A) and control (Panel B) group, and restricted to observations in the year prior to treatment. We weight the treated (control) individuals by the share of the control (treatment) group within each firm-seniority-year cell.

Appendix Table A13: CEO Appointment of Former Coworker and Job Mobility (Industry Switch)

	Industry Switch				
	(1)	(2)	(3)	(4)	(5)
Treat	0.002*				
	(0.001)				
Post	-0.004***	-0.007***	-0.008***		
	(0.001)	(0.001)	(0.001)		
Treat × Post	-0.001	0.001	0.001	0.003**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.006	0.161	0.163	0.186	0.215
Observations	14,144,297	14,144,297	14,144,297	14,144,297	12,898,708
Pre-Treatment Control Mean	0.042	0.042	0.042	0.042	0.041
Year fixed effects	✓	✓	✓		
Individual fixed effects		✓	✓	✓	✓
Firm-Seniority fixed effects			✓		
Firm-Seniority-Year fixed effects				✓	✓
MSA-Naics4-Year fixed effects					✓

Notes: The dependent variable in all regressions is a dummy equal to one in the last year before an individual switches across NAICS-4 industries. *Treat* is an indicator for having worked alongside a future CEO. *Post* is an indicator for periods following the CEO appointment. The fixed effects and standard errors refer to the position the individual worked in alongside the future CEO. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A14: CEO Appointment of Former Coworker and Job Mobility (Upward Firm Switch)

	Firm and Upward Switch				
	(1)	(2)	(3)	(4)	(5)
Treat	0.001**				
	(0.001)				
Post	0.002***	0.000	-0.001**		
	(0.000)	(0.000)	(0.000)		
Treat × Post	-0.000	-0.000	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
R^2	0.004	0.090	0.091	0.105	0.134
Observations	22,777,381	22,777,381	22,777,381	22,777,381	16,139,755
Pre-Treatment Control Mean	0.025	0.025	0.025	0.025	0.025
Year fixed effects	✓	✓	✓		
Individual fixed effects		✓	✓	✓	✓
Firm-Seniority fixed effects			✓		
Firm-Seniority-Year fixed effects				✓	✓
MSA-Naics4-Year fixed effects					✓

Notes: The dependent variable in all regressions is a dummy equal to one in the last year before an individual switches firms and rises to a higher seniority level. *Treat* is an indicator for having worked alongside a future CEO. *Post* is an indicator for periods following the CEO appointment. The fixed effects and standard errors refer to the position the individual worked in alongside the future CEO. Standard are errors clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A15: CEO Appointment of Former Coworker and Job Mobility (Lateral Firm Switch)

	Firm and Lateral Switch				
	(1)	(2)	(3)	(4)	(5)
Treat	0.002***				
	(0.001)				
Post	-0.002***	-0.004***	-0.005***		
	(0.000)	(0.000)	(0.000)		
Treat × Post	-0.001*	-0.002***	-0.002***	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.004	0.110	0.111	0.129	0.160
Observations	22,777,381	22,777,381	22,777,381	22,777,381	16,139,755
Pre-Treatment Control Mean	0.029	0.029	0.029	0.029	0.029
Year fixed effects	✓	✓	✓		
Individual fixed effects		✓	✓	✓	✓
Firm-Seniority fixed effects			✓		
Firm-Seniority-Year fixed effects				✓	✓
MSA-Naics4-Year fixed effects					✓

Notes: The dependent variable in all regressions is a dummy equal to one in the last year before an individual switches firm but remains at the same seniority level. *Treat* is an indicator for having worked alongside a future CEO. *Post* is an indicator for periods following the CEO appointment. The fixed effects and standard errors refer to the position the individual worked in alongside the future CEO. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A16: CEO Appointment of Former Coworker and Job Mobility (Across Firms and Job Categories)

	Switch Across Firms and Job Categories				
	(1)	(2)	(3)	(4)	(5)
Treat	-0.002***				
	(0.001)				
Post	-0.003***	-0.007***	-0.008***		
	(0.001)	(0.001)	(0.001)		
Treat × Post	0.001**	0.002***	0.002***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.003	0.127	0.127	0.144	0.176
Observations	22,777,381	22,777,381	22,777,381	22,777,381	16,139,755
Pre-Treatment Control Mean	0.034	0.034	0.034	0.034	0.033
Year fixed effects	✓	✓	✓		
Individual fixed effects		✓	✓	✓	✓
Firm-Seniority fixed effects			✓		
Firm-Seniority-Year fixed effects				✓	✓
MSA-Naics4-Year fixed effects					✓

Notes: The dependent variable in all regressions is a dummy equal to one in the last year before an individual switches firm and job category. *Treat* is an indicator for having worked alongside a future CEO. *Post* is an indicator for periods following the CEO appointment. The fixed effects and standard errors refer to the position the individual worked in alongside the future CEO. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A17: CEO Appointment of Former Coworker and Job Mobility (Across Firms, Within Job Categories)

	Switch Across Firms Within Job Categories				
	(1)	(2)	(3)	(4)	(5)
Treat	0.000				
	(0.001)				
Post	-0.007***	-0.010***	-0.011***		
	(0.001)	(0.001)	(0.001)		
Treat × Post	0.001	0.000	0.000	0.002***	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.009	0.139	0.140	0.160	0.191
Observations	22,777,381	22,777,381	22,777,381	22,777,381	16,139,755
Pre-Treatment Control Mean	0.060	0.060	0.060	0.060	0.061
Year fixed effects	✓	✓	✓		
Individual fixed effects		✓	✓	✓	✓
Firm-Seniority fixed effects			✓		
Firm-Seniority-Year fixed effects				✓	✓
MSA-Naics4-Year fixed effects					✓

Notes: The dependent variable in all regressions is a dummy equal to one in the last year before an individual switches firms but stays in the same job category. *Treat* is an indicator for having worked alongside a future CEO. *Post* is an indicator for periods following the CEO appointment. The fixed effects and standard errors refer to the position the individual worked in alongside the future CEO. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A18: CEO Appointment of Former Coworker and Job Mobility—Placebo Test

	Any Firm	Upward	Lateral	Downward	Any Sector
	(1)	(2)	(3)	(4)	(5)
Treat × Post	-0.0019	-0.0005	-0.0012	-0.0002	-0.0036
	(0.0022)	(0.0012)	(0.0011)	(0.0013)	(0.0026)
R^2	0.21794	0.15915	0.18694	0.15936	0.25047
Observations	2,130,135	2,130,135	2,130,135	2,130,135	1,009,521
Pre-Treatment Control Mean	0.1462	0.0518	0.0467	0.0478	0.0721
Individual fixed effects	✓	✓	✓	✓	✓
Firm-Seniority-Year fixed effects	✓	✓	✓	✓	✓

Notes: The specification equals Column (4) from the baseline tables. The sample includes individuals who left the initial firm between one and five years before the prospective CEO was hired at that firm. *Treat* is an indicator for having worked alongside a future CEO. *Post* is an indicator for periods following the CEO appointment. The fixed effects and standard errors refer to the position the individual worked in alongside the future CEO. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A19: Heterogeneity by Length of Shared Tenure

	Any Firm	Upward	Lateral	Downward	Any Sector
	(1)	(2)	(3)	(4)	(5)
Treat × Post	-0.003**	-0.002***	-0.003***	0.002**	-0.001
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Treat × Post × High Overlap	0.037***	0.006***	0.013***	0.019***	0.016***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.166	0.105	0.129	0.111	0.186
Observations	22,777,381	22,777,381	22,777,381	22,777,381	14,144,297
Pre-Treatment Control Mean	0.094	0.025	0.029	0.041	0.042
Individual fixed effects	✓	✓	✓	✓	✓
Firm-Seniority-Year fixed effects	✓	✓	✓	✓	✓

Notes: The specification equals Column (4) from the baseline tables. *High Overlap* is a dummy equal to 1 if the length of the overlapping period of the individual and the future CEO working in the same company is in the highest quartile, and zero otherwise. *Treat* is an indicator for having worked alongside a future CEO. *Post* is an indicator for periods following the CEO appointment. The fixed effects and standard errors refer to the position the individual worked in alongside the future CEO. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A20: Effects on Individuals at Seniority Level below Future CEO

	Any Firm	Upward	Lateral	Downward	Any Sector
	(1)	(2)	(3)	(4)	(5)
Treat × Post	0.002*	-0.001***	-0.000	0.003***	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Treat × Post × Two Levels Below	0.000	-0.000	0.000	-0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
R^2	0.162	0.103	0.127	0.106	0.181
Observations	53,842,096	53,842,096	53,842,096	53,842,096	33,975,831
Pre-Treatment Control Mean	0.102	0.033	0.030	0.038	0.045
Individual fixed effects	✓	✓	✓	✓	✓
Firm-Seniority-Year fixed effects	✓	✓	✓	✓	✓

Notes: The specification equals Column (4) from the baseline tables, with the sample restricted to those working at the two seniority levels directly below the future CEO. For the workers two levels below the future CEO, we focus on a random 50% subsample of all individuals to maintain computational feasibility. *Treat* is an indicator for having worked alongside a future CEO. *Post* is an indicator for periods following the CEO appointment. The fixed effects and standard errors refer to the position the individual worked in alongside the future CEO. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A21: Effects on Individuals at Seniority above Future CEO

	Any Firm (1)	Upward (2)	Lateral (3)	Downward (4)	Any Sector (5)
Treat × Post	0.005**	-0.001	0.001	0.004***	0.003*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Treat × Post × Two Levels Above	0.001	0.003***	-0.000	-0.002	0.002
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
R^2	0.170	0.112	0.135	0.120	0.189
Observations	13,119,386	13,119,386	13,119,386	13,119,386	8,465,394
Pre-Treatment Control Mean	0.091	0.019	0.029	0.042	0.041
Individual fixed effects	✓	✓	✓	✓	✓
Firm-Seniority-Year fixed effects	✓	✓	✓	✓	✓

Notes: The specification equals Column (4) from the baseline tables, with the sample restricted to those working at the two seniority levels directly above the future CEO. *Treat* is an indicator for having worked alongside a future CEO. *Post* is an indicator for periods following the CEO appointment. The fixed effects and standard errors refer to the position the individual worked in alongside the future CEO. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A22: Time Variation in Effect of CEO Appointment of Former Coworker and Job Mobility (5-Year Bins)

	Any Firm (1)	Upward (2)	Lateral (3)	Downward (4)	Any Sector (5)
Treat × Post	-0.003*	-0.001	-0.002**	-0.000	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Treat × Post × 1990–1994	0.009**	-0.000	0.005**	0.004	0.008**
	(0.004)	(0.002)	(0.003)	(0.003)	(0.004)
Treat × Post × 1995–1999	0.003	0.001	0.003	-0.001	0.002
	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)
Treat × Post × 2005–2009	0.006**	-0.000	0.002*	0.004**	0.003
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
Treat × Post × 2010–2014	0.015***	0.002*	0.004***	0.009***	0.008**
	(0.003)	(0.001)	(0.001)	(0.002)	(0.003)
R^2	0.147	0.092	0.114	0.093	0.164
Observations	13,829,579	13,829,579	13,829,579	13,829,579	8,685,741
Pre-Treatment Control Mean	0.079	0.021	0.024	0.035	0.035
Individual fixed effects	✓	✓	✓	✓	✓
Firm-Seniority-Year fixed effects	✓	✓	✓	✓	✓

Notes: The specification equals Column (4) from the baseline tables. The indicators for the 5-year bins refer to the year of the CEO appointment. The sample is restricted to CEO appointments between 1990 and 2014. *Treat* is an indicator for having worked alongside a future CEO. *Post* is an indicator for periods following the CEO appointment. The baseline period includes the years 2000 to 2004. The fixed effects and standard errors refer to the position the individual worked in alongside the future CEO. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A23: Heterogeneity by Mobility of CEO

	Any Firm	Upward	Lateral	Downward	Any Sector
	(1)	(2)	(3)	(4)	(5)
Treat × Post	0.003***	-0.001**	-0.000	0.005***	0.002*
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Treat × Post × High Mobility CEO	0.004*	0.001	0.001	0.002*	0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
R^2	0.166	0.105	0.129	0.111	0.186
Observations	22,777,381	22,777,381	22,777,381	22,777,381	14,144,297
Pre-Treatment Control Mean	0.094	0.025	0.029	0.041	0.042
Individual fixed effects	✓	✓	✓	✓	✓
Firm-Seniority-Year fixed effects	✓	✓	✓	✓	✓

Notes: The specification equals Column (4) from the baseline tables. "High Mobility CEO" is a dummy equal to 1 if the number of positions held by the CEO between leaving the firm and being appointed to CEO is in the highest quartile, and zero otherwise. *Treat* is an indicator for having worked alongside a future CEO. *Post* is an indicator for periods following the CEO appointment. The fixed effects and standard errors refer to the position the individual worked in alongside the future CEO. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A24: Heterogeneity by Direction of CEO Switch

	Any Firm	Upward	Lateral	Downward	Any Sector
	(1)	(2)	(3)	(4)	(5)
Treat × Post	0.005***	0.000	0.000	0.005***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Treat × Post × Lateral Switch	-0.002	-0.002*	-0.001	0.001	-0.004**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Treat × Post × Downward Switch	0.003	-0.001	0.001	0.003*	0.003
	(0.003)	(0.001)	(0.001)	(0.002)	(0.003)
R^2	0.166	0.105	0.129	0.111	0.186
Observations	22,777,381	22,777,381	22,777,381	22,777,381	14,144,297
Pre-Treatment Control Mean	0.094	0.024	0.028	0.041	0.041
Individual fixed effects	✓	✓	✓	✓	✓
Firm-Seniority-Year fixed effects	✓	✓	✓	✓	✓

Notes: The specification equals Column (4) from the baseline tables. "Lateral Switch" ("Downward Switch") are dummies equal to 1 if the future CEO leaves the company while staying at the same seniority level (switching to a lower seniority level), and zero otherwise. *Treat* is an indicator for having worked alongside a future CEO. *Post* is an indicator for periods following the CEO appointment. The fixed effects and standard errors refer to the position the individual worked in alongside the future CEO. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A25: Heterogeneity by Size Quartile of Current Firm

	Any Firm (1)	Upward (2)	Lateral (3)	Downward (4)	Any Sector (5)
Quartile = 2	0.036***	0.007***	0.010***	0.019***	0.018***
	(0.002)	(0.0006)	(0.0007)	(0.001)	(0.002)
Quartile = 3	0.051***	0.008***	0.011***	0.032***	0.032***
	(0.002)	(0.0009)	(0.0009)	(0.002)	(0.002)
Quartile = 4	0.066***	0.009***	0.014***	0.042***	0.045***
	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)
Treat × Post	0.007***	-0.004***	-0.0010	0.013***	0.010***
	(0.001)	(0.0007)	(0.0007)	(0.0008)	(0.002)
Treat × Post × Quartile = 2	0.007***	0.007***	0.004***	-0.005***	-0.002
	(0.002)	(0.0008)	(0.0010)	(0.001)	(0.002)
Treat × Post × Quartile = 3	0.003	0.008***	0.003***	-0.008***	-0.004
	(0.003)	(0.001)	(0.001)	(0.002)	(0.003)
Treat × Post × Quartile = 4	-0.029***	0.0002	-0.005***	-0.024***	-0.024***
	(0.004)	(0.002)	(0.002)	(0.003)	(0.004)
R^2	0.168	0.105	0.129	0.112	0.187
Observations	22,777,381	22,777,381	22,777,381	22,777,381	14,144,297
Individual fixed effects	✓	✓	✓	✓	✓
Firm-Seniority-Year fixed effects	✓	✓	✓	✓	✓

Notes: The specification equals Column (4) from the baseline tables. The quartiles refer to the firm the individual works for in a given year. Firm size is measured by number of employees. *Treat* is an indicator for having worked alongside a future CEO. *Post* is an indicator for periods following the CEO appointment. The fixed effects and standard errors effects refer to the position the individual worked in alongside the future CEO. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A26: CEO Appointment of Former Coworker and Job Mobility (Downward Firm Switch) By Firm Size of Current vs. Destination Firm

	Larger Firm (1)	Smaller Firm (2)	Higher Quartile (3)	Same Quartile (4)	Smaller Quartile (5)	Highest Quartile (6)
Treat × Post	0.001***	0.005***	0.001***	0.001***	0.004***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.112	0.101	0.109	0.117	0.096	0.102
Observations	22,745,916	22,745,916	22,745,916	22,745,916	22,745,916	22,745,916
Pre-Treatment Control Mean	0.013	0.029	0.008	0.011	0.022	0.005
Individual fixed effects	✓	✓	✓	✓	✓	✓
Firm-Seniority-Year fixed effects	✓	✓	✓	✓	✓	✓

Notes: The dependent variable in all regressions is a dummy equal to one in the final year before an individual switches firms and moves to a position with lower seniority. We differentiate transitions by the relative size of the destination firm, measured by the number of employees. We distinguish between switches to firms that are larger (Column 1) or smaller (Column 2) than the individual's current firm, as well as moves to a higher (Column 3), the same (Column 4), or a lower (Column 5) firm size quartile. In Column (6), we focus on switches toward firms in the highest size quartile. *Treat* is an indicator for having worked alongside a future CEO. *Post* is an indicator for periods following the CEO appointment. The fixed effects and standard errors refer to the position the individual worked in alongside the future CEO. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A27: CEO Appointment of Former Coworker and Salary Growth

	Log Salary in First Differences				
	(1)	(2)	(3)	(4)	(5)
Treat	0.002***				
	(0.000)				
Post	0.001**	-0.002***	-0.003***		
	(0.000)	(0.000)	(0.000)		
Treat × Post	-0.001	-0.001	-0.001	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
R^2	0.000	0.052	0.052	0.070	0.098
Observations	22,739,139	22,739,139	22,739,139	22,739,139	16,111,774
Pre-Treatment Control Mean	0.016	0.016	0.016	0.016	0.016
Year fixed effects	✓	✓	✓		
Individual fixed effects		✓	✓	✓	✓
Firm-Seniority fixed effects			✓		
Firm-Seniority-Year fixed effects				✓	✓
MSA-Naics4-Year fixed effects					✓

Notes: The dependent variable in all regressions is log salary in first differences. *Treat* is an indicator for having worked alongside a future CEO. *Post* is an indicator for periods following the CEO appointment. The fixed effects and standard errors refer to the position the individual worked in alongside the future CEO. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D CEO Age and Firm-Level Outcomes

This section summarizes the literature on the link between CEO age and firm-level outcomes, complemented with a number of own analyses. Summary statistics for all outcome variables are provided in Table A30.

D.1 Correlational Evidence

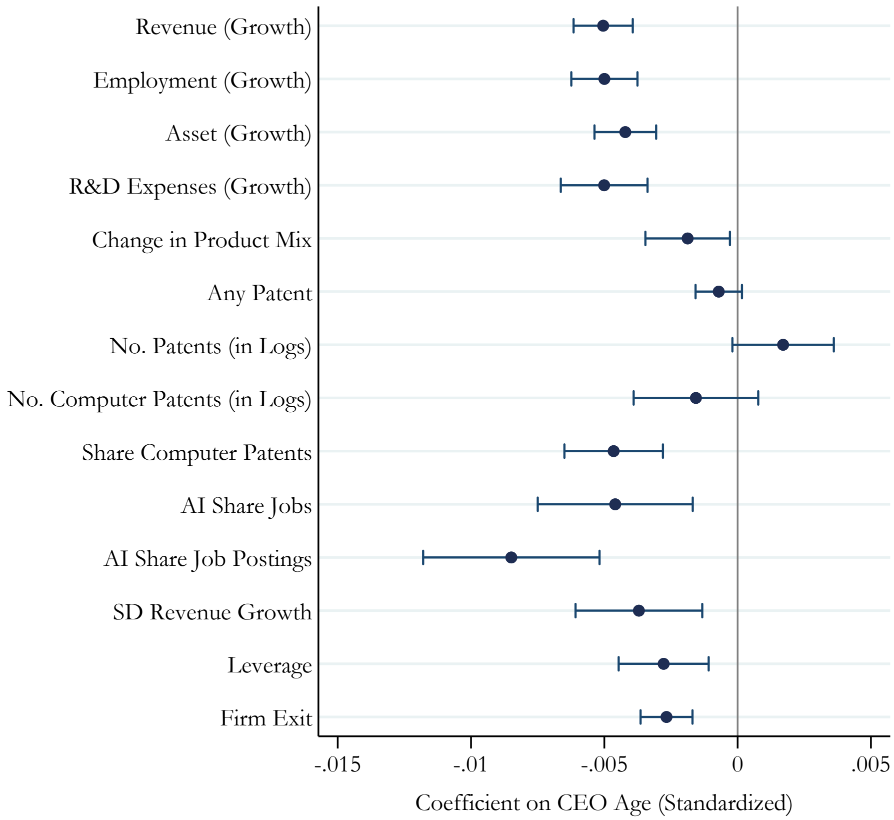
Motivated by upper echelons theory (Hambrick and Mason, 1984), a vast body of research explores the role of executive characteristics in determining company outcomes (Bertrand and Schoar, 2003). This literature has established an association between higher CEO age and reduced levels of business dynamism and firm risk. Our analysis revisits this relationship, yielding results in line with previous research. Figure A28 summarizes the estimated coefficients, obtained by regressing firm-level outcomes on CEO age alongside NAICS-4-year fixed effects and lagged controls.

We find that CEO age is negatively associated with growth rates of revenue, employment, and total assets. A large strand of literature, starting with Child (1974) and Hart and Mellors (1970) has established a negative correlation between CEO age and firm growth: older CEOs are associated with lower investment and sales growth (Acemoglu et al., 2022); asset growth (Barba Navaretti et al., 2022); profitability (Belenzon et al., 2019); firm value, operating performance, and corporate deal-making activity (Cline and Yore, 2016); return on assets (Waelchli and Zeller, 2013); employment growth (Li et al., 2017); firm valuation (Nguyen et al., 2018), and a higher propensity of receiving a takeover bid (Jenter and Lewellen, 2015). Furthermore, firms that undergo strategic change are characterized by management teams with a lower average age (Wiersema and Bantel, 1992; Datta et al., 2003). Recently, return-to-office policies have been found to be more prevalent among firms with older CEOs (Flynn et al., 2025), reflecting a more traditional management approach within this group.

Our analysis also reveals that CEO age is systematically related to innovative activity. This pattern is evident across several dimensions: research inputs, such as R&D expenses (consistent with Serfling, 2014, Li et al., 2017 and Barker and Mueller, 2002); the extensive margin of research output, measured as changes in a firm's product mix; and the intensive margin of research output as captured by the share of computer-related patents. Notably, overall patenting exhibits no clear association with CEO age.[50] In line with this, Acemoglu et al. (2022) document lower levels of radical innovation among firms with older CEOs, while the same pattern does not hold for incremental innovation. Consistent with evidence from other contexts (Kitchell, 1997), we observe reduced technology adoption in firms with older CEOs, specifically in the creation of AI-related jobs.

[50] To document these patterns, we draw on data from the *United States Patent and Trademark Office* provided via *PatentsView*. We merge assignee organizations with company names from BoardEx using the same fuzzy merge algorithm as described above. From these data, we construct an indicator for whether a firm applied for a patent in a given year and calculate the natural logarithm of the number of patents. We define computer-related patents as those invention patents in product class G06. Based on this, we calculate both the natural logarithm of the number of computer-related patents and their share among all invention patents.

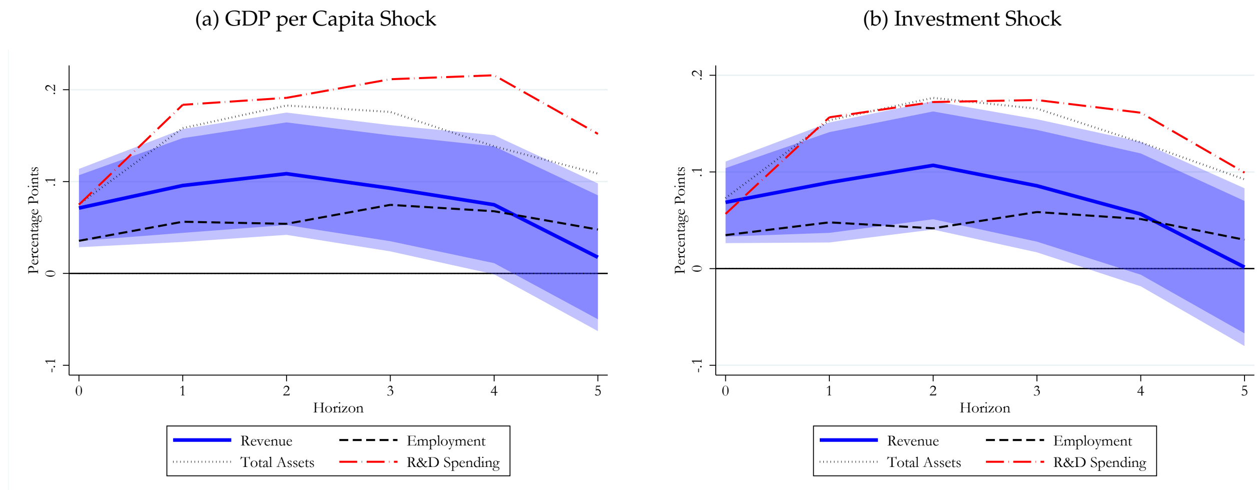
Appendix Figure A28: Correlations of CEO Age and Firm-Level Outcomes



Notes: The figure plots correlations of firm-level outcomes with current CEO age, controlling for fixed effects at the NAICS-4-year level, as well as the natural logarithm of employment and firm age (both obtained from employment history data). Each coefficient stems from a separate regression. For the sake of exposition, the coefficients are standardized by dividing by the standard deviation of the outcome variable. The sample starts in 2000 and ends in 2022. The outcomes are the symmetric growth rates of revenue, employment, assets, and R&D expenses (all obtained from Compustat), changes in the product mix (Hoberg et al., 2014), an indicator for filing any patent, the natural logarithm of the number of patents, the natural logarithm of the number of computer-related patents (share of inventional patents of product class G06), and the share of computer patents (derived from USPTO data), the share of computer patents , the shares of AI jobs and job postings (Babina et al., 2024), the 5-year ahead standard deviation of revenue growth, leverage and firm exit (derived from Compustat). Standard errors are clustered at the NAICS-4 level.

Given these drawbacks, why would firms appoint older CEOs? One reason may be that CEO age is systematically linked to lower firm risk. In our sample, older CEOs tend to manage firms with lower variation in 5-year ahead revenue growth, lower leverage, and a smaller probability of firm exit. Accordingly, the literature has found CEO age to be associated with lower idiosyncratic risk, stock return volatility (Peltomäki et al., 2021), stock price crash risk (Andreou et al., 2017), and higher firm survival rates (Belenzon et al., 2019). This finding of reduced risk-taking extends to the banking sector (Ahmed et al., 2023). One explanation for this pattern is that older managers adopt more conservative investment strategies (Vroom and Pahl, 1971). Serfling (2014) documents that older CEOs take fewer risks as they age, showing that firms managed by older CEOs are more diversified across business segments. Efforts to reduce risk also manifest in that firms with older

Appendix Figure A29: Cyclical Fluctuations of Firm-Level Outcomes—Differential Effect by CEO Age



Notes: The figure shows results from local projections, obtained from h-step-ahead symmetric growth rates of the outcome variables compared to $t-1$ on CEO age, alone and interacted with different shock series. The plots shows the estimated coefficients on this interaction term. Panels (a) and (b) show the results for the real GDP per capita shock and the investment shock series, respectively, which have been obtained from Angeletos et al. (2020). The shock series have been averaged by year, standardized to mean zero and a standard deviation of one, and included in first lags. We control for the natural logarithm of employment and firm age (both obtained from employment history data) as well as CEO tenure. We also include fixed effects at the NAICS-4-year and firm level. The sample runs from 1980 to 2016. The plot shows point estimates alongside 90% and 95% confidence bands, obtained from standard errors clustered at the firm level. Confidence intervals are based on the estimated standard errors for the result on firm revenue.

CEOs tend to have higher financial reporting quality (Huang et al., 2012) and take longer to IPO (Yang et al., 2011). Conversely, younger CEOs are more likely to pursue acquisitions (Yim, 2013), aggressive takeovers (Levi et al., 2010), and strategic restructuring (Li et al., 2017).

Desir et al. (2024) report lower levels of managerial ability among older CEOs. This correlation is particularly strong in high-tech firms, but it is reversed in mature and more regulated firms. An obvious but rather understudied question is whether these correlations merely reflect assortative sorting of CEOs and firms, or whether they can be interpreted as causal. Younger CEOs are more common in smaller, high-growth firms, while larger, complex firms tend to select older CEOs (Joos et al., 2003). Acemoglu et al. (2022) find that radical innovation often precedes the appointment of younger CEOs, suggesting a sorting effect, while the causal effects of younger CEOs on innovation are comparatively small.

D.2 CEO Age and Adjustments to Macroeconomic Shocks

We now scrutinize whether these associations are also reflected in how firms react to aggregate shocks. To this end, we estimate the impact of business cycle fluctuations on firm-level outcomes over a longer time horizon, focusing on heterogeneity by CEO age. Figure A29 presents results from local projections using the shock series from Angeletos et al. (2020). Panel (a) shows the

Appendix Table A28: CEO Age and Firm-Level Outcomes—Results from IV Regressions

	Emp. Gr.	R&D Gr.	Any Patent	Log(Patent)	Log(Comp. Patents)	Share Comp. Patent
	(1)	(2)	(3)	(4)	(5)	(6)
CEO Age	-0.016	-0.036***	-0.017	0.038	-0.057**	-0.022***
	(0.010)	(0.011)	(0.017)	(0.038)	(0.023)	(0.008)
R^2	-0.206	-0.853	-0.196	-0.053	-0.364	-0.441
Observations	2,505	1,138	9,919	1,951	1,951	1,951
MSA-Year fixed effects	✓	✓	✓	✓	✓	✓
Naics4-Year fixed effects	✓	✓	✓	✓	✓	✓
Kleibergen-Paap F-Statistic	11.159	33.357	14.694	10.049	10.049	10.049

Notes: The table shows results from estimating Equation (21). The dependent variables are the firm-by-CEO fixed effects $\hat{v}_{wj}$, which we estimate as described in Equation (21) for the following variables: (1) symmetric growth rates of employment, (2) symmetric growth rates of R&D expenditure, (3) an indicator for filing any patent, (4) the natural logarithm of the number of patents, (5) the natural logarithm of the number of computer-related patents, and (6) the share of computer-related patents. The independent variable is CEO age, which we instrument with the interaction of the flight time (in hours) to the closest MBB office with the cross-sectional standard deviation of the symmetric growth rate of firm revenue within a firm's NAICS-4 industry. The sample is restricted to those MSAs without MBB presence. All regression controls for fixed effects at the MSA-year and NAICS-4-year level. Standard errors are double-clustered at the NAICS-4 industry and MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

differential responses of revenue, employment, total assets, and R&D spending to an exogenous one standard deviation decrease in the cyclical component of real GDP per capita. Across all outcomes, the coefficients are positive, highly significant, and persistent over several years, even conditional on fixed effects at the NAICS-4-year and firm level. Quantitatively, the effects are sizeable: with an estimated coefficient of around 0.1, a ten-year older CEO increases revenue growth by about 1 percentage point following a negative one standard deviation business cycle shock. Panel (b) presents analogous estimates using the investment shock series, revealing a similar pattern. These results are consistent with Schoar et al. (2024), who document systematic variation in the role of managers in shaping firms' risk exposure. Together, these results suggest that older CEOs enhance firms' resilience to aggregate fluctuations.

D.3 IV Regressions

We establish causality through a two-stage estimation approach that leverages our finding that greater industry-level uncertainty leads to older CEOs in the absence of other generalists (Section 5.1). First, we estimate firm-by-CEO fixed effects for various time-varying firm-level outcomes to capture the average performance of each CEO throughout their tenure. Second, we regress these fixed effects on the CEO's age at appointment, instrumenting age at appointment with firms' demand for generalists. This identification strategy is motivated by the idea that shifts in the demand for certain skills lead to the appointment of systematically different types of CEOs, with causal consequences for firm-level policies and outcomes (Fee et al., 2013).

In the first step, consider a CEO w in firm j, industry i, and year τ. We then estimate the following equation for a time-varying firm outcome $v_{j\tau}$

$$v_{j\tau} = \nu_{wj} + \phi_{i\tau} + X_{j\tau} + \epsilon_{j\tau}, \tag{20}$$

where ν_{wj} are firm-by-CEO fixed effects and $\phi_{i\tau}$ denote NAICS-4-year fixed effects. The vector of controls, $X_{j\tau}$, includes the natural logarithm of the number of employees and firm age, both obtained from employment history data, as well as the natural logarithm of the CEO's tenure at the firm. The coefficients of interest are the estimated firm-by-CEO fixed effects $\hat{\nu}_{wj}$, which capture a firm's performance throughout a CEO's tenure, net of time-varying industry conditions and firm-level characteristics.

In the second step, we use this measure to estimate the causal effect of CEO age at appointment t on the match-specific firm outcomes $\hat{\nu}_{wj}$, leveraging our plausibly exogenous measure of demand for more experienced CEOs as an instrument. Specifically, we run the following regression

$$\hat{\nu}_{wj} = \beta \widehat{Age}_j + \gamma_{mt} + \phi_{it} + \epsilon_{jt}, \tag{21}$$

where $\widehat{Age}_{jt}$ is the predicted age at appointment based on Equation 1. That is, we exploit variation in the demand for generalist skills, as captured by the interaction of industry-level uncertainty and travel time to the offices of top strategy consulting firms, to instrument for CEO age at appointment and identify its causal effect on our measures of CEO performance. Analogously to our first-stage regression described by Equation 1, we control for time-varying characteristics at the level of metro areas and NAICS-4 industries.

We conduct this analysis for two different types of outcomes. On one side, we consider balance sheet variables, specifically the symmetric growth rates of employment and R&D expenditures. On the other side, we exploit information on firms' patenting activity, both overall and restricted to computer-related patents. The results are shown in Table A28. While we find no significant coefficient for employment growth (Column 1), we detect a negative effect for R&D expenditure growth. Further, we find no evidence of a causal effect of CEO age on overall patenting behavior, whether measured by an indicator for filing any patent in a given year (Column 3) or the number of patents (Column 4). Lastly, our results reveal a significantly negative effect on the number of computer patents (Column 5) and on the share of computer patents among total patents (Column 6). The instrument is relevant throughout, with an F-statistic above 10 in all specifications. In terms of magnitude, having a CEO who is one year older is associated with a decrease in employment and R&D expenditure growth of 1.7 and 3.6 percentage points, respectively, as well as a 2.2% reduction in the share of computer-related patents.[51]

[51] One potential concern is that the reported standard errors may be understated, as they do not explicitly factor in the uncertainty stemming from the first-step estimation. In Table A29, we address this by bootstrapping the first step to obtain a distribution of point estimates, which we then combine with the analytical standard errors from the second-step estimation using Rubin's rules for multiple imputation. The results remain qualitatively unchanged, with all coefficients except that on employment growth remaining statistically significant.

Appendix Table A29: CEO Age and Firm-Level Outcomes—Results from IV Regressions (Adjusted Standard Errors)

	Emp. Gr.	R&D Gr.	Any Patent	Log(Patent)	Log(Comp. Patents)	Share Comp. Patent
	(1)	(2)	(3)	(4)	(5)	(6)
CEO Age	-0.016	-0.036*	-0.016	0.038	-0.057**	-0.022**
	(0.014)	(0.020)	(0.018)	(0.042)	(0.025)	(0.010)
R^2	-0.206	-0.853	-0.196	-0.053	-0.364	-0.441
Observations	2,505	1,138	9,919	1,951	1,951	1,951
MSA-Year fixed effects	✓	✓	✓	✓	✓	✓
Naics4-Year fixed effects	✓	✓	✓	✓	✓	✓
Kleibergen-Paap F-Statistic	11.159	33.357	14.694	10.049	10.049	10.049

Notes: The table shows results from estimating (21). The dependent variables are the firm-by-CEO fixed effects $\hat{v}_{wj}$, which we estimate as described in (21) for the following variables: (1) symmetric growth rates of employment, (2) symmetric growth rates of R&D expenditure, (3) an indicator for filing any patent, (4) the natural logarithm of the number of patents, (5) the natural logarithm of the number of computer-related patents, and (6) the share of computer-related patents. The independent variable is CEO age, which we instrument with the interaction of the flight time (in hours) to the closest MBB office with the cross-sectional standard deviation of the symmetric growth rate of firm revenue within a firm's NAICS-4 industry. The sample is restricted to those MSAs without MBB presence. All regressions control for fixed effects at the MSA-year and NAICS-4-year level. Standard errors are generated using a bootstrapping procedure with $R = 500$ repetitions, in which we stratify draws with replacement within CEO spells in the first step to obtain a distribution of estimated second-step coefficients $\hat{\beta}_r$, where r indexes the estimation. The corresponding analytical standard errors $\hat{\sigma}_r$ are obtained from double-clustering at the NAICS-4 industry and MSA level. We compute the between-variance $\hat{\sigma}^2_{\beta}$ as the variance over all $\hat{\beta}_r$, and the within-variance $\hat{\sigma}^2$ by averaging over all squares of $\hat{\sigma}_r$. The reported standard errors are then obtained by combining both components using the formula for multiple imputation described in Rubin (1987) as $\sqrt{\hat{\sigma}^2 + (1 + \frac{1}{R})\hat{\sigma}^2_{\beta}}$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A30: Summary Statistics—Firm-Level Outcomes

	Mean	SD	P25	P50	P75	N
Panel 1: Firm-Level Outcomes						
Revenue (Growth)	10.57	38.70	-1.61	8.19	20.78	86458
Employment (Growth)	5.51	26.71	-3.59	3.29	13.33	84701
Asset (Growth)	9.83	31.63	-2.82	6.14	18.34	88672
R&D Expenses (Growth)	9.17	39.74	-5.74	8.08	24.27	40131
Change in Product Mix	17.48	15.46	7.32	13.76	23.15	79281
Any Patent	0.20	0.40	0.00	0.00	0.00	328690
Number of Patents	17.35	108.54	1.00	2.00	6.00	64665
Number of Computer Patents	2.86	31.11	0.00	0.00	0.00	64665
Share Computer Patents	0.15	0.32	0.00	0.00	0.00	64665
AI Share Jobs (in %)	0.10	0.36	0.00	0.00	0.06	33103
AI Share Job Postings (in %)	0.28	1.55	0.00	0.00	0.00	18509
SD Revenue Growth	21.77	27.47	7.06	13.18	24.94	71720
Leverage	0.89	1.62	0.06	0.41	1.01	86711
Firm Exit	0.03	0.17	0.00	0.00	0.00	92654
Panel 2: Firm-Level Outcomes, Fixed Effects Estimates						
Employment (Growth)	-0.01	0.29	-0.17	0.02	0.18	4,420
R&D Expenses (Growth)	-0.02	0.38	-0.21	0.02	0.20	2,153
Any Patent	0.05	0.36	-0.21	-0.09	0.26	11,120
Number of Patents (in Logs)	-0.10	1.03	-0.76	-0.28	0.35	3,209
Number of Computer Patents (in Logs)	0.02	0.82	-0.41	-0.24	0.12	3,198
Share Computer Patents	0.01	0.32	-0.16	-0.14	-0.02	3,209

Notes: Shows summary statistics for outcome variables used to analyze the link between firm-level effects of CEO age.

E Details on BoardEx CEO Sample

E.1 Alternative Data Preparation

For the descriptive analysis, we transform the data into a panel to allow for a meaningful decomposition of employment histories and job turnover. One drawback of removing parallel spells is that it decreases the probability of classifying a CEO appointment as internal. Since our analysis focuses on changes over time rather than levels, this issue is practically irrelevant for our purposes. Nevertheless, we show below that our main conclusions do not hinge on this classification. We proceed as follows: starting from the spell-level data, we retain each individual's first CEO appointment per firm and classify it as internal if the individual held any other position in the same firm during the preceding year. For individuals with overlapping CEO spells, we remove all spells but the one that began earliest.

First, as shown in Figure A30, CEO age at appointment increases by almost eight years over the sample period (Panel a). Second, when decomposing total work experience into tenure accumulated before and after joining the firm where the individual became CEO, we find that the increase is entirely driven by a rise in external experience, while internal experience remains stable over time (Panel b). Third, external experience becomes more important, irrespective of the seniority level at which a CEO joined the firm. Both internally and externally appointed CEOs are entering at later career stages with more external experience (Panel c), whereas internal experience remained stable (Panel d).

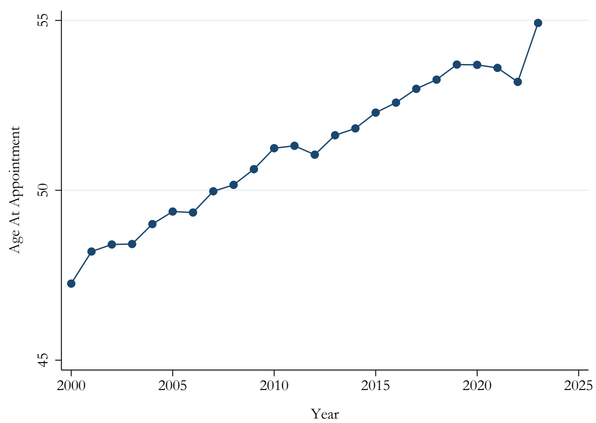
The key difference that emerges relative to our baseline analysis is the frequency of internal appointments. In comparison to our baseline probability of 20%, the corresponding figure is now at 32%. To document heterogeneity by firm size and listing status, Figure A31 reproduces Figure A14, which plots the share of internal appointments, stratified by these two variables. Consistent with our prior analysis, firms in the S&P 500 are far more likely than unlisted firms to hire internally (74% vs. 25%). A very similar pattern is evident when comparing firms in the largest with those in the smallest employment quartile (60% vs. 25%).

E.2 Sample Composition

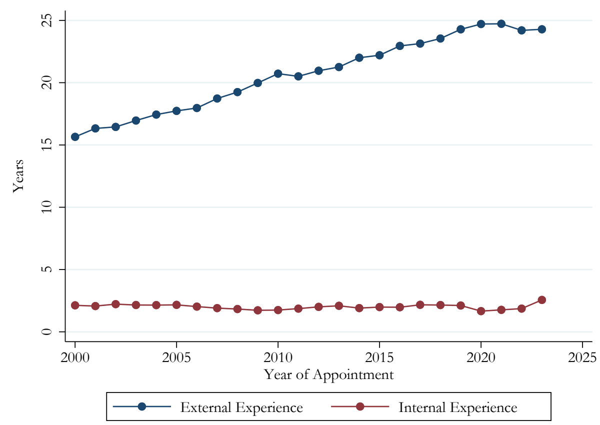
Another potential concern relates to BoardEx's inclusion criteria. In particular, once an individual becomes CEO of a large firm, BoardEx might retrospectively add their entire employment history, including prior CEO appointments at smaller firms that would not appear in the data otherwise. This could mechanically generate a pattern whereby younger CEOs are more likely to appear in smaller firms in earlier years, while a similar bias would not be present for larger firms. Thus, the inclusion criteria could spuriously produce the gradient in CEO age with respect to firm size that we document in the main analysis. To address this concern, we reproduce Panel (b) of Figure 2 excluding all individuals who ever held a CEO position at a smaller firm before later becoming CEO of a larger firm. The results are shown in Figure A32. Reassuringly, albeit being overly conservative, excluding this group of CEOs leaves the pattern unchanged.

Appendix Figure A30: CEO Age At Appointment Over Time, Alternative Data Preparation

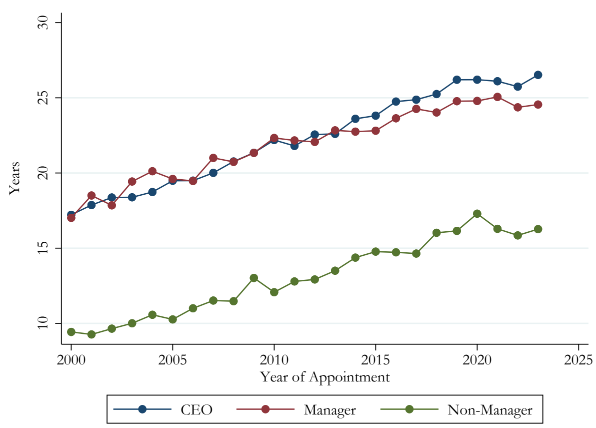
(a) Age



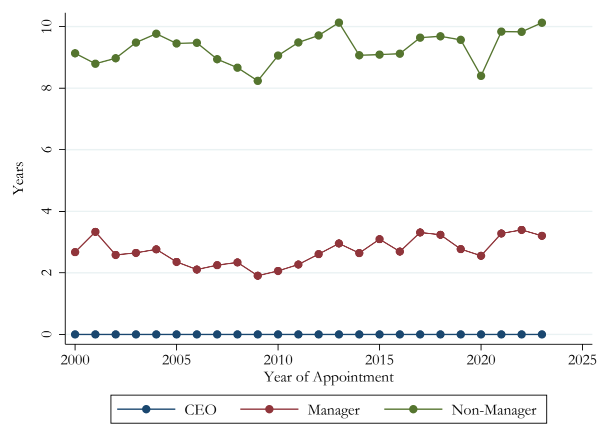
(b) External vs. Internal Work Experience



(c) External Experience, by Seniority of First Position

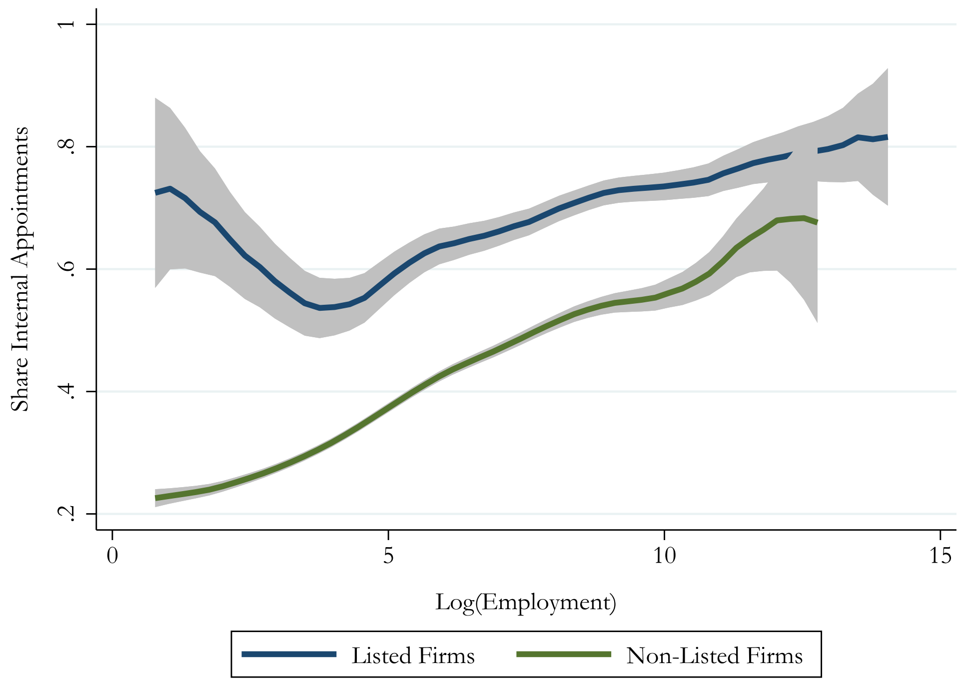


(d) Internal Experience, by Seniority of First Position



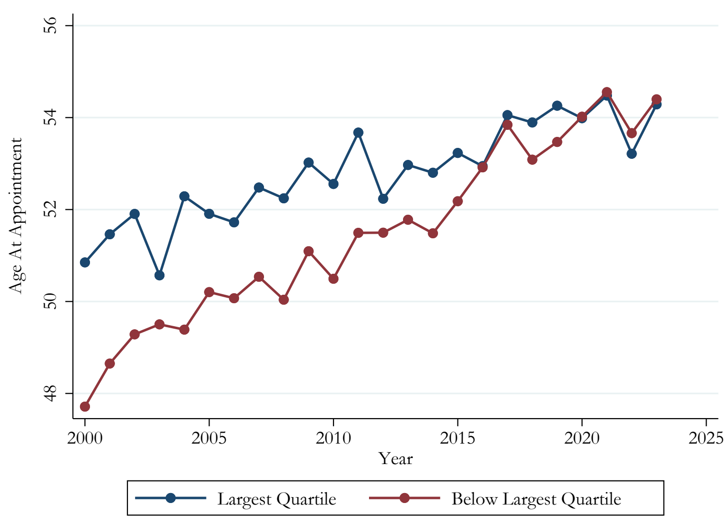
Notes: Panel (a) shows the average age at appointment of CEOs in the United States over time. Panel (b) plots the average external vs. internal work experience prior to appointment. Panels (c) and (d) show the average years of external and internal experience, respectively, stratified by the seniority of their first position in the firm.

Appendix Figure A31: Share of Internal Appointments by Firm Size and Listing Status, Alternative Data Preparation



Notes: Plots the share of internal appointments against firm size measured by the natural logarithm of employment (obtained from employment histories). The data are smoothed with a local polynomial with Epanechnikov kernel and bandwidths of 0.91 and 0.78, respectively, consistent with Figure A14. Point estimates are shown alongside 95% confidence intervals.

Appendix Figure A32: Average CEO Age over Time by Firm Size (Number of Employees), Restricted Sample



Notes: The plot shows age at appointment separately for those in the largest firm quartile and for those in the other three quartiles. Size quartiles are generated separately by year. The sample excludes all individuals who ever held a CEO position at a smaller firm before later becoming CEO of a larger firm

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