AGING AT THE VERY TOP

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February 6, 2026

Abstract

We document that since 2000 U.S. CEOs are on average 7 to 8 years older upon appointment. Using employment history data from BoardEx and LinkedIn, we show that this development is driven by later appointments and a greater variety of prior work experiences. We hypothesize that these trends reflect a shift toward generalist skills. Using exogenous variation in the proximity to strategy consulting firms and their employees, we show that firms increase their demand for generalist skills in response to greater industry-level uncertainty and complexity, and subsequently appoint older CEOs when generalist consultants are not readily available. Our results also indicate that prospective CEOs strategically respond to these evolving skill requirements. Exploiting the network structure resulting from employment histories, we demonstrate that job mobility increases in response to positive information shocks about the value of job transitions. In particular, workers are more likely to accept positions at lower seniority levels at other firms, reflecting that they are willing to sacrifice short-run wage growth for the longer-run purpose of acquiring generalist skills.

JEL codes: D22, J21, M12, M51

Keywords: CEOs, aging, internal labor markets, managers, promotions, dynamism

We thank Thomas Dohmen, James Dow, Benjamin Friedrich, Nicola Gennaioli, Charles Hadlock, Dirk Jenter, Nicola Limodio, Wladislaw Mill, Christian Moser, Paige Ouimet, Kelly Shue, Adam Spencer, as well as seminar participants at University of Bonn, University of Zurich, HEC Paris, Max Planck Institute for Behavioral Economics, the 2025 NBER Economics of Executive Compensation Research Conference, the 8th UniBg Industrial Organization Winter Symposium, and the 2026 European Winter Finance Conference for excellent comments. We also thank Russell Weinstein for providing data. This paper uses microdata provided by Eurostat under research proposal RPP 204/2023-LFS. Kecht and Saidi acknowledge funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy (EXC 2126/2 – 390838866). Saidi acknowledges funding by the Deutsche Forschungsgemeinschaft through CRC TR 224 (Project C03).

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1 Introduction

We uncover a striking evolution in the age of CEOs over the last few decades, and attempt to understand its causes and consequences. Between 2000 and 2023, the average age of CEOs in the United States has increased by ten years, five times the increase for the college-educated labor force. Similar patterns have emerged in Europe. This trend may partly be due to longer tenures or entrenchment of CEOs. However, 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 other potential explanations and conclude that this aging trend is largely due to firms' increased demand for generalist skills. We also discuss how executives alter their career paths in response to this changed demand.

We document a number of other important changes in the career profiles of managers and executives during our sample period. First, we uncover a change in the experience profile of individuals who eventually become CEOs: their external experience has increased by roughly ten years compared to 2000, whereas internal experience has remained almost unchanged. This holds true both for external appointments but also for internal appointments, especially at smaller firms. Second, we consider the composition of this additional experience. At appointment, compared to 2000, CEOs, especially in smaller firms, hold a larger number of positions, across more firms and sectors. 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 consider several competing explanations to understand this aging of corporate leadership, which broadly fall into two categories. The first category reflects inefficiencies and encompasses firm-level responses to agency conflicts, e.g., preventing managerial entrenchment by mechanically shortening tenure through hiring older CEOs, or changes in market structure such as rising concentration that reduce the supply of CEO positions. We find no evidence supporting these channels. The second category reflects market-based forces that affect the matching of firms and CEOs.

To formalize this mechanism, we consider a many-to-one matching model with the following ingredients. Workers have multidimensional skills: they vary in both innate ability (which peaks at mid-career) and experience (which increases in age). Firms differ in productivity (related to firm size) and have multiple, hierarchically ranked, positions with different productivity requirements. Our main result considers how the equilibrium assignment changes when the value of experience in worker productivity increases relative to ability. Under mild conditions on the shape of the functions determining productivity, we show that, as in the data, in response to a change in the value of experience, older workers become more likely to be assigned to top positions, and especially so at lower-productivity (smaller) firms. Furthermore, also consistent with the data, CEOs in lower-productivity, or smaller, firms are younger on average.

The value of experience may have increased because of a number of possible changes in the environment, two of which we consider. First, experience helps executives manage conditions with elevated uncertainty (Baker et al., 2016). Second, the CEO job has become more complex,

as evidenced by firms simultaneously expanding across geographies and business lines while navigating increasingly complex regulatory environments (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.

To test these hypotheses, we use granular data from BoardEx and LinkedIn on executives' career trajectories in the U.S. 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 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. Consistent with our hypothesized mechanism, the results are stronger for small firms where external experience is in shorter supply, and this is indeed reflected by our finding of a larger gradient in external experience of small firms' CEOs over time. Therefore, the value added of generalist consultants as substitutes for experience is arguably higher for small firms.

To assess how overlapping trends in evolving, and more complex, 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.

On the supply side, we investigate how executives have adapted their career strategies in light of firms' growing demand for generalist skills. In line with this demand shift, prospective CEOs now exhibit substantially higher turnover across positions, firms, and sectors before their appointments. This pattern suggests that executives are strategically responding to the increasing premium for broad managerial capabilities. To explore this hypothesis, we start from the idea that executives learn about career-enhancing moves through professional networks. If the acquisition of generalist skills is revealed to be an important career ingredient, then this can lead to greater willingness to accept lower-level positions and pay in the short run in exchange for building a generalist skill set that enhances their long-term career prospects.

To test this, we consider changes in workers' career paths after they learn about CEO appointments of former peers. Individuals who worked contemporaneously at the same firm, at a similar seniority level, and 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. Furthermore, on average, these individuals

accept reduced compensation in the short run in exchange for the presumed value of additional experience. This is most clearly reflected in the prevalence of downward switches across firms—where executives accept positions at lower seniority levels—but also in more frequent transitions across sectors. These responses to peer information shocks are more pronounced for coworkers with a 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, and that the aging trend is neither a demographic inevitability nor merely a reflection of changing workforce composition. We leverage these insights to decompose the overall age trend and show that around 37% of the increase 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.

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 the negative association between CEO age and reduced levels of business dynamism and firm risk.[1]

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 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 therefore 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]

Our analysis makes three 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 develop identification strategies that separately estimate demand- and supply-side factors contributing to these changes. Third, we demonstrate how professional networks transmit information about optimal career strategies in the market for CEOs, leading to widespread behavioral changes among executives.

[1] For a comprehensive discussion of the nexus between CEO age and firm-level outcomes, we refer to Appendix Section D.

[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).

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 to a shift toward generalist skills.[3] Custódio et al. (2013) document a pay premium for generalist CEOs, while Adams et al. (2018) 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 towards 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, making use of 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 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.

[3] A large literature discusses the role of CEO hiring patterns, as the share of internal vs. 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). 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. Contrasting these results, Gompers et al. (2023) examine private equity buyouts and find that most CEOs are hired externally. Other studies also point towards 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; 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. such as 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.

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 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 towards 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). Notably, 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), 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

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

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 also been increasing over the past decades, particularly among grant winners.[7] Daniels (2015) attribute this trend to longer pre-grant career paths, while Fons-Rosen et al. (2023) point to slower hiring and delayed retirements. Similarly, 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 20th 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.

2 Data and Stylized Facts

2.1 Data

The empirical analysis mainly relies on data on CEOs from BoardEx and employment biographies obtained 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 *Delinean*. This dataset provides comprehensive details on executives' employment histories and demographic characteristics. While

[6] Taussig and Joslyn (1932) report the median age of American business leaders in the early 1930s to range 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 Europe, 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 20th 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

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 North America (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, more senior positions and those with earlier start dates are prioritized.[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 during the last observation prior to their appointment, while all others are considered externally appointed. This implies that external insiders, i.e., returning executives, are included in this latter group. Among internally appointed CEOs, we further distinguish those who initially joined the firm at a managerial level from those who entered at lower levels.

Summary statistics are shown in Table A1, Panel A. The average CEO age at appointment is 52. Around 20% of CEOs are appointed internally, split evenly between those entering at the managerial level and those entering below it. The median firm in our sample 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.[9]

For the reduced-form analysis, 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 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.

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,

[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]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 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.

alongside a seniority ranking based on job titles ranging from 1 (lowest) to 7 (highest).[10] 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.[11] 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 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 1st and above the 99th percentile. We define firm age as the number of years since the first appearance in the sample, and firm exit as an identifier equal to one when we observe a firm for the last time in the sample.

For the balance sheet variables, we 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 sectors.

[10] For examples, see here.

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

MSA-Level Data: Our identification strategy in Section 4.1 exploits plausibly exogenous variation in the supply of 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.[12]

2.2 Stylized Facts

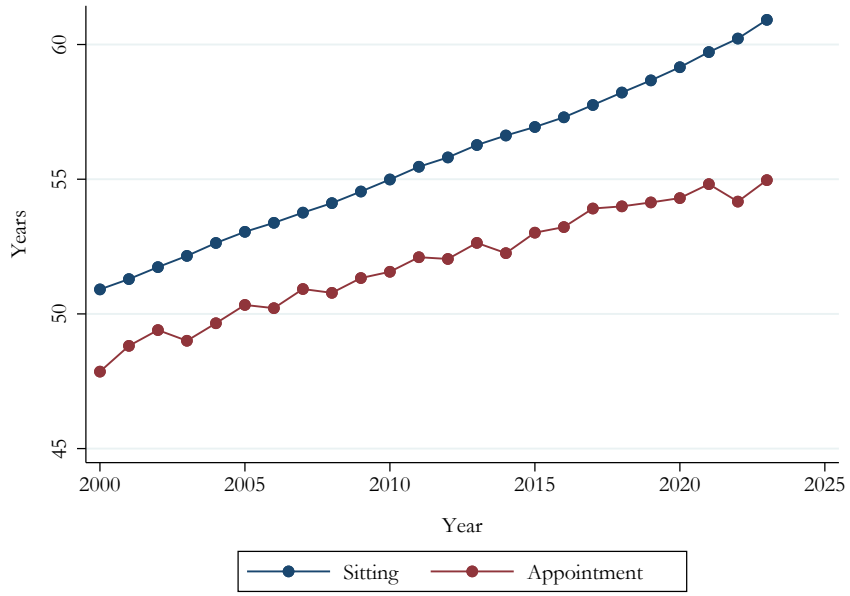
We now use the BoardEx data to present two stylized facts about the role of age in the labor market for CEOs. First, we report a steady increase in the average age of sitting CEOs, largely driven by higher age at appointment, in particular among smaller firms. Second, we show that prospective CEOs bring more external experience, which they accumulate across an increasing number of firms and sectors.

CEO Age Developments: In Figure 1, we document a consistent increase in CEO age since 2000. Panel (a) plots the average age of CEOs in the United States over time. We observe an increase of approximately 10 years for the overall sample of CEOs, reaching an average age of 61 in 2023. We are particularly interested in the average age at appointment, which also rose noticeably from less than 48 to 55 years.[13] The corresponding patterns for Europe, shown in Figure A2, are very similar and even more pronounced. As we show in Figure A3, the magnitude of the age increase is roughly three times that of the overall labor force. The difference is even larger relative to college-educated workers, who arguably represent a more appropriate reference group. This implies that the upward age trend is largely resulting from the appointment of older CEOs rather than prolonged CEO tenure. Moreover, the age increase is pervasive and not limited to specific segments of the distribution of newly appointed CEOs. Figure A4, 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.

[12] 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.

[13] This increase suggests that the aging trend is unlikely to arise solely from later retirement or CEO entrenchment. Section 5 discusses this issue in more detail.

Figure 1: Average CEO Age Over Time



Notes: The plot shows the average age of CEOs in the United States over time, separately for sitting CEOs and CEOs at appointment.

Next, 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 A5.

Absent controls, the predicted age difference between 2000 and 2023 is slightly 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 discussed in the related literature. Considering 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 (both derived from the data on employment biographies), the estimate shrinks only slightly. 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.

We further examine this aspect in Figure A6. 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 place these findings 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 A7, the average CEO age in this sample barely changed between 1940 and 1990. However, this masks an increase in age at appointment as well as 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. This long-run analysis yields two important insights. First, it underscores the critical role of firm heterogeneity, particularly firm size, in tracking CEO age trends over time. Second, it suggests that simple demographic explanations may be insufficient to fully account for the patterns of interest.

Changes in Career Paths: Having established the rise in CEO age since 2000, we now examine how career paths have evolved over the same period. In Figure 2, 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 markedly 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).[15] 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 towards a *boundaryless career* in this segment of the labor market (Arthur and Rousseau, 1996).[16]

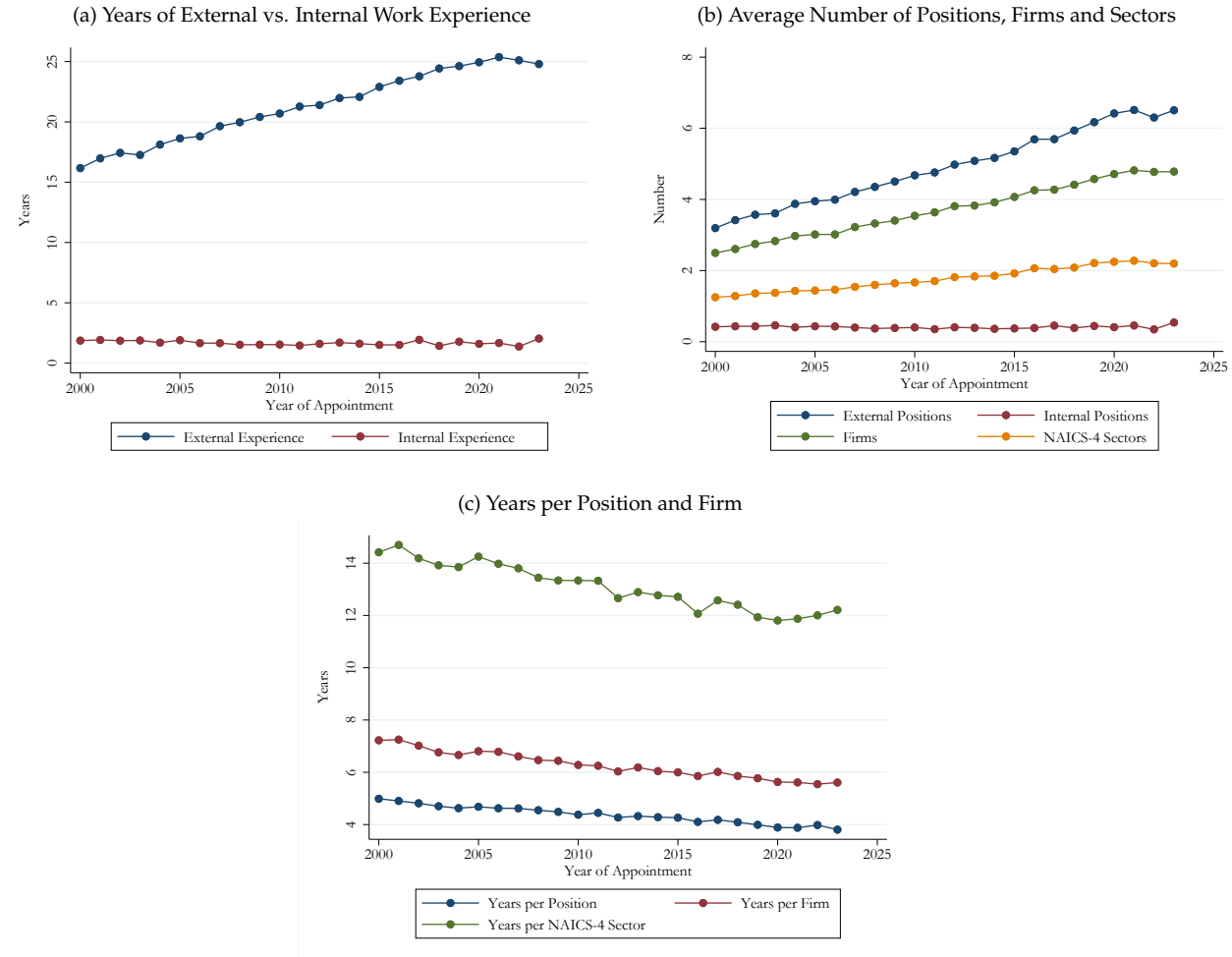
Even though our results highlight the importance of generalist skills, the broadening of career paths has not unfolded uniformly across backgrounds. In Figure A8, we show that an increasing share of CEOs previously held positions as CFO or COO, but this trend is confined to those who served in these roles at other companies. Furthermore, Decressin et al. (2025) document that CEOs

[14] In Appendix Section E, we document that this result is not a mere artifact of the sample composition.

[15] 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).

[16] 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 2: Work Experience Prior to CEO Appointment Over Time



Notes: The figure plots work experience of CEOs over time. Panel (a) plots the average external vs. 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 a prospective CEO worked in. Panel (c) shows the average number of years per position and firm.

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 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 A9 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.[17] As we show in Table A3, this is due to the comprehensive coverage of smaller firms, which are more likely to hire CEOs externally, while larger firms tend to favor internal candidates.[18] 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).[19] Given that prospective CEOs are gaining increasing amounts of external experience (Appendix Figure A11), the prevalence of external hiring among smaller firms is consistent with our finding that these firms are the primary drivers 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. To this end, 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 A12 and A13, we replicate Figure 2, 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 sectors. These differences are more pronounced for non-executive managers, who are more distant from the CEO position. Over time, most of these gaps become significantly 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 industries. In the latter comparison, internal experience also exhibits a widening gap, owing to a decline in internal experience among non-executive managers (Figure A13, 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.

3 Model

To formalize the link between generalist skills and the aging trends, we study a frictionless many-to-one matching model with transfers between workers and firms. Workers are heterogeneous along

[17] 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%.

[18] This result holds when firm size is measured by employment and becomes even more pronounced when stratifying by a firm's listing status. Figure A10 illustrates that these two effects are cumulative, as a firm's listing status remains relevant even after accounting for the number of employees.

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

two dimensions: ability and experience.[20] Firms differ in terms of productivity, which is related to firm size, and feature multiple hierarchical positions with associated productivity requirements.[21] Our main result demonstrates that CEOs in higher-productivity (larger) firms are older on average, generating a negative correlation between CEO ability and age. We also predict that the increased importance of experience leads older workers to be more frequently assigned to top positions.

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 $[\underline{z}, \bar{z}]$ with distribution G and *capacity* (mass of job positions) $m(z) \geq 0$. Total capacity is $M := \int m(z)\, dG(z)$. Positions are a continuum; within each firm the *top slot* is a measure-zero point. Aggregate across firms by *capacity rank* $q^\star(z)$, which measures the share of all positions accounted for by firms with productivity below z:

$$C(z) := \int_{z' < z} m(z')\, dG(z'), \qquad q^\star(z) := \frac{C(z)}{M} \in [0, 1).$$

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. We are going to call the worker in rank 1 the "CEO" of the firm 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*

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

[20] 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).

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

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.[22] 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 this is a transferable utility setting, and the matching surplus is given by $\pi = z \cdot \phi$, which is supermodular, the efficient and hence also stable assignment is assortative: capacity ranks $q \in [0, 1)$ match to worker *index* ranks q.

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 selects 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.

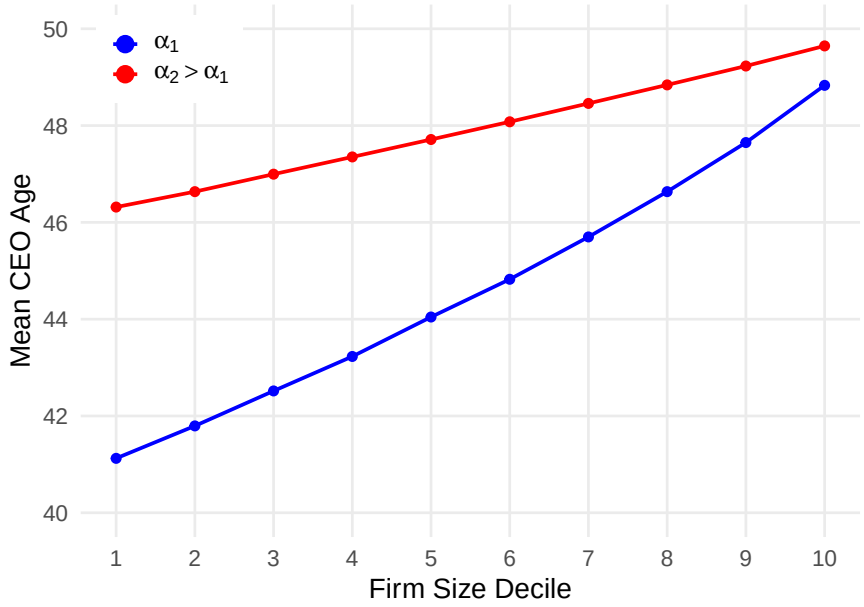
(ii) *Age and ability of CEOs are negatively correlated.* As older workers benefit from the positive contribution of age to the score, they can clear a given threshold with lower ability, whereas younger workers must compensate with higher ability. This selection induces a negative relationship between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

Part (iii) is the more delicate part of the result as there are potentially conflicting forces. If there were only one firm, it would be obvious that this firm would shift older workers to more senior positions

[22] 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 3: Illustrative Age Profiles at the Top Position by Firm Size



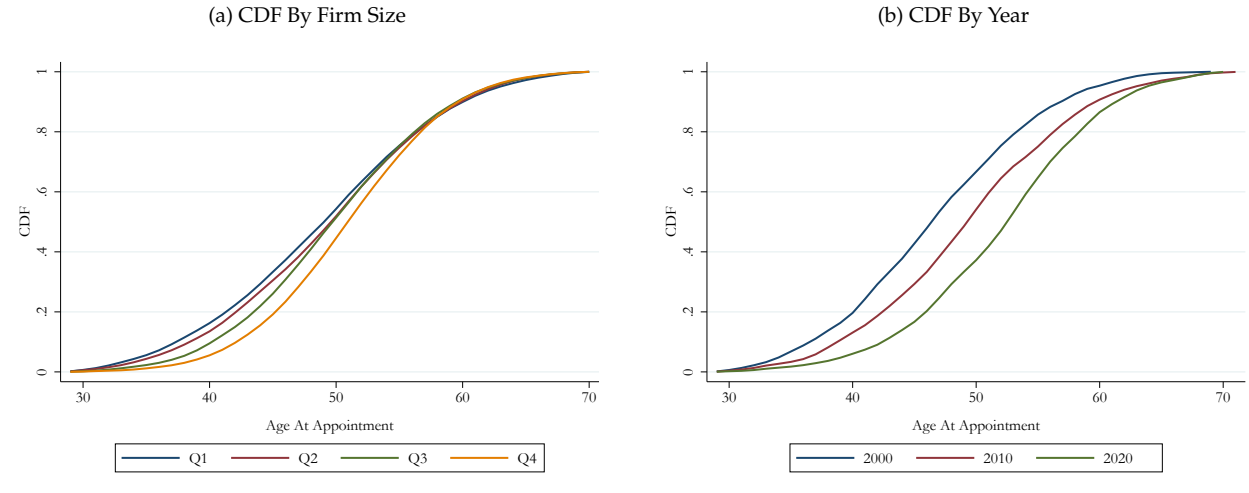
Notes: The figure plots illustrative CEO age profiles across firm size deciles for two values of α: $\alpha_1 = 0.4$ (blue line) and $\alpha_2 = 0.8$ (red line). We simulate 100,000 workers with ability $a \sim U(0, 200)$ and age $t \sim U(0, 50)$. Skills are defined as $h(t) = -0.04t(t - 50)$ and $y(t) = -0.1t(t - 150)$. 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 size decile. The simulation is repeated 500 times, and results are averaged across all replications.

when experience becomes more valuable. However, if there were only one worker per firm, then such a reallocation could not 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, its "price" must also rise, potentially leading some firms to economize on experience, especially in less senior positions. There are a variety of conditions one could impose to guarantee that the distribution of CEOs of firms stochastically increases when α increases. In the Appendix we provide conditions on the conditional tail densities.[23]

Figure 3 illustrates the predictions by plotting the predicted CEO age profiles across the firm size distribution for different values of α. 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 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

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

Figure 4: CEO Age Across the Firm Size Distribution and Over Time



Notes: Panel (a) shows the CDF 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) shows the CDF 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.

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 A1).

Empirical Evidence on Model Predictions: Before disentangling the role of demand- and supply-side factors in driving CEO age, we revisit the descriptive analysis in light of these 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 4 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.

Second, selection generates a negative relationship between CEO age at appointment and ability in the model. As our data do not contain direct measures of ability, we use information on educational backgrounds from BoardEx to construct different proxies for college selectivity.[24] Consistent with our theory, college selectivity is negatively correlated with CEO age at appointment (Table A2).

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

[24] 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.

Indeed, the age distribution in more recent years first-order stochastically dominates that in previous periods.[25]

Potential Extensions: First, for the concept of a CEO position to be meaningful, firms must have multiple positions in the hierarchy. 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.

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.

Third, the model assumes that all workers are matched to firms. Allowing for unemployment would imply that the least productive and disproportionately young workers remain unmatched, which would strengthen our existing results.

Lastly, dynamic extensions of the model appear particularly promising, albeit challenging. Their main advantage is that they would allow for supply-side responses to changes in α, generating an increase in turnover. While inheriting the key properties of the static environment, introducing dynamics requires adjustment costs to prevent instantaneous reallocation in every period. Once such costs are present, any age increase generates stronger reordering when α is high than when α is low. That is, for a given adjustment cost, a rise in α would increase turnover.

4 Reduced-Form Evidence

4.1 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 wide range of functional areas. In this section, we propose a demand-based narrative. We argue that there may be growing firm-level demand for generalist skills because of heightened uncertainty and complexity, resulting in firms appointing executives that have taken longer career paths before reaching CEO positions and are, thus, older upon being appointed. As shown in the model of Section 3, increased demand for generalist skills predicts age patterns that match those observed in the data.

We seek to identify the causal effect of increased levels of economic uncertainty on the characteristics of appointed CEOs, in particular their level of generalist skills as proxied by their age. We start with economic uncertainty and later extend our results to factors capturing economic complexity. Our rationale for the necessity to show robustness to these measures is that while uncertainty and

[25] Over time, the negative correlation between age and education also becomes larger in absolute values (columns (4) to (6) of Table A2). While not a formal prediction of the model, this is consistent with the idea that as α increases, the ability cutoff for older workers drops further, reinforcing the negative selection mechanism. Similarly, we highlight that the heterogeneous trends across the firm size distribution (Figure A6) are closely aligned with the results from the simulation exercise (Figure 3).

complexity have generally increased over time (cf. Figure A16), different components thereof may matter more at different points in time, which we remain agnostic about.

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 increased demand for generalists is challenging. Moreover, even then, comparing CEO age across high- and low-uncertainty (complexity) firms would yield the estimand of interest only if the supply of qualified CEOs were sufficiently elastic.

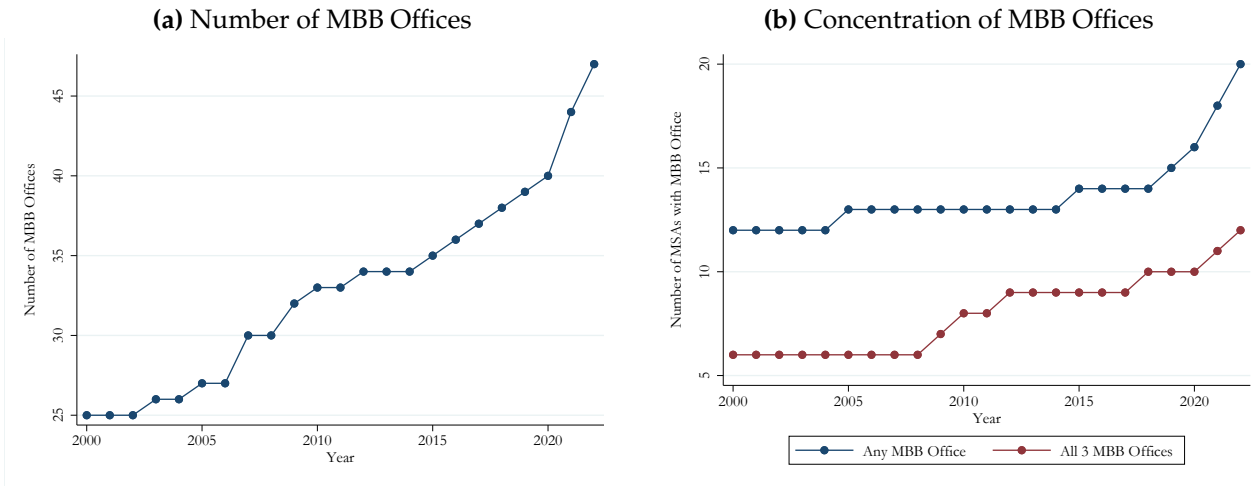
To address these issues, our empirical approach exploits information on both the demand and the supply side. Specifically, we use plausibly exogenous variation in the availability of generalist skills and study its *differential* effect on CEO appointments in high- vs. low-uncertainty (complexity) environments. As a supply shifter, we rely on spatial variation in firms' access to elite strategy 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).[26] 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 *ex-ante* 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, as shown in Figure 5, panel (a). Despite this growth, their offices remain clustered in relatively few cities. As illustrated in panel (b) of Figure 5, 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 more than 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 supplied.

[26]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 5: 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).

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:

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

where Age_{jt} denotes CEO age at appointment constructed from the BoardEx data, $Uncertainty_{it}$ is an uncertainty (or complexity) measure at the industry-time level[27], 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, revenues, and 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., strategy consultants). This interpretation hinges on two assumptions. First, proximity to an MBB office

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

tilts the age composition of the available generalist talent pool, expanding firms' access to younger generalists more than to older generalists. Second, the part of the variation in uncertainty that is associated with CEO age responds to travel time due to firms' increased 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 these 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 consultants and more experienced executives. Instead, we exploit the supply of consultants as a source of variation to test our mechanism of interest.

To measure uncertainty, we use the cross-sectional standard deviation of the symmetric growth rate of firm revenue within each NAICS-4 sector. This variable has the main advantage that it captures broader, industry-wide fluctuations and is unaffected by idiosyncratic shocks experienced by individual firms. Figure A14 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.

To measure firms' travel time to the closest MBB office, we rely on time-varying flight times that are computed as described in the data section, considering only direct connections. We then combine the data on flight times with information on the expansion of MBB offices across the United States. Using this information, 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.[28]

The baseline results obtained from estimating Equation 1 are shown in Table 1. Column (1) includes the results from a simple regression with controls, showing a positive and marginally significant coefficient on the interaction term. By consecutively adding fixed effects for MSAs, NAICS-4 sectors, 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,

[28]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 to closest office* 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 sector, 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 sector and MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 turbulence shifts 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 use lagged values of travel time. In Column (3), we replace the linear measure of travel time to the nearest MBB office with a dummy for above-median values of travel time. In Column (4), 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 directly part of the pool of potential 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 (5), we use the full sample, which includes metro areas with an MBB office and, thus, a travel time of zero. Lastly, in Column (6), we restrict the sample to firms in metro areas that do not experience any office entry throughout the entire sample period.

Second, we provide evidence that the treatment shifts CEO appointments in smaller firms towards 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.

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

	CEO Age					
	(1)	(2)	(3)	(4)	(5)	(6)
Travel Time × Industry-Level SD	0.527**	0.640***	0.366**	0.517*	0.469***	0.572*
	(0.219)	(0.205)	(0.149)	(0.284)	(0.112)	(0.327)
R^2	0.365	0.360	0.360	0.381	0.252	0.397
Observations	14,954	14,132	14,132	12,291	33,006	10,912
MSA-Year fixed effects	✓	✓	✓	✓	✓	✓
Naics4-Year fixed effects	✓	✓	✓	✓	✓	✓
Change Compared to Baseline	NAICS-2 SD	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 sector, 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 the first lag of travel time; Column (3) replaces the linear measure of travel time to the nearest MBB office with a dummy for above-median travel time; Column (4) controls for average executive age constructed from the employment history data; Column (5) uses the entire sample including those metro areas with an MBB office; Column (6) 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 sector and MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Column (1) shows that the effect on CEO age is entirely driven by smaller firms. The remaining columns further probe our main mechanism. Columns (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 sectors. We also consider years within the same NAICS-4 sector (Column 4) and firm (Column 5) as placebos, both with insignificant responses. Columns (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 sectors worked in, with very similar conclusions drawn from OLS and quasi-Poisson estimations. By contrast, the estimated coefficients for larger firms are consistently insignificant.

Third, we scrutinize our empirical approach through the lens of a difference-in-differences framework, for which we show event study estimates in Figure 6. 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.

Fourth, we plot the coefficient on the interaction term separately for 5-year sub-periods. The estimated coefficients, shown in Figure A15, 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.

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

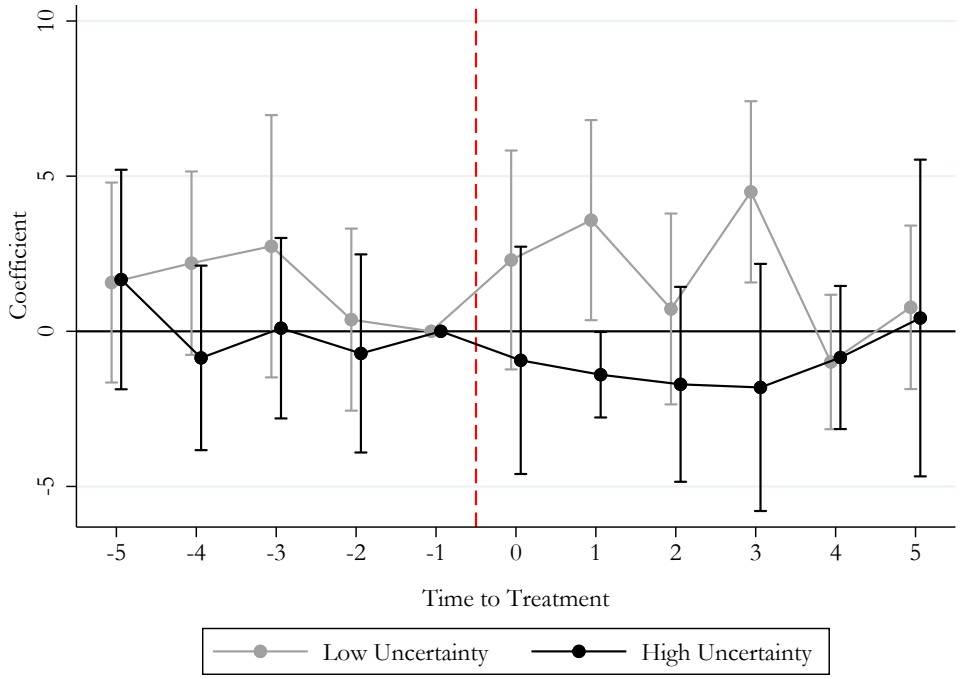
Notes: The dependent variables refer to the time, firm, or sector of CEO appointment: CEO age (Column 1), years of experience in other NAICS-4 sectors (Column 2), years of experience in other NAICS-2 sectors (Column 3), years of experience in the same NAICS-4 sector (Column 4), years of international experience within the same firm (Column 5), and the number of NAICS-4 sectors the CEO has worked in (Columns 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 sector, 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). Columns (1) to (6) are estimated using OLS, while Column (7) uses quasi-Poisson estimation. Standard errors are double-clustered at the NAICS-4 sector and MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 in several, possibly correlated and compounding factors have likely 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.

We construct a first measure of business diversification from the employment history data by counting the number of vice presidents (VPs) in distinct job roles.[29] VPs are transparently identifiable in the employment history data, with their titles revealing the specific 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 A16, the average firm-level number of VPs in distinct roles has increased

[29]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 6: 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 sectors. 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 sector. 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 sector and MSA level.

substantially over time. In column (1) of Table 4, we use this count 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 related to, e.g., size, we control for the interaction of travel time with the overall number of VPs.[30] 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 A4, very similar results obtain when using the taxonomy at higher or lower levels of disaggregation.

[30] Equivalently, our results are robust to using the ratio of the number of different VP roles over 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 defined as 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 sectors and use their natural logarithm. Further details are provided in Table A4. 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 sector. Further details are provided in Table A5. 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 A6. 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 sector and MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 contrasting implications for national and local concentration. In a similar vein, we use the employment history 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 A16, 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 A5 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,[31] 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.[32] 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 A6. 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 A7 replicates these regressions using import shares, yielding small and insignificant coefficients across the board.

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

[32] By construction, the ECI exhibits no trend on average. To allow for an interpretation of 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 increased steadily since the late 1990s (Panel (c) of Figure A16).

To summarize these results in Table 4, we re-estimate the specification using the sum of all four normalized drivers for generalists as the regressor of interest. We show specifications with and without EECI, since this variable is available only for manufacturing. Using the index constructed from industry-level uncertainty, 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).

Lastly, 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.

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 observe. 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, while executives who climb the ranks through other channels take longer to match the required skills. 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 data with employment flow data from Revelio Labs. 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 A8. Inflows from MBB firms are consistently and positively associated with CEO age. 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.[33] 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 0.1 years for those without MBB experience. This suggests that if the local supply of young generalists in Tables 1 to 4 translates, among other margins of adjustment, to hiring former consultants at lower organizational levels, then our estimated effects on CEO age constitute lower bounds.

4.2 Supply-Side Factors

We now shift the focus to the supply-side dynamics. In the earlier 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.[34] 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.[35] Figure 7 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

[33] The results from a number of additional robustness checks are shown in Table A9.

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

[35] 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).

is much larger. Consistent with these findings, Figure A17 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.[36]

We now examine whether these labor market mobility patterns reflect voluntary switches by considering 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 also believe that increased mobility will be beneficial for their careers. We therefore expect exposure to information supporting this narrative 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 sectors. That is, we test whether individuals respond to such information shocks by increasing their own job mobility.

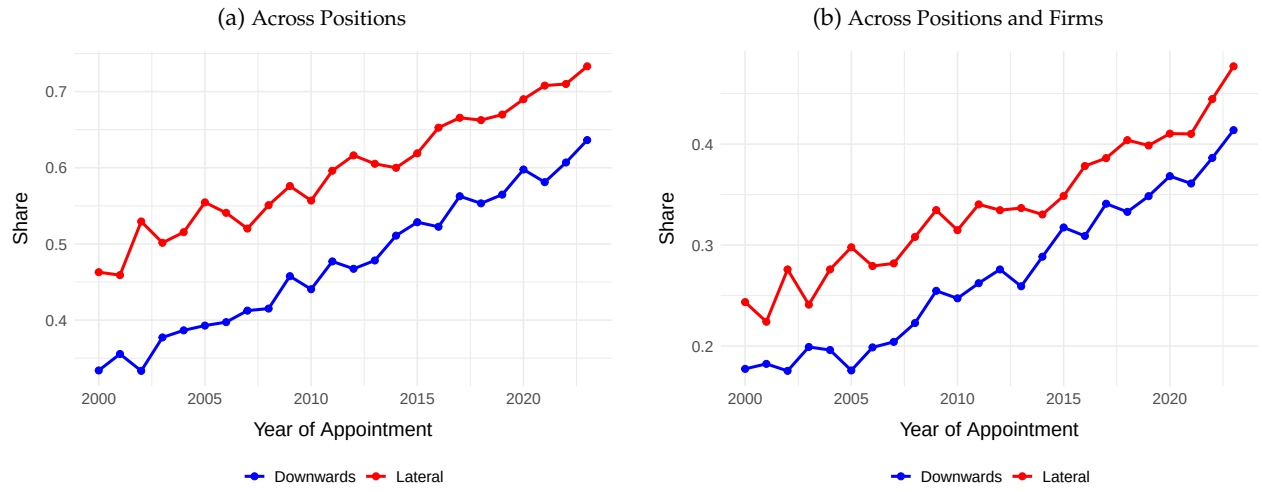
Specifically, consider a worker w in year t, who worked alongside a future CEO in firm j, metro-area m, and seniority level s. We implement a difference-in-differences design by estimating equations of the following form:

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

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.

[36]The results are similar when we only consider moves from smaller to larger firms.

Figure 7: Share of CEOs That Ever Moved Downwards/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.

To construct the sample, we start by identifying a list of CEO employment spells, considering only the first CEO appointment for each individual.[37] We then extract the employment histories of 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 A10, 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

[37] 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.

are slightly older, more experienced, and work at higher seniority levels, with somewhat higher imputed salaries, although these differences are small.

Our main outcome comprises a set of indicators for job switches across firms between two consecutive observations.[38] 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 dummies, their interaction, and year fixed effects. While the coefficient on the treatment dummy is insignificant, the coefficient on the post dummy is negative, suggesting that job mobility during the post 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

[38] 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.

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 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 in job mobility across narrow sectors and geographic locations. 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 sectors, with the results included in Table A11. 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 A12 and A13).

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.[39] The estimates in Tables A14 and A15 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.

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

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. All fixed effects refer to the position the individual worked in alongside the future CEO. Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

As a first robustness check, we augment our preferred specification to obtain event study estimates, presented in Figure A18. 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.

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 aspect in Table A16 by including an interaction with a dummy equal to one for those, whose shared tenure is in the highest quartile. The estimated coefficients on the triple interaction are large and significant across the board, suggesting that this group reacts more strongly to the information shock. Figure A19 shows the coefficients on the marginal effect for downward mobility (column 4) 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 A17 and A18 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

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. All fixed effects 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 A19, 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 towards 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 A20, the idea is 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 across the board. Moreover, we experimented with 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 A21 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 sector 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 their current firm, with results shown in Table A22 and Figure A20. As anticipated, 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 A23 reveal that the rise in turnover is driven by switches to smaller firms, both in absolute terms and compared to the current employer.[40]

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 A24 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 interpretation that the observed trends are at least partially influenced by an increase in generalist skills on the supply side. We have provided 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.

4.3 Decomposing Variation in the Aging Pattern

In this section, we decompose the aging trend into a sectoral and a geographical dimension. Our results in Section 4.1 suggest that sectoral shocks, specifically shifts in uncertainty and complexity 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

[40]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 A21, 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 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 of generalist skills.

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:

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

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

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

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

As before, Age_{jt} denotes CEO age at appointment. The fixed effects ϕ_i and γ_m are at the MSA and NAICS-4 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. That is, 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.

The results are shown in Table 7. 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 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 across all specifications.[41]

Taken together, the three components can be interpreted as capturing distinct forces behind the rising CEO age at appointment. In light of our results from Section 4.1, 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 age increase. 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.[42] 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 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, lending support to the use of plausibly exogenous variation in the supply of generalist skills for a causal interpretation of our demand-side results in Section 4.1.

5 Alternative Explanations

Our previous discussion offers an explanation for the aging of CEOs that is based on an efficient market response to changes in the importance and availability of different skill components among CEOs. Given that many features of firms and the economy more broadly have changed since 2000, it is important to consider a range of potential alternative explanations. This section reviews several competing narratives and argues that none of these convincingly account for the patterns we document.

CEO Aging as a Demographic Inevitability: One possible explanation centers on demographic shifts across Western countries, which have paralleled the age trends among executives. However, as we report in Figure A3, the age increase among CEOs in the United States and Europe is more

[41] 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.

[42] 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.

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 number of employees, firm age, and average age of other executives (obtained from the employment history data). Standard errors obtained from bootstrapping (100 replications) contained in brackets.

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. As a result, it is unlikely that the CEO aging trend reflects mere demographic changes.

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 has been 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 A22 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 conjecture. Relatedly, as we document in Table 2, board age does not appear to drive our demand-side findings.[43]

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

[43]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.

positions at large firms, an effect that may be amplified by the tendency of such firms to appoint older CEOs. To test this idea, we correlate CEO age at appointment with market concentration measures from the Economic Census. The results, presented in Table A25, reveal a negative but statistically insignificant association.

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 A24. 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 older age at graduation among postgraduate degree recipients and by a rising share of CEOs holding such 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 (Table A25), alongside a broader expansion in business education (Acemoglu et al., 2022b). Conceptually, while this hypothesis is consistent with the supply-side patterns we describe, it conflicts with our demand-side findings. CEO aging is especially pronounced among firms with high inflows from MBB alumni (Table A8), who typically promote strong learning and development cultures. Taken together, these results do not support the view that supply-side scarcity of executive skill drives our results, but instead that demand for general skills has increased.

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 A23. 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. One plausible interpretation of these patterns is that delisted firms were more likely to be run by young founders during the period. Still, the

evidence does not support the notion that our results are driven by a rebound effect following the late 1990s.

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, often at the cost of 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.

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ONLINE APPENDIX

A Model Appendix

A.1 Overview

We now elaborate and prove on the results discussed in the model section. Workers are ordered by a score that is a linear combination of an ability component and age-dependent components. Under transferable utility and a multiplicative surplus, equilibrium matching is positively assortative in firm productivity and the worker score. Consequently, age patterns across the firm productivity distribution can be studied through the distribution of worker age conditional on being in a high-score tail.

The analysis delivers two distinct results:

1. **Within-α tail aging (Theorem 1).** For a fixed score specification (fixed α), more selective score cutoffs select stochastically older workers. This is a pure *selectivity* result: holding the weighting of ability versus experience fixed, raising the bar selects older workers whenever age is conditionally stochastically increasing in the score.

2. **Across-α comparative statics (Theorem 3).** Holding the tail fraction fixed, the tail age distribution shifts upward (in first-order stochastic dominance) as α rises. This is a *weight-change* result: at a fixed level of selectivity, increasing the weight on experience-related components shifts the composition toward older workers.

A parametric example with exponential ability illustrates how the key monotonicity condition for the second result reduces to a simple restriction on the age-output profile.

A.2 Environment and equilibrium sorting

A.2.1 Firms, workers, and surplus

Firms have productivity z distributed according to a continuous CDF G_z on $[\underline{z}, \bar{z}]$ with $\underline{z} > 0$. Workers are characterized by ability A and age (or tenure/experience) T.

Match surplus is

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

where the worker score is

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

Define the population score random variable

$$\Phi_\alpha := \phi(A, T; \alpha).$$

It is convenient to rewrite the score as

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

Definition 1 (Survival function)**.** For any random variable X with CDF F_X, the survival function is $\bar{F}_X(x) := 1 - F_X(x) = \mathbb{P}(X \geq x)$.

A.2.2 Continuity and uniqueness of score cutoffs

Assumption 1 (Continuous score)**.** For each α under consideration, Φ_α has a continuous distribution (no atoms).

Remark 2 (Positive assortative matching). Under transferable utility, stable matchings maximize total surplus. Since (11) is multiplicative in z and depends on the worker only through Φ_α, equilibrium matching is positively assortative in (z, Φ_α): higher-productivity firms match with higher-score workers. Assumption 1 ensures that score cutoffs defining fixed tail fractions are unique.

A.2.3 Monotonicity of the composite age component

Assumption 2 (Monotone composite age contribution)**.** For each α under consideration, $g_\alpha(\cdot)$ is weakly increasing on the relevant age range $[\underline{t}, \bar{t}]$.

Remark 3 (Interpretation). Assumption 2 allows $h(\cdot)$ to be nonmonotone (e.g. single-peaked) provided that the composite term $g_\alpha = (1-\alpha)h + \alpha y$ is weakly increasing over the age range of interest. This is a joint restriction on h, y, and α.

A.3 Preliminaries: stochastic monotonicity and dominance

For random variables Y, Y' on $\mathbb{R}$, we write $Y' \geq_{st} Y$ to say that Y' stochastically dominates Y .

Definition 2 (Stochastically increasing)**.** A random variable Y is *stochastically increasing in* X, denoted $\mathrm{SI}(Y \mid X)$, if for every y the function $x \mapsto \mathbb{P}(Y > y \mid X = x)$ is nondecreasing in x.

Definition 3 (TP2 / MLR)**.** A bivariate density $f(x, y)$ is *totally positive of order 2*, (TP2) if for all $x_1 < x_2$ and $y_1 < y_2$,

$$f(x_1, y_1) f(x_2, y_2) \geq f(x_1, y_2) f(x_2, y_1).$$

Equivalently, the likelihood ratio $f(x, y_2)/f(x, y_1)$ is nondecreasing in x for $y_1 < y_2$. When the joint density of (X, Y) is TP2, we say Y dominates in the monotone likelihood ratio (MLR) order as X increases.

Lemma 1 (TP2 implies conditional stochastic monotonicity)**.** *If (X, Y) has a TP2 joint density, then $\mathrm{SI}(Y \mid X)$ holds.*

Remark 4 (Intuition). The property $\mathrm{SI}(T \mid \Phi_\alpha)$ formalizes the idea that, among workers with higher scores, the conditional distribution of age shifts upward. This property is the key input behind Theorem 1: selecting workers from a higher score tail selects a stochastically older group.

A.3.1 Sufficient conditions for $\mathrm{SI}(T \mid \Phi_\alpha)$

Assumption 3 (Independence)**.** A and T are independent in the population.

Assumption 4 (Log-concave ability density)**.** A has a log-concave density f_A on its support.

Lemma 2 (Primitive sufficient conditions for $\mathrm{SI}(T \mid \Phi_\alpha)$)**.** *Under Assumptions 3, 4, and 2, we have* $\mathrm{SI}(T \mid \Phi_\alpha)$.

Proof. Assume densities exist for A and T. Under $A \perp T$, (A, T) has density $f_A(a)f_T(t)$. From (13), the change of variables $(a, t) \mapsto (x, t)$ with $x = (1-\alpha)a + g_\alpha(t)$ yields

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

If f_A is log-concave, then the kernel $K(u, v) = f_A(u - v)$ is TP2 in (u, v) (Karlin, 1968). Let $u(x) = x/(1-\alpha)$ and $v(t) = g_\alpha(t)/(1-\alpha)$. By Assumption 2, $v(\cdot)$ is increasing, so $f_A(u(x) - v(t))$ is TP2 in (x, t) by closure of TP2 under increasing compositions. Multiplying by the positive factor $f_T(t)/(1-\alpha)$ preserves TP2, hence $f_{\Phi_\alpha,T}$ is TP2. Lemma 1 then implies $\mathrm{SI}(T \mid \Phi_\alpha)$. □

A.4 Fixed-α tail results: selectivity and age

Fix α throughout this section and write $\Phi := \Phi_\alpha$.

A.4.1 Score tails and quantile cutoffs

For any cutoff $\kappa \in \mathbb{R}$, define the upper score tail event

$$C(\kappa) := \{\Phi \geq \kappa\}.$$

Given a tail fraction $\theta \in (0, 1)$, Assumption 1 implies there is a unique cutoff $\kappa(\theta)$ such that

$$\mathbb{P}(\Phi \geq \kappa(\theta)) = \theta. \tag{15}$$

We refer to $C(\kappa(\theta))$ as the *top-θ score tail*.

We can now state the result that we can interpret as relating the age of CEOs and firm productivity.

Theorem 1 (More selective score tails are stochastically older)**.** *Assume* $\mathrm{SI}(T \mid \Phi)$. *If* $\kappa_2 > \kappa_1$, *then*

$$T \mid C(\kappa_2) \;\geq_{st}\; T \mid C(\kappa_1).$$

Equivalently, if $0 < \theta_2 < \theta_1 < 1$, *then*

$$T \mid \{\Phi \geq \kappa(\theta_2)\} \;\geq_{st}\; T \mid \{\Phi \geq \kappa(\theta_1)\}.$$

Proof. Fix an age threshold t and define $q_t(x) := \mathbb{P}(T > t \mid \Phi = x)$, which is nondecreasing in x by $\mathrm{SI}(T \mid \Phi)$. For any cutoff κ,

$$\mathbb{P}(T > t \mid \Phi \geq \kappa) = \mathbb{E}\big[q_t(\Phi) \mid \Phi \geq \kappa\big].$$

If $\kappa_2 > \kappa_1$, then $\Phi \mid \{\Phi \geq \kappa_2\}$ first-order stochastically dominates $\Phi \mid \{\Phi \geq \kappa_1\}$, and the expectation of the increasing function $q_t(\cdot)$ is therefore weakly larger under $\{\Phi \geq \kappa_2\}$. Thus $\mathbb{P}(T > t \mid \Phi \geq \kappa_2) \geq \mathbb{P}(T > t \mid \Phi \geq \kappa_1)$ for all t, which is FOSD. □

Remark 5 (Intuition). Theorem 1 is a pure selection statement: if higher scores make higher ages more likely (the SI property), then restricting attention to workers with higher scores selects a stochastically older group. Positive assortative matching then transfers this conclusion to firms: more productive firms, which match with higher-score workers, have stochastically older workers.

Corollary 1 (Primitive sufficient condition)**.** *Under Assumptions 3, 4, 2, and 1, the conclusion of Theorem 1 holds.*

Proof. Lemma 2 implies $\mathrm{SI}(T \mid \Phi)$, then apply Theorem 1. □

A.4.2 Selection-induced age–ability correlation within a score tail

This subsection records a complementary selection implication that is often useful empirically. While Theorem 1 describes how the *marginal distribution* of age shifts in higher score tails, selection into a score tail can also distort *joint* relationships among worker characteristics.

Fix a cutoff κ and consider the selected set $C(\kappa) = \{\Phi \geq \kappa\}$. Using (13), membership in $C(\kappa)$ can be written as an age-dependent ability truncation:

$$C(\kappa) = \{A \geq c_\kappa(T)\}, \qquad c_\kappa(t) := \frac{\kappa - g_\alpha(t)}{1 - \alpha}. \tag{16}$$

Assumption 2 implies that $c_\kappa(\cdot)$ is weakly decreasing: older workers face (weakly) lower required ability to enter the same score tail.

Lemma 3 (Negative age–ability covariance under decreasing truncation)**.** *Assume $A \perp T$, A is continuous, and $\mathbb{E}[A^2] < \infty$. Let $c(\cdot)$ be measurable and suppose $C := \{A \geq c(T)\}$ has positive probability.*

(i) If $c(\cdot)$ is weakly decreasing, then $\mathrm{Cov}(A, T \mid C) \leq 0$.

(ii) If $c(\cdot)$ is strictly decreasing on a set of positive T-measure and $\mathrm{Var}(T \mid C) > 0$, then $\mathrm{Cov}(A, T \mid C) < 0$.

Proof. Let $m(x) := \mathbb{E}[A \mid A \geq x]$, which is weakly increasing in x for any integrable continuous A. Under $A \perp T$,

$$\mathbb{E}[A \mid T = t, C] = \mathbb{E}[A \mid A \geq c(t)] = m(c(t)).$$

If $c(\cdot)$ is weakly decreasing, then $t \mapsto m(c(t))$ is weakly decreasing. By the law of total covariance,

$$\mathrm{Cov}(A, T \mid C) = \mathrm{Cov}\big(\mathbb{E}[A \mid T, C],\, T \mid C\big) = \mathrm{Cov}\big(m(c(T)),\, T \mid C\big) \le 0,$$

with strict inequality under the stated conditions. □

Theorem 2 (Negative age–ability correlation in high-score tails)**.** *Maintain Assumptions 3 and 2. Fix any cutoff κ such that $\mathbb{P}(C(\kappa)) > 0$. Then*

$$\mathrm{Cov}(A, T \mid C(\kappa)) \le 0.$$

If g_α is strictly increasing on a set of positive T-measure and $\mathrm{Var}(T \mid C(\kappa)) > 0$, then

$$\mathrm{Cov}(A, T \mid C(\kappa)) < 0 \quad \textit{and} \quad \mathrm{Corr}(A, T \mid C(\kappa)) < 0.$$

In particular, the statement applies to the top-θ score tail $C(\kappa(\theta))$ for any $\theta \in (0, 1)$.

Proof. By (16), $C(\kappa) = \{A \ge c_\kappa(T)\}$ with $c_\kappa(\cdot)$ weakly decreasing whenever $g_\alpha(\cdot)$ is weakly increasing. Apply Lemma 3 with $c = c_\kappa$. □

Remark 6 (Intuition). The result captures a familiar selection mechanism. To clear a fixed score cutoff, an older worker benefits mechanically from the higher value of the age component $g_\alpha(t)$ and therefore can qualify with lower ability. As a consequence, within a high-score tail, older selected workers tend to have lower ability than younger selected workers, generating a negative age–ability relationship even when age and ability are independent in the population.

A.5 Comparative statics in α: weight changes at fixed selectivity

We now ask: holding the tail fraction θ fixed, how does the age distribution among selected workers change when α increases? This isolates the effect of changing the *weights* in the score from the effect of changing *selectivity*.

A.5.1 Unified notation for cutoff schedules

Fix a tail fraction $\theta \in (0, 1)$ and let $\alpha_1 < \alpha_2$ be two parameter values. For each α, let $\kappa_\alpha(\theta)$ denote the unique score cutoff satisfying

$$\mathbb{P}(\Phi_\alpha \ge \kappa_\alpha(\theta)) = \theta.$$

Define the tail event and the age-dependent ability cutoff schedule:

$$C_\alpha(\theta) := \{\Phi_\alpha \ge \kappa_\alpha(\theta)\} = \{A \ge c_\alpha(T; \theta)\}, \tag{17}$$

$$c_\alpha(t; \theta) := \frac{\kappa_\alpha(\theta) - g_\alpha(t)}{1 - \alpha}. \tag{18}$$

That is, a worker of age t enters the top-θ tail if and only if her ability exceeds $c_\alpha(t; \theta)$.

When comparing α_1 and α_2 at a fixed θ, we abbreviate

$$C_i := C_{\alpha_i}(\theta), \qquad c_i(t) := c_{\alpha_i}(t;\theta), \qquad i = 1, 2.$$

Lemma 4 (Cutoff schedules are decreasing in age)**.** *Under Assumption 2, each cutoff function $c_\alpha(\cdot\,;\theta)$ is weakly decreasing on $[\underline{t}, \bar{t}]$. If g_α is differentiable, then*

$$\frac{\partial}{\partial t} c_\alpha(t;\theta) = -\frac{g'_\alpha(t)}{1-\alpha} \leq 0.$$

Proof. Since $g_\alpha(\cdot)$ is weakly increasing and $1 - \alpha > 0$, the map $t \mapsto \kappa_\alpha(\theta) - g_\alpha(t)$ is weakly decreasing, and scaling by $(1-\alpha)^{-1}$ preserves this order. □

Remark 7 (Interpretation). The ability threshold for entering the top tail is lower for older workers: age substitutes for ability. This is a direct consequence of the composite age component $g_\alpha(t)$ being increasing.

A.5.2 How cutoff schedules compare across α

The following result characterizes when $\alpha_2 > \alpha_1$ implies a uniformly lower ability cutoff for older workers.

Lemma 5 (Cutoff ordering across α)**.** *Assume g_{α_1} and g_{α_2} are differentiable. Then*

$$c_2(t) - c_1(t) = \underbrace{\left(\frac{\kappa_2}{1-\alpha_2} - \frac{\kappa_1}{1-\alpha_1}\right)}_{\text{constant in } t} - \underbrace{\left(\frac{\alpha_2}{1-\alpha_2} - \frac{\alpha_1}{1-\alpha_1}\right)}_{\text{positive since } \alpha_2 > \alpha_1} \cdot y(t). \tag{19}$$

In particular:

(i) If $y(\cdot)$ is weakly increasing, then $c_2(t) - c_1(t)$ is weakly decreasing in t.

(ii) The cutoff schedules cross at most once: there exists t^* such that $c_2(t) \geq c_1(t)$ for $t \leq t^*$ and $c_2(t) \leq c_1(t)$ for $t \geq t^*$.

Proof. Using $c_i(t) = [\kappa_i - g_{\alpha_i}(t)]/(1-\alpha_i)$ and $g_\alpha(t) = (1-\alpha)h(t) + \alpha y(t)$, we have

$$c_i(t) = \frac{\kappa_i}{1-\alpha_i} - h(t) - \frac{\alpha_i}{1-\alpha_i} y(t).$$

Taking differences yields (19). Since $\alpha_2 > \alpha_1$, the coefficient on $y(t)$ is positive. Parts (i) and (ii) follow immediately. □

Remark 8 (Intuition). When α increases, the score places more weight on the experience-output component $y(t)$. If $y(t)$ is increasing in age, this shift *relatively* favors older workers: the ability cutoff under α_2 falls faster with age than under α_1. The cutoff schedules may cross (with $c_2 > c_1$ for

young workers and $c_2 < c_1$ for old workers), but the *slope* of c_2 is weakly steeper, which drives the comparative statics.

A.5.3 Conditional tail densities

Lemma 6 (Tail conditional density)**.** *Assume $A \perp T$ and that densities exist. Then for each α,*

$$f_{T|C_\alpha(\theta)}(t) = \frac{f_T(t)\,\bar{F}_A(c_\alpha(t;\theta))}{\int_{\underline{t}}^{\bar{t}} f_T(u)\,\bar{F}_A(c_\alpha(u;\theta))\,du}. \tag{20}$$

Consequently, the likelihood ratio of the tail age densities under α_2 versus α_1 is

$$\frac{f_{T|C_2}(t)}{f_{T|C_1}(t)} \propto \frac{\bar{F}_A(c_2(t))}{\bar{F}_A(c_1(t))}. \tag{21}$$

Proof. By Bayes' rule and independence,

$$f_{T|C_\alpha(\theta)}(t) \propto f_T(t)\,\mathbb{P}(A \geq c_\alpha(t;\theta)) = f_T(t)\,\bar{F}_A(c_\alpha(t;\theta)).$$

Normalizing yields (20), and (21) follows. □

Remark 9 (Intuition). Conditioning on membership in a top score tail reweights the baseline age density $f_T(t)$ by the probability that a worker of age t clears the implied ability cutoff. Comparative statics in α therefore reduce to understanding how the reweighting function $\bar{F}_A(c_\alpha(t;\theta))$ changes across ages when α changes.

A.5.4 The likelihood-ratio condition and main result

Assumption 5 (Tail likelihood-ratio monotonicity (TLR))**.** The function

$$t \mapsto \frac{\bar{F}_A(c_2(t))}{\bar{F}_A(c_1(t))}$$

is weakly increasing on $[\underline{t}, \bar{t}]$.

Theorem 3 (Tail age distribution shifts upward with α)**.** *Under Assumptions 3, 1, and 5,*

$$T \mid C_2 \;\geq_{st}\; T \mid C_1.$$

Proof. By Lemma 6, the likelihood ratio $f_{T|C_2}(t)/f_{T|C_1}(t)$ is proportional to $\bar{F}_A(c_2(t))/\bar{F}_A(c_1(t))$. Assumption 5 states that this ratio is nondecreasing in t, i.e. the conditional distribution under α_2 dominates that under α_1 in the monotone likelihood ratio order. MLR dominance implies FOSD (Whitt, 1982), hence $T \mid C_2 \geq_{st} T \mid C_1$. □

Remark 10 (Intuition). Theorem 3 is a comparative selection statement. Raising α changes the age-specific cutoff schedule that determines which workers enter the top score tail. Assumption 5 requires that this change favors older ages in a likelihood-ratio sense: relative to α_1, the probability of being selected into the tail under α_2 rises (weakly) with age. The induced reweighting then shifts the tail age distribution upward.

A.5.5 Sufficient conditions for TLR

This section provides two routes to verifying Assumption 5: a transparent parametric case (exponential ability) and a general hazard-rate condition.

Exponential ability: TLR reduces to monotonicity of $y(\cdot)$.

Assumption 6 (Monotone experience-output profile)**.** The function $y(\cdot)$ is weakly increasing on $[\underline{t}, \bar{t}]$.

Proposition 1 (Exponential ability implies TLR)**.** *Assume $A \perp T$ and that A has an exponential survival function on the relevant cutoff range:*

$$\bar{F}_A(x) = \exp(-\lambda x) \qquad \text{for all } x \in \{c_1(t), c_2(t) : t \in [\underline{t}, \bar{t}]\},$$

for some $\lambda > 0$. If Assumption 6 holds, then Assumption 5 holds for any $\alpha_2 > \alpha_1$ and any tail fraction $\theta \in (0, 1)$.

Proof. With an exponential survival function,

$$\frac{\bar{F}_A(c_2(t))}{\bar{F}_A(c_1(t))} = \exp\{-\lambda(c_2(t) - c_1(t))\}.$$

By Lemma 5(i), $c_2(t) - c_1(t)$ is weakly decreasing in t when $y(\cdot)$ is weakly increasing. Hence $-\lambda(c_2(t) - c_1(t))$ is weakly increasing in t, and so is its exponential. This is Assumption 5. □

Remark 11 (Why exponential is special). The exponential distribution has a constant hazard rate, so selection probabilities depend only on *differences* in cutoffs rather than their levels. This eliminates the need to track how $c_1(t)$ and $c_2(t)$ individually affect selection probabilities—only their difference matters. When $y(t)$ is increasing, Lemma 5 ensures this difference shrinks with age, which is precisely what TLR requires.

The exponential case is the boundary between increasing and decreasing hazard rate distributions. For IFR (increasing failure rate) distributions, additional conditions on cutoff levels are needed, as developed below.

General hazard-rate condition.

Assumption 7 (Increasing hazard rate (IFR))**.** The ability distribution has weakly increasing hazard rate

$$h_A(x) := \frac{f_A(x)}{\bar{F}_A(x)}.$$

Lemma 7 (Derivative of the likelihood ratio)**.** *Assume $\bar{F}_A$ is differentiable and $g_{\alpha_1}, g_{\alpha_2}$ are differentiable. Then*

$$\frac{d}{dt}\log\frac{\bar{F}_A(c_2(t))}{\bar{F}_A(c_1(t))} = h_A(c_1(t))\cdot\frac{g'_{\alpha_1}(t)}{1-\alpha_1} - h_A(c_2(t))\cdot\frac{g'_{\alpha_2}(t)}{1-\alpha_2}. \tag{22}$$

Proof. Differentiate using $(\log \bar{F}_A)'(x) = -h_A(x)$ and $c_i'(t) = -g'_{\alpha_i}(t)/(1-\alpha_i)$ from Lemma 4. □

To interpret (22), note that

$$\frac{g'_\alpha(t)}{1-\alpha} = h'(t) + \frac{\alpha}{1-\alpha}y'(t),$$

which is increasing in α whenever $y'(t) > 0$.

Proposition 2 (Hazard-weighted slope condition)**.** *Assume $A \perp T$, $\bar{F}_A$ is differentiable, and $g_{\alpha_1}, g_{\alpha_2}$ are differentiable. If*

$$h_A(c_1(t))\cdot\frac{g'_{\alpha_1}(t)}{1-\alpha_1} \;\geq\; h_A(c_2(t))\cdot\frac{g'_{\alpha_2}(t)}{1-\alpha_2} \qquad \text{for all } t\in[\underline{t},\bar{t}], \tag{23}$$

then Assumption 5 holds, and consequently Theorem 3 applies.

Proof. By Lemma 7, condition (23) implies that $\frac{d}{dt}\log\{\bar{F}_A(c_2(t))/\bar{F}_A(c_1(t))\} \geq 0$, so the ratio is increasing in t. □

Remark 12 (Interpreting the condition). Condition (23) balances two forces:

- The "slope effect": $g'_{\alpha_2}(t)/(1-\alpha_2) > g'_{\alpha_1}(t)/(1-\alpha_1)$ when $y'(t) > 0$, which pushes toward TLR.
- The "level effect": Under IFR, $h_A(c_2(t)) > h_A(c_1(t))$ when $c_2(t) > c_1(t)$ (young workers), which pushes against TLR.

The condition requires the slope effect to dominate the level effect. This is automatic for exponential ability (constant hazard), but requires verification for IFR distributions.

Corollary 2 (Sufficient condition under IFR)**.** *Under Assumptions 3, 2, 7, and 6, suppose that $c_2(t) \leq c_1(t)$ for all $t \in [\underline{t},\bar{t}]$. Then Assumption 5 holds.*

Proof. If $c_2(t) \leq c_1(t)$, then $h_A(c_2(t)) \leq h_A(c_1(t))$ by IFR. Since $g'_{\alpha_2}(t)/(1-\alpha_2) \geq g'_{\alpha_1}(t)/(1-\alpha_1)$ by $y'(t) \geq 0$, both factors favor (23). □

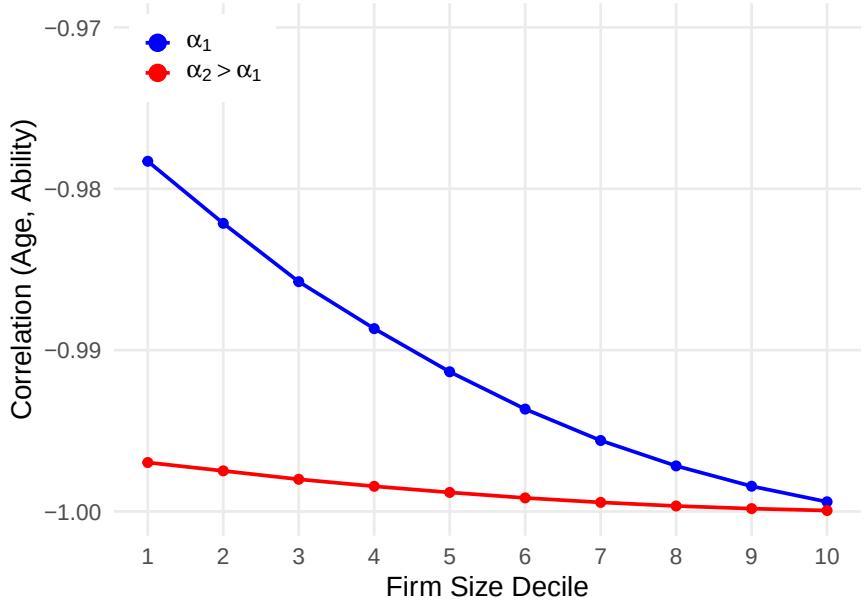
Remark 13 (When does $c_2(t) \leq c_1(t)$ hold?). By (19), $c_2(t) \leq c_1(t)$ for all t if and only if the constant term is nonpositive:

$$\frac{\kappa_2}{1-\alpha_2} \leq \frac{\kappa_1}{1-\alpha_1} + \left(\frac{\alpha_2}{1-\alpha_2} - \frac{\alpha_1}{1-\alpha_1}\right)\underline{y},$$

where $\underline{y} = \min_t y(t)$. This depends on how the quantile cutoffs κ_1, κ_2 adjust to maintain the same tail fraction θ as α changes. When $y(t)$ is large relative to $h(t)$ (experience-weighted output dominates human capital), the adjustment typically ensures $c_2 \leq c_1$.

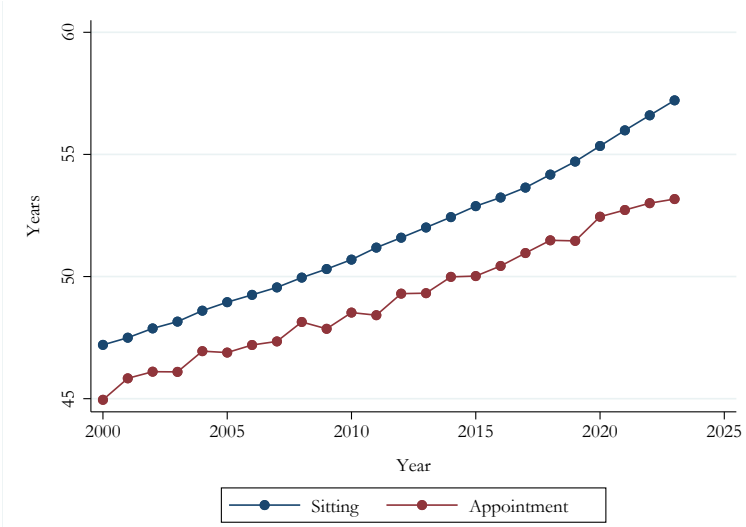
B Additional Figures

Appendix Figure A1: Illustrative Correlation of Age and Ability at the Top Position by Firm Size



Notes: The figure plots the correlation of age and ability across firm size 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 size decile. The simulation is repeated 500 times, and results are averaged across all replications.

Appendix Figure A2: Average CEO Age Over Time — Europe

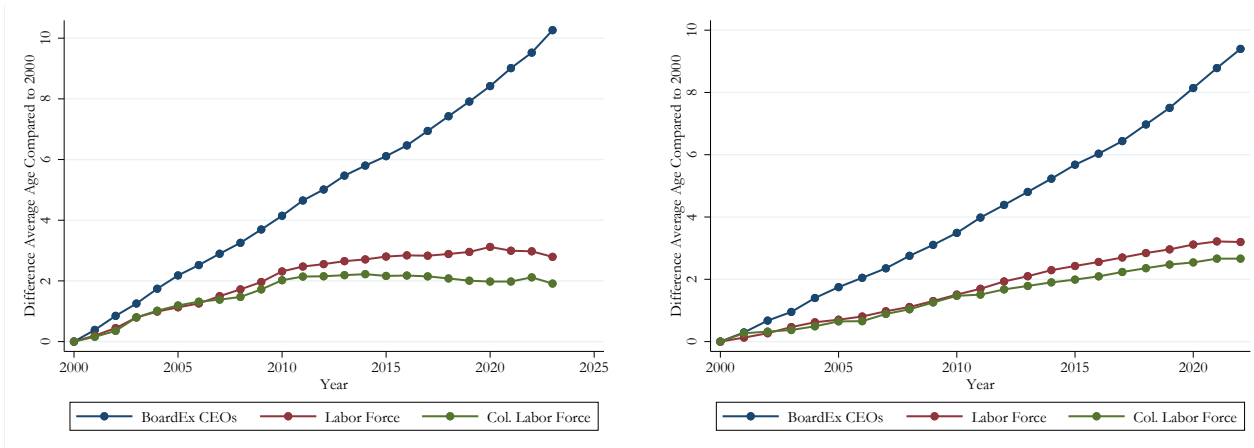


Notes: The plot shows the average age of CEOs in Europe over time, separately for sitting CEOs and CEOs at appointment. The countries included are Austria, Belgium, Switzerland, Cyprus, Germany, Denmark, Estonia, Greece, Spain, Finland, France, Hungary, Italy, Lithuania, Luxembourg, Norway, Poland, Portugal,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

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

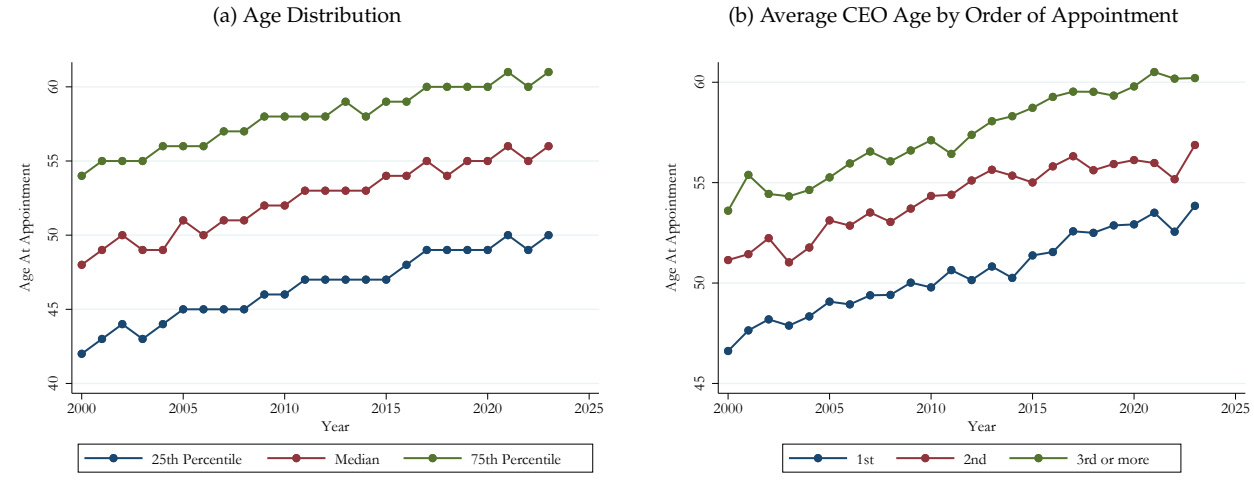
(a) United States

(b) Europe



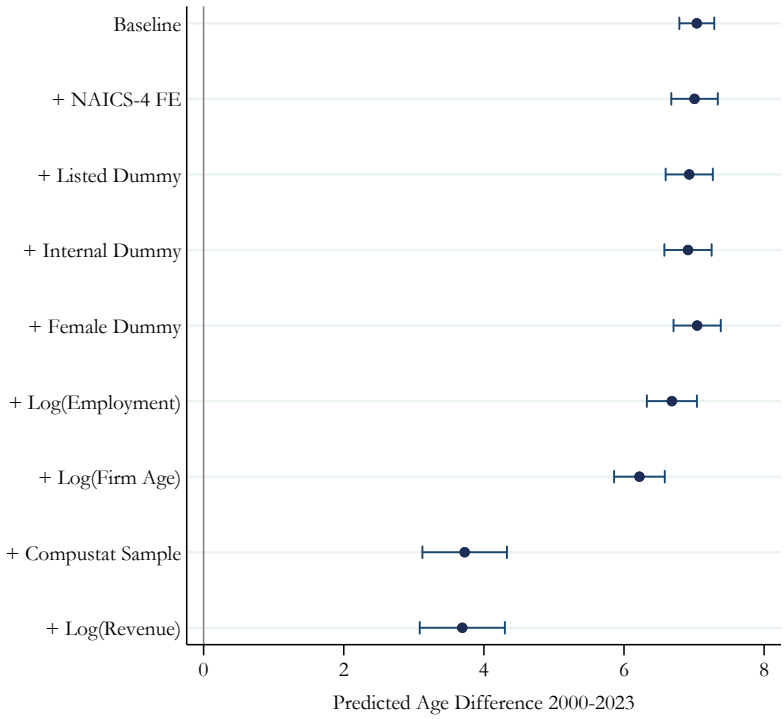
Notes: The figure compares the average age of sitting CEOs from BoardEx with that of the overall and the college-educated labor force, calculated from survey data. Panel (a) uses data from the *Current Population Survey*, showing the average age of all respondents in the labor force, calculated using 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: CEO Age at 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.

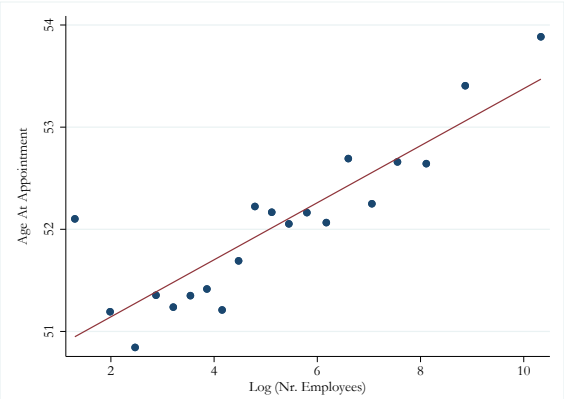
Appendix Figure A5: CEO Age at Appointment—Predicted Age Difference 2000 - 2023 Conditional on Controls



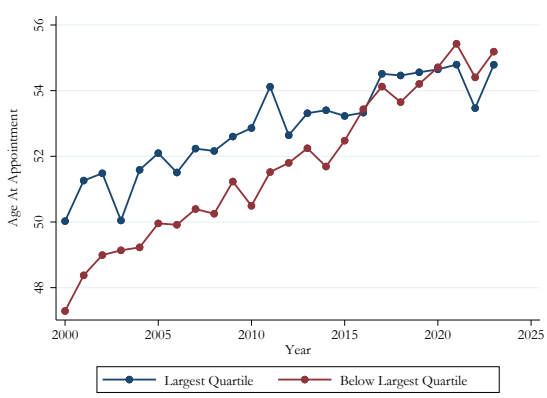
Notes: The figure shows coefficients obtained from regressing CEO age at appointment on a linear time trend since 2000 (normalized to range between 0 and 1). While the baseline specification includes no controls, we then consecutively control for NAICS-4 fixed effects, dummies for whether a firm is listed, 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 A6: CEO Age at Appointment and Firm Size (Number of Employees)

(a) Binscatter Average CEO Age vs. Firm Size

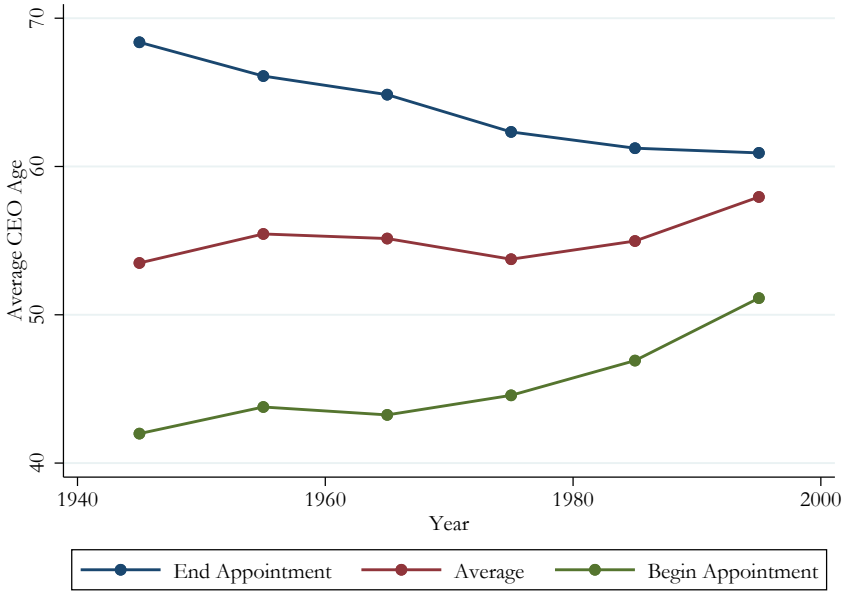


(b) Average CEO Age over Time by Firm Size



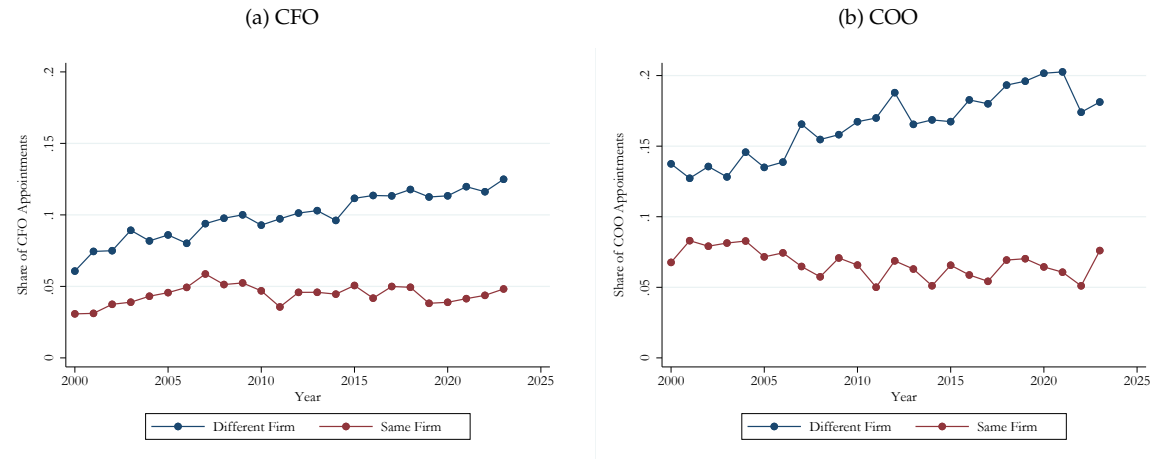
Notes: Panel (a) shows a binscatter plot of age at appointment against the natural logarithm of the number of employees. Panel (b) plots age at appointment separately for those in the largest firm quartile and for those in the other three quartiles. Size Quartiles are generated separately by year.

Appendix Figure A7: Long-Run CEO Age Patterns



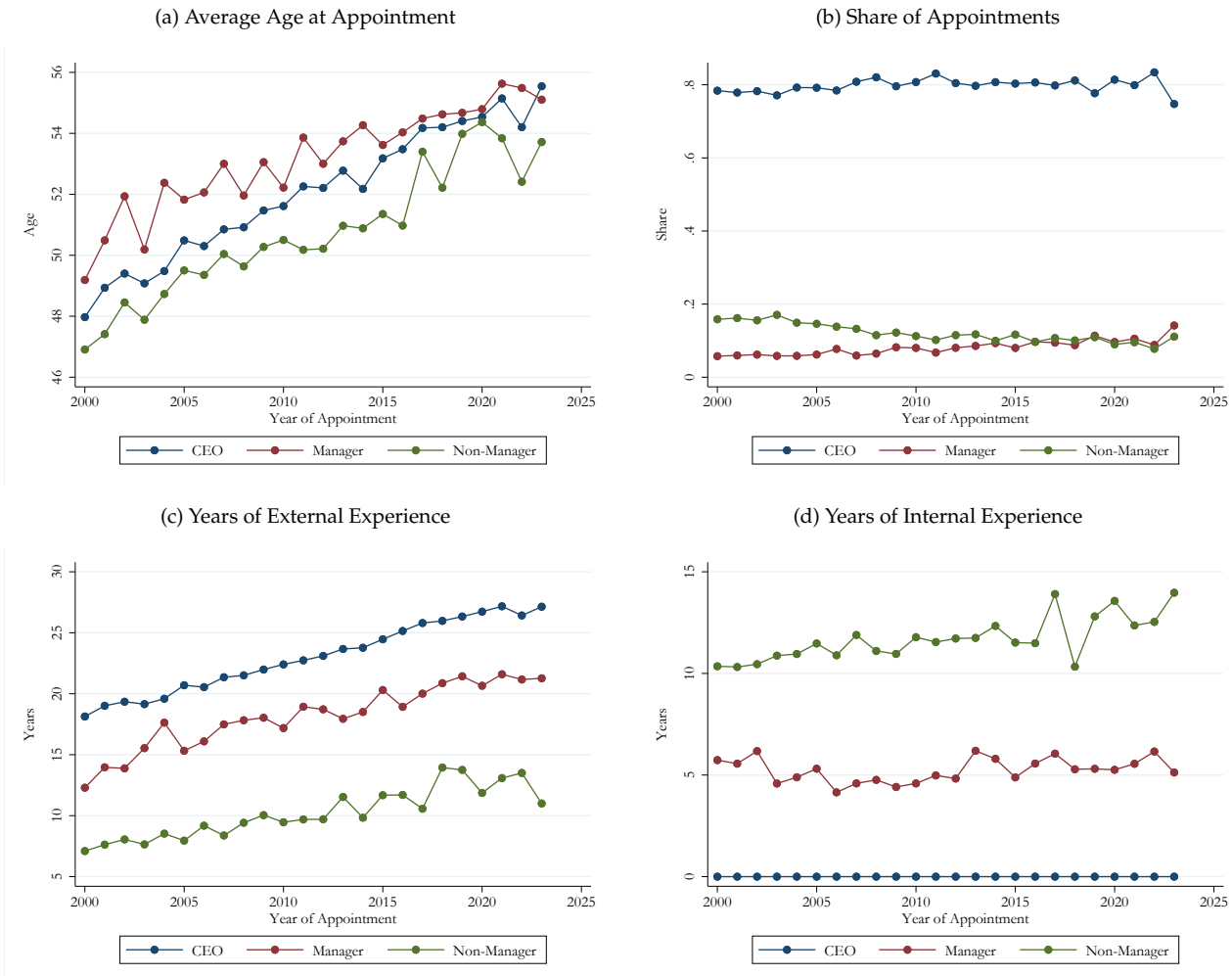
Notes: Plots long-run developments in average age as well as age at the begin and the end of the appointment of American executives, obtained from the *Great American Business Leaders of the 20th Century database* (https://www.hbs.edu/leadership/20th-century-leaders). We show aggregates by decade to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

Appendix Figure A8: Share of CEO Appointments with Experience as CFO or COO Over Time



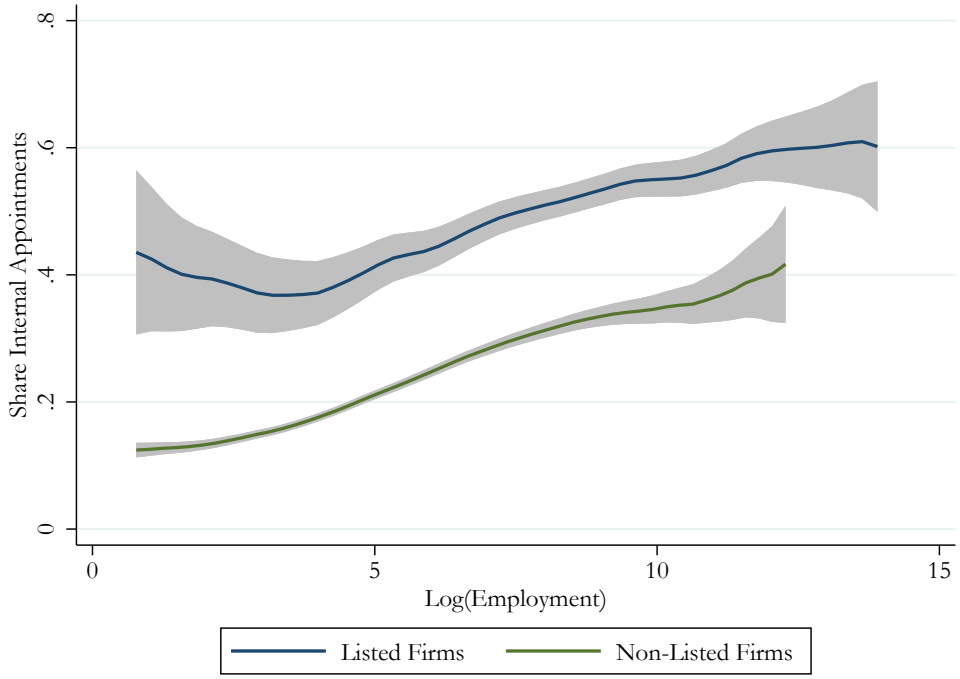
Notes: This figure shows the share of appointed CEOs who previously worked as CFO (Panel a) or COO (Panel b), distinguishing between those who served in this role at the same firm or a different firm from the one that promoted them to CEO. CFOs are identified by role names containing any of the following 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 A9: 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.

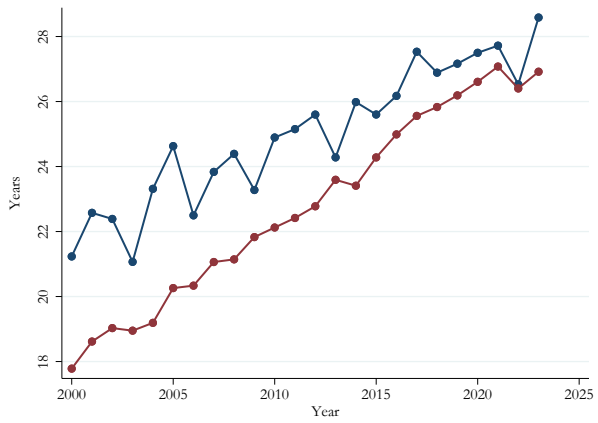
Appendix Figure A10: Share of Internal Appointments by Firm Size and Listing Status



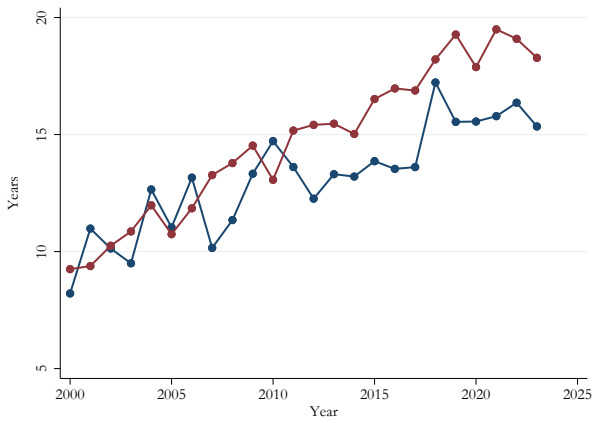
Notes: Plots the share of internal appointments against firm size measured by the natural logarithm of employment (obtained from employment histories). The data are smoothed with a local polynomial with Epanechnikov kernel and bandwidths of 0.91 and 0.78, respectively, which have been obtained via optimal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

Appendix Figure A11: Years of External vs. Internal Experience by Firm Size

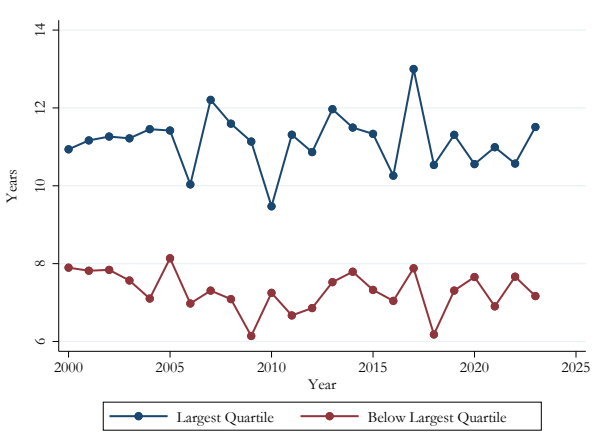
(a) External Appointments, External Experience



(b) Internal Appointments, External Experience



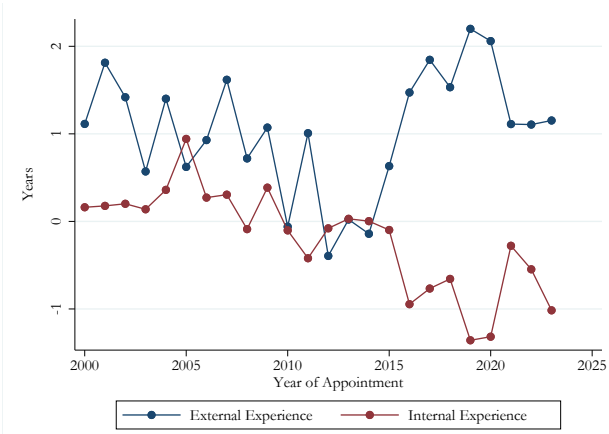
(c) Internal Appointments, Internal Experience



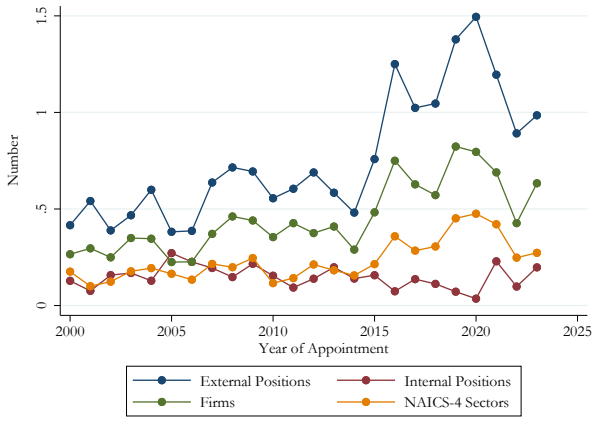
Notes: The figure plots years of experience, separately for those in the largest firm quartile and for those in the other three quartiles. Panel (a) shows years of external experience for externally appointed CEOs, panel (b) shows years of external experience for internally appointed CEOs, and panel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

Appendix Figure A12: Work Experience At First Appointment to Most Senior Position: CEOs vs. Non-CEO Executives

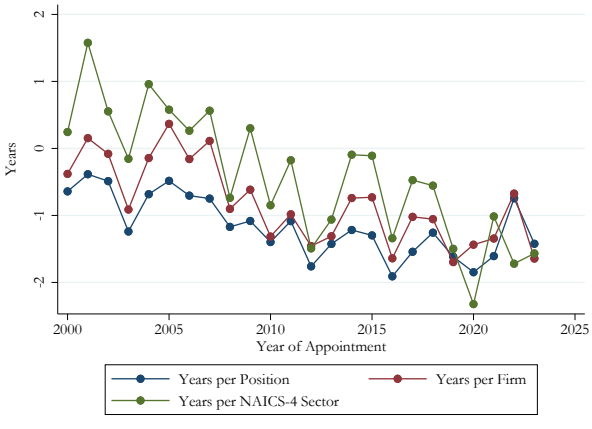
(a) Years of External vs. Internal Work Experience



(b) Average Number of Positions, Firms and Sectors



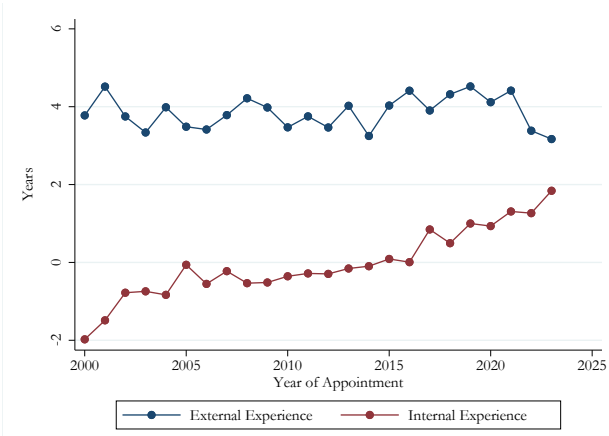
(c) Years per Position and Firm



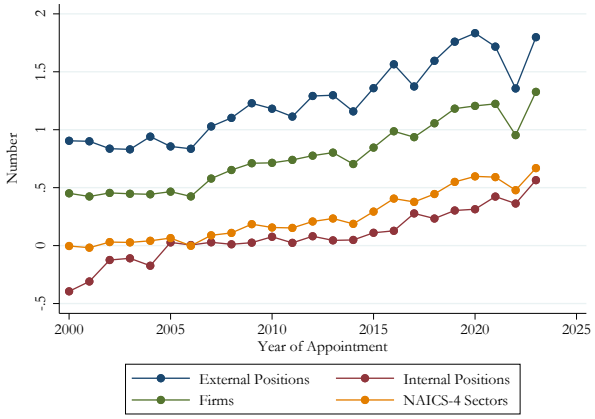
Notes: The figure plots work experience of CEOs vs. non-CEO executives over time, computed as the CEO average minus the non-CEO executive average in each year. The groups are defined based on the most senior position reached by the individual throughout the sample, focusing on the first appointment. Panel (a) plots the average external vs. 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 a prospective CEO worked in. Panel (c) shows the average number of years per position and firm.

Appendix Figure A13: Work Experience At First Appointment to Most Senior Position: CEOs vs. Other Managers

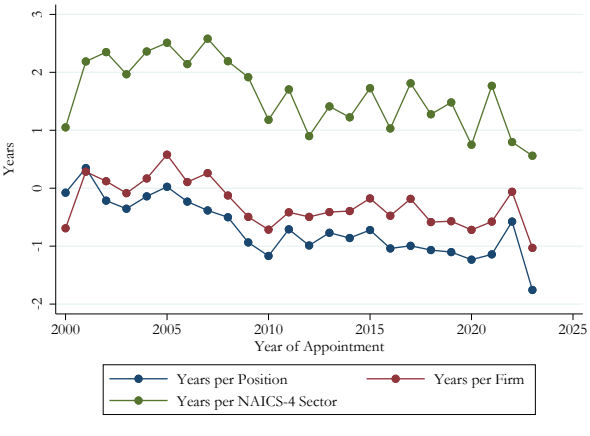
(a) Years of External vs. Internal Work Experience



(b) Average Number of Positions, Firms and Sectors

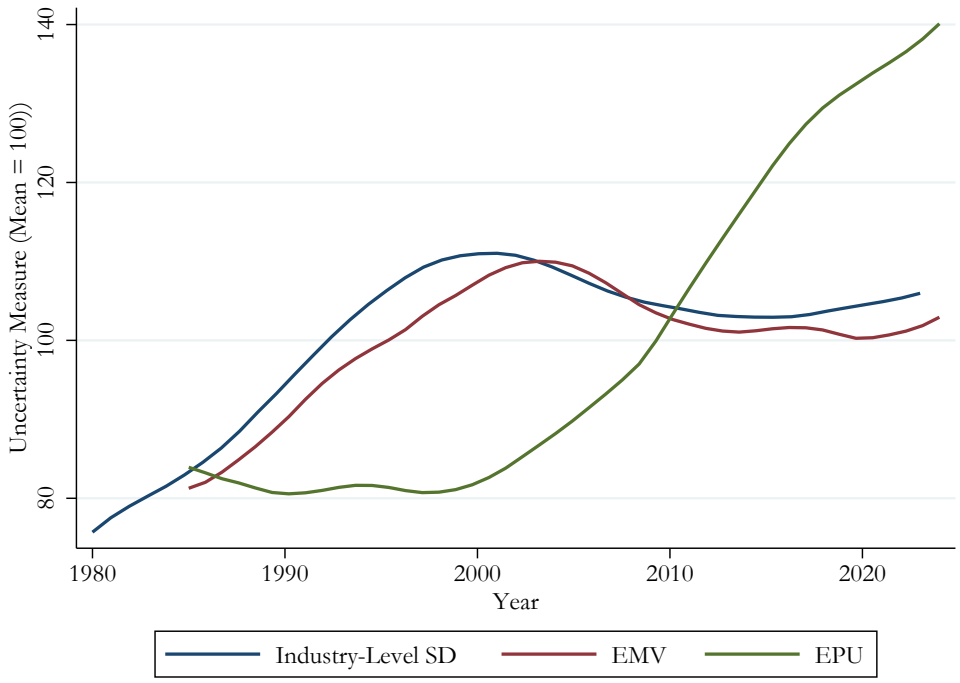


(c) Years per Position and Firm



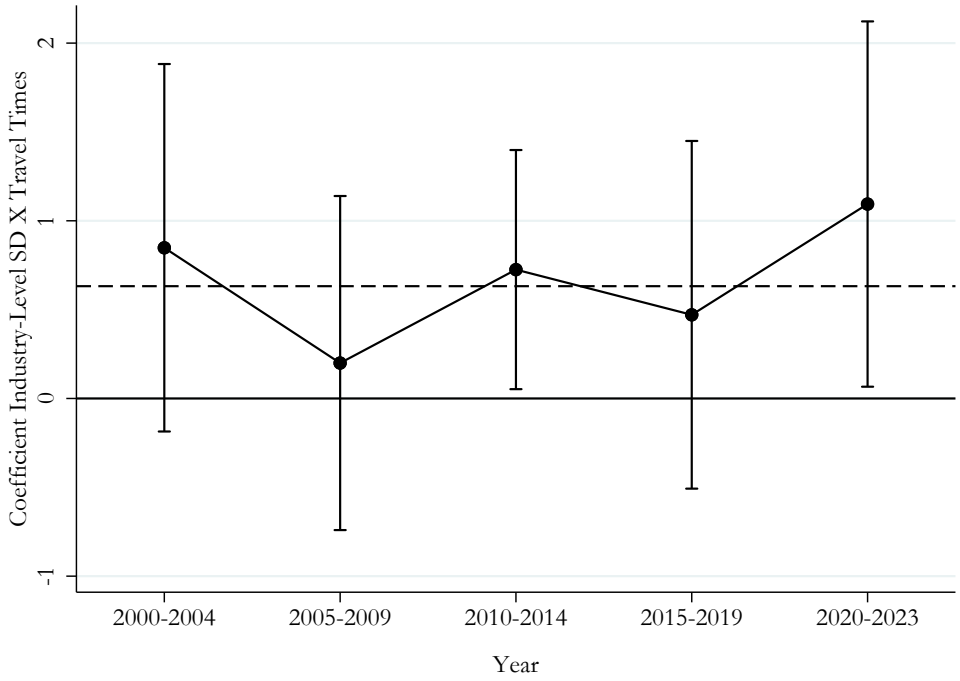
Notes: The figure plots work experience of CEOs vs. non-executive managers over time, computed as the CEO average minus the non-executive manager average in each year. The groups are defined based on the most senior position reached by the individual throughout the sample, focusing on the first appointment. Panel (a) plots the average external vs. 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 a prospective CEO worked in. Panel (c) shows the average number of years per position and firm.

Appendix Figure A14: Uncertainty Indices Over Time



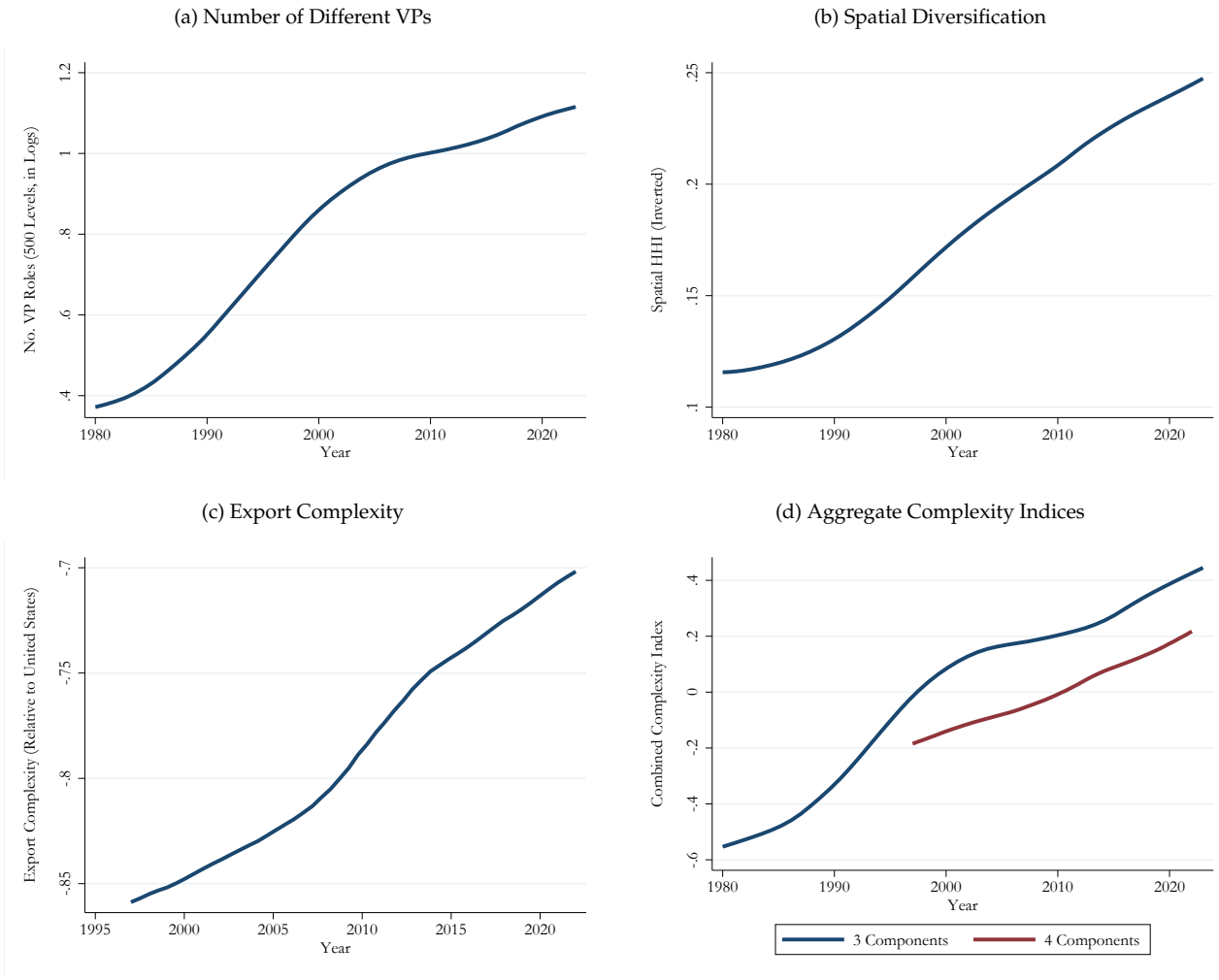
Notes: Plots measures of aggregate uncertainty over time. *Industry-Level SD* is the cross-sectional (NAICS-4-level) standard deviation of revenue growth rate (obtained from Compustat), which we aggregate by weighting with revenue. *EMV* is a newspaper-based Equity Market Volatility index constructed 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 A15: MBB Market Entry, Uncertainty and CEO Age—Time-Varying Estimates



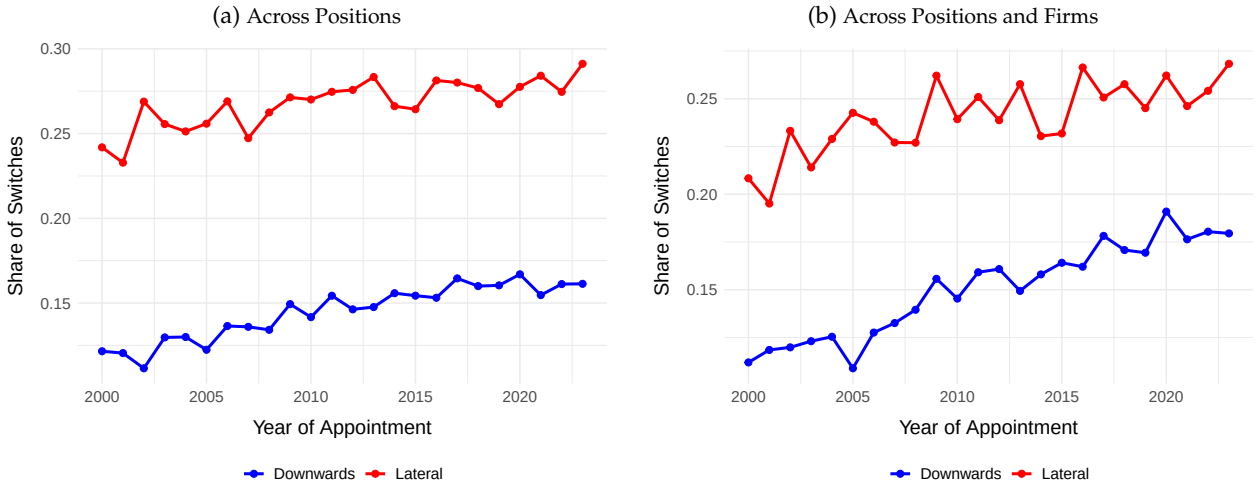
Notes: The plot shows coefficients from time-varying estimates, obtained by augmenting the specification from Table (1), Column (4) with interactions for 5-year bins. Uncertainty, calculated as the cross-sectional standard deviation of the symmetric growth rate of firm revenue within a firm's NAICS-4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

Appendix Figure A16: Complexity Measures Over Time



Notes: This figure shows different measures of sectoral complexity over time, smoothed using a local polynomial. Panel (a) reports the average number of distinct VPIs per firm, taking the median at the NAICS-4 level and the natural logarithm. Panel (b) presents 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 and invert 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. To express this as distance from the complexity frontier, we subtract 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 together with the measures from panels (a) and (b); the 4-component index additionally uses the export complexity measure from Panel (c).

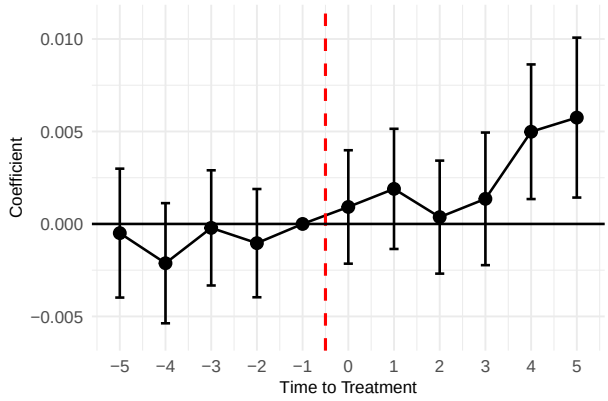
Appendix Figure A17: Share of Downward/Lateral Switches of CEOs Prior to Appointment



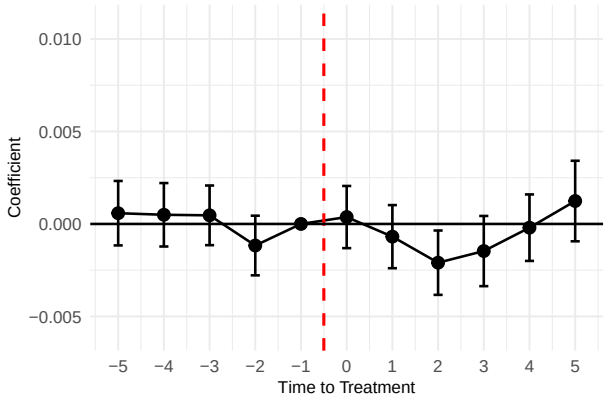
Notes: Plots the share of downward/lateral switches of CEOs prior to appointment by year of appointment, calculated as the ratio between the number of downward or lateral switches over the number of total switches. Panel (a) includes all switches across positions, panel (b) focuses on those across positions 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 A18: CEO Appointment of Former Coworker and Job Mobility—Event Study

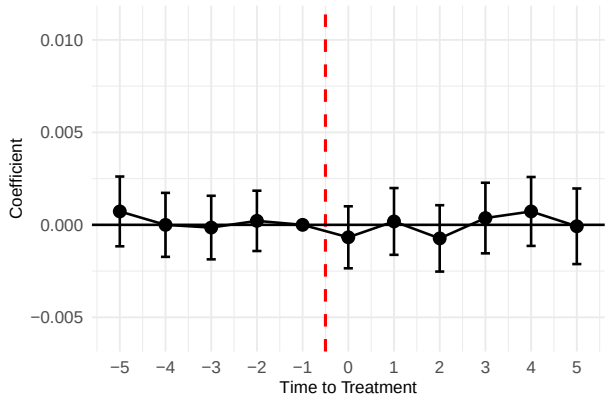
(a) Any Firm Switch



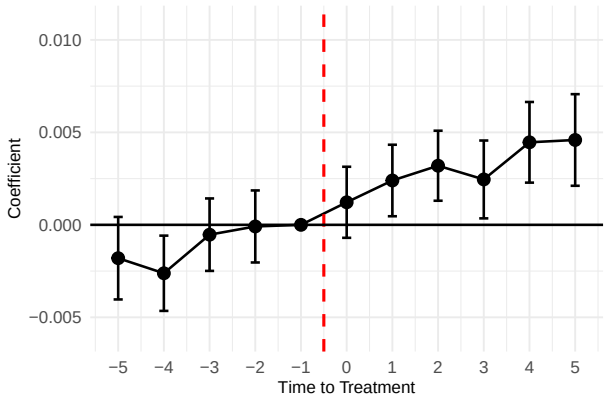
(b) Upward Firm Switch



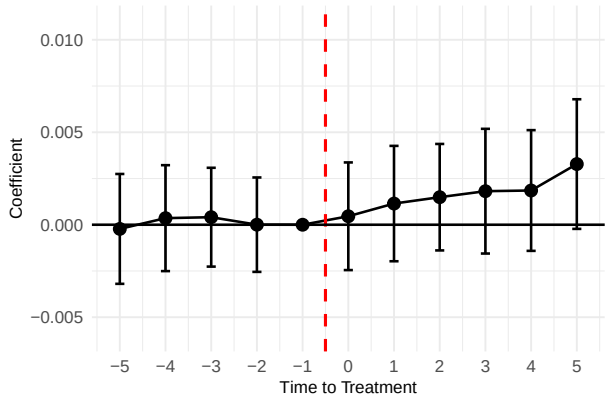
(c) Lateral Firm Switch



(d) Downward Firm Switch

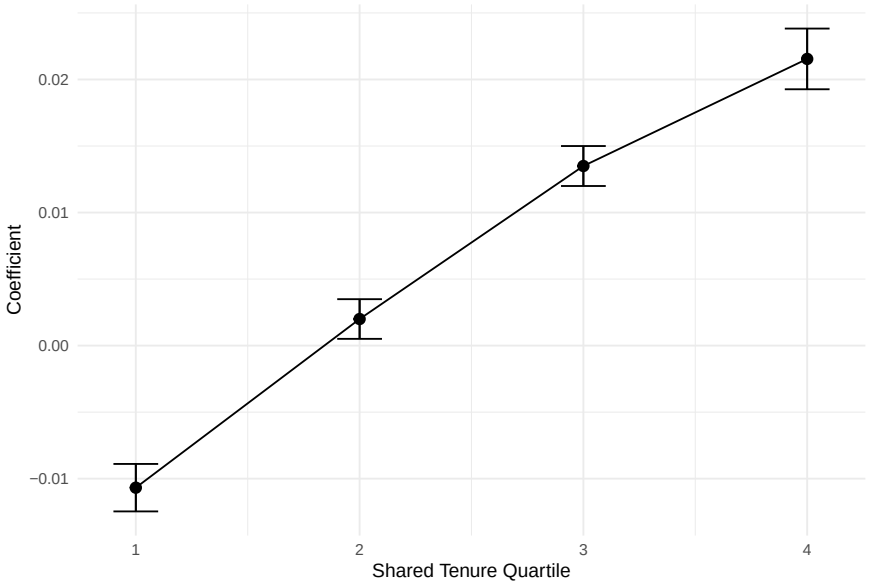


(e) Any Sector Switch



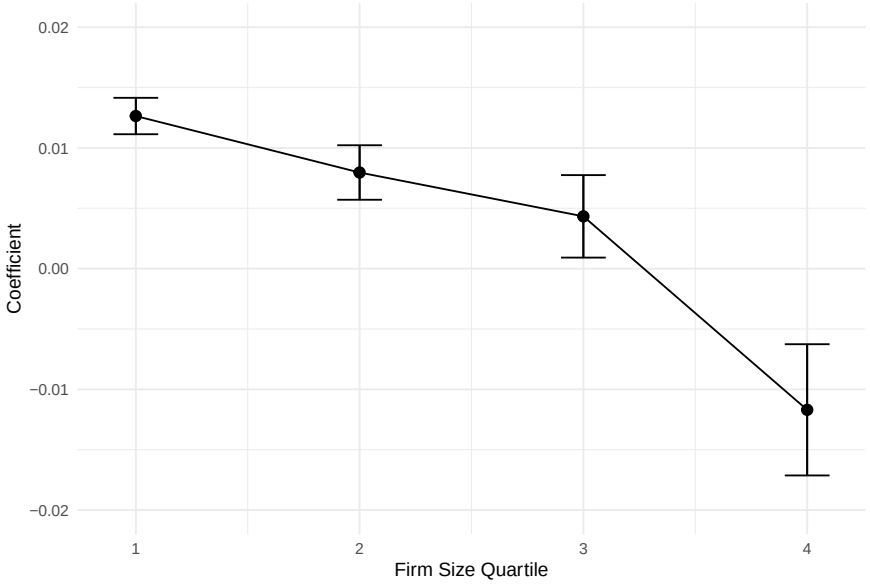
Notes: The specification equals column (4) from Table 5 (Panel a), Table 6 (Panel b), Table A12 (Panel c), Table A13 (Panel d), and Table A11 (Panel e), respectively, replacing *Post* by indicators for the number of years until treatment. The endpoints are binned at $t = -6$ and $t = 6$, while $t = -1$ 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 A19: Heterogeneity for Downward Mobility Response by Quartile of Shared Tenure



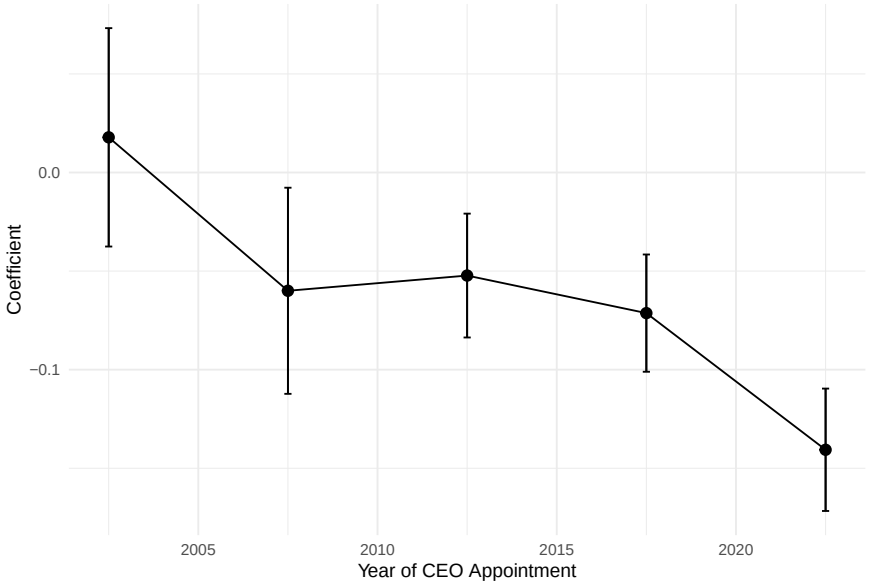
Notes: The specification equals column (4) from Table A16. Shows the point estimates for the coefficients on $Treat \times Post \times Quartile = k \; \forall k = 1, 2, 3, 4$ alongside 95% confidence intervals. Standard errors clustered at the firm level in parentheses.

Appendix Figure A20: Heterogeneity for Downward Mobility Response by Size Quartile of Current Firm



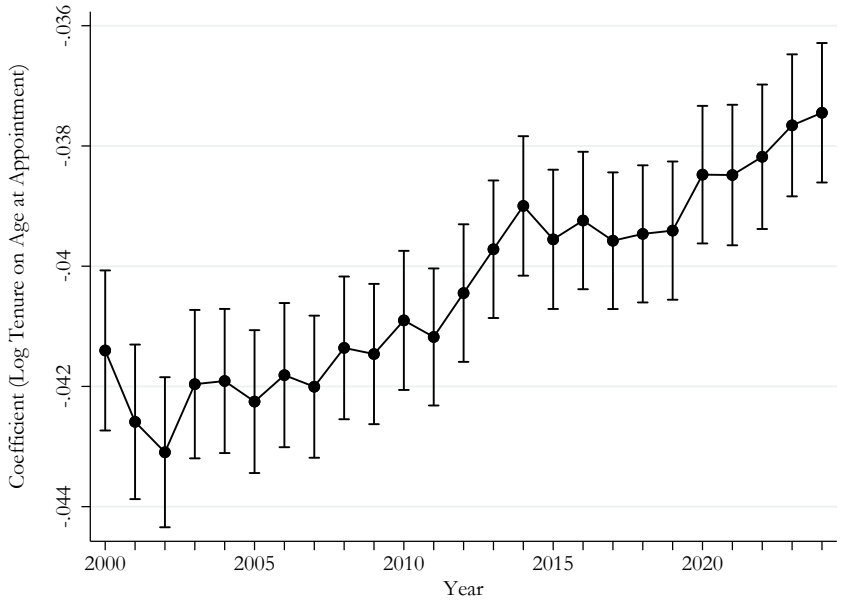
Notes: The specification equals column (4) from Table A22. Shows the point estimates for the coefficients on $Treat \times Post \times Quartile = k \; \forall k = 1, 2, 3, 4$ alongside 95% confidence intervals. Standard errors clustered at the firm level in parentheses.

Appendix Figure A21: 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 ln(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%-CIs. Standard errors are clustered at the CEO level.

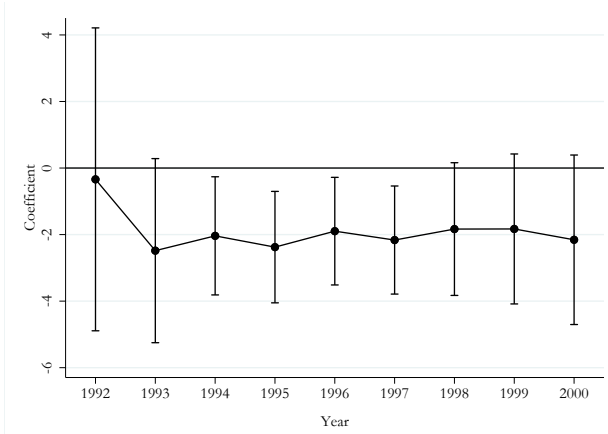
Appendix Figure A22: Time-Varying Correlation of CEO Tenure and Age at Appointment



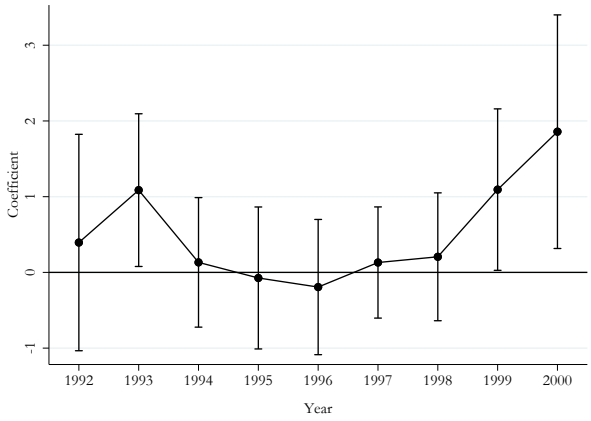
Notes: Shows the time-varying correlation of CEO tenure with age at appointment. The data are at the CEO-year level. The coefficients are obtained from regressions of the natural logarithm of tenure on year dummies, both alone and interacted with CEO age at appointment. Point estimates are plotted alongside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

Appendix Figure A23: CEO Age of Firms Delisted 1997-2002 — Differential Effects

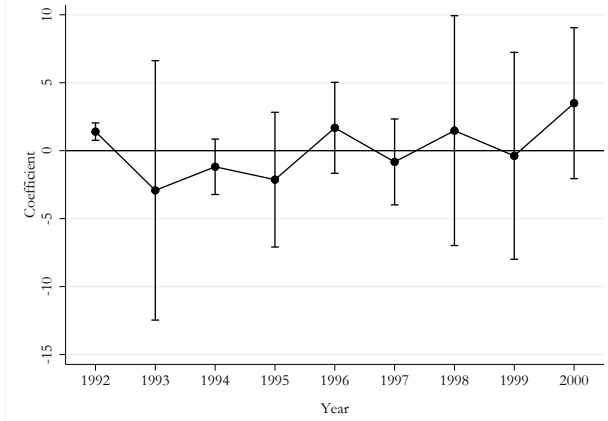
(a) Involuntary Delisting, Sitting CEOs



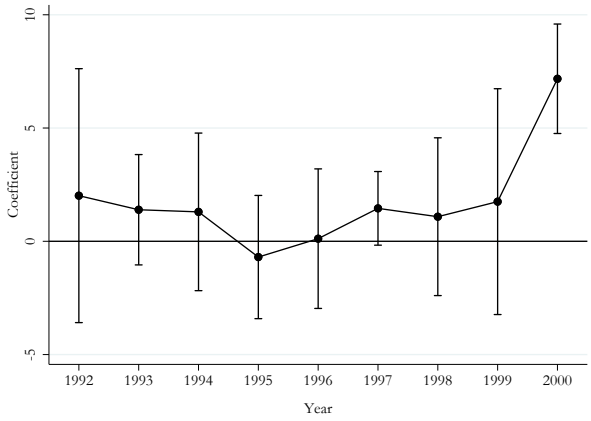
(b) M&A, Sitting CEOs



(c) Involuntary Delisting, Appointed CEOs



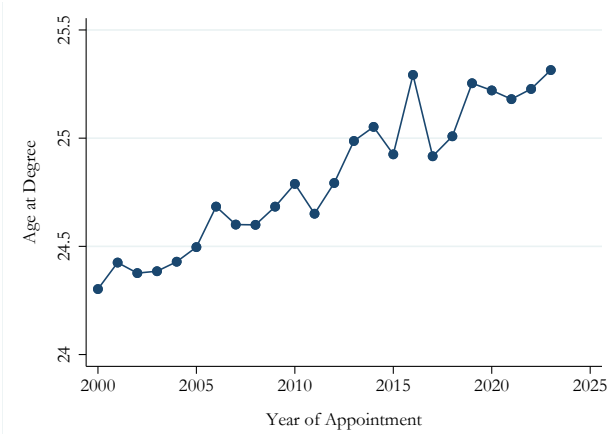
(d) M&A, Appointed CEOs



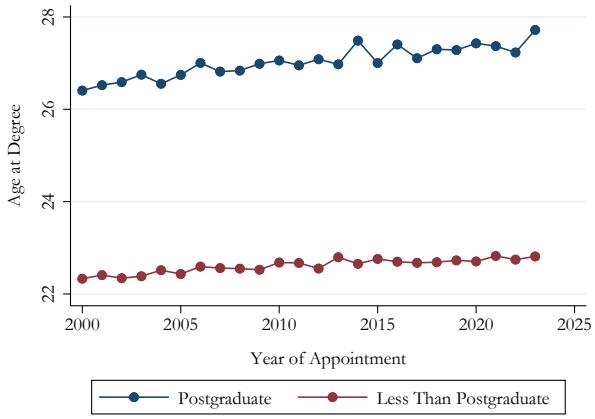
Notes: Shows coefficients from regressions of CEO age on year fixed effects interacted with indicators for different types of delistings (involuntary delistings in panels (a) and (c) and delistings due to M&A activity in panels (b) and (d)). The CEO data are from Execucomp and cover the S&P1500 during 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%-CIs. Standard errors clustered at the NAICS-4 level.

Appendix Figure A24: CEO Education By Year of Appointment

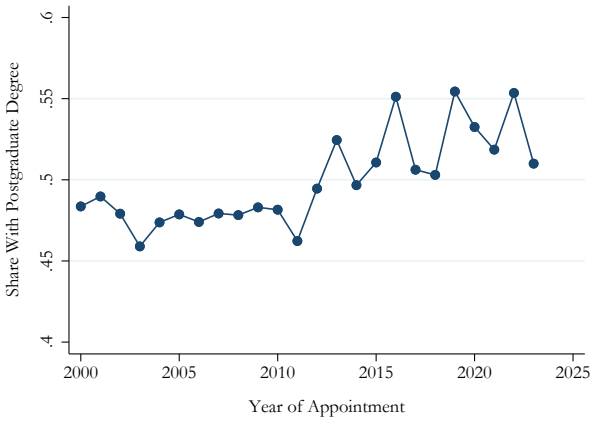
(a) Average Age at Highest Full-Time Degree



(b) Age at Highest Degree By Degree Type

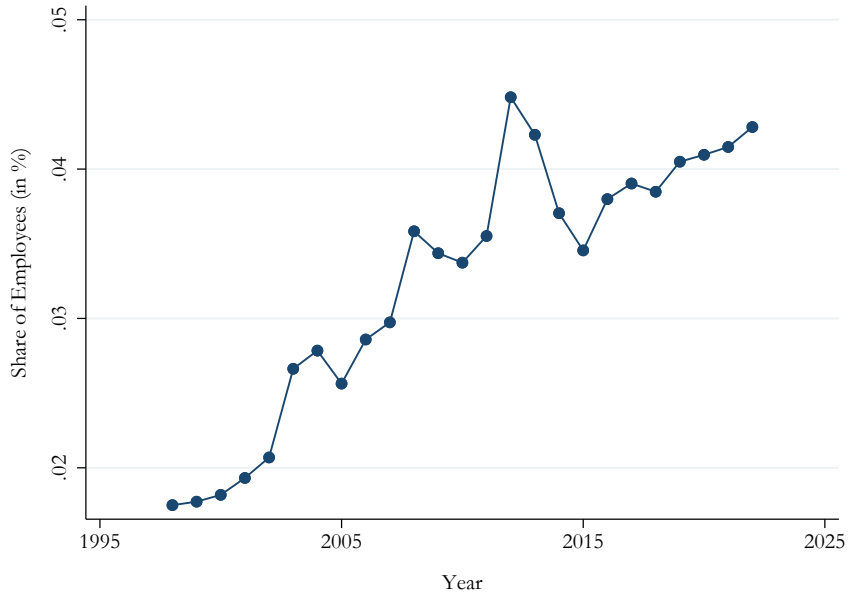


(c) Share of CEOs with Postgraduate Degree



Notes: Shows CEO education by year of appointment, focusing on full-time degrees obtained after at most 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, differentiating between postgraduate and less than postgraduate degrees. Panel (c) plots the share of CEOs with a postgraduate degree.

Appendix Figure A25: Employment Share of "Professional and Management Development Training"



Notes: Shows number of employees employed in 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.

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 (in %)	0.80	4.66	0.00	0.03	0.20	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 2.2 and 4.1.

Appendix Table A2: CEO Age and College Selectivity

	CEO Age					
	(1)	(2)	(3)	(4)	(5)	(6)
College Selectivity	-2.184***	-1.874***	-9.858***	-1.024**	-1.215***	-6.288***
	(0.212)	(0.157)	(0.723)	(0.443)	(0.326)	(1.479)
College Selectivity × Years Since 2000				-0.094***	-0.054**	-0.300***
				(0.032)	(0.024)	(0.109)
Selectivity Measure	Ivy Plus	Selective	Ln(SAT)	Ivy Plus	Selective	Ln(SAT)
R^2	0.252	0.253	0.265	0.252	0.254	0.266
Observations	16,181	16,181	13,108	16,181	16,181	13,108
Controls	✓	✓	✓	✓	✓	✓
Naics4-Year fixed effects	✓	✓	✓	✓	✓	✓

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 A3: Share of Appointments by Firm Size and Listing Status

Panel A: By Firm Size Quartile					
	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 tables tabulate 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: MBB Availability, Number of Different 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. VPs* is a count variable of the number of VPs. We aggregate these measures to the year-specific median within NAICS-4 sectors 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 sector and MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A5: MBB Availability, Spatial Diversification and CEO Age

	CEO Age			
	(1)	(2)	(3)	(4)
Travel Time × HHI, Upper Decile	4.244***			
	(1.262)			
Travel Time × HHI, Upper Quartile		2.409***		
		(0.723)		
Travel Time × HHI, Top Decile (Office = 10 Individuals)			3.784**	
			(1.478)	
Travel Time × Share Employees Non-HQ, Upper 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 = 5 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 sector. 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 sector and MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A6: 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 ≥ 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 sector 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 sector and MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A7: 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 sector 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 sector and MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A8: Substitutability of MBB Experience and Age

	CEO Age					
	(1)	(2)	(3)	(4)	(5)	(6)
MBB Inflows	0.0974***	0.0833***	0.0751***	0.0774***	0.0788***	0.0332
	(0.0206)	(0.0191)	(0.0207)	(0.0197)	(0.0236)	(0.0513)
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 × MBB Experience	-0.0945***	-0.0738**	-0.0973***	-0.0879**	-0.0949**	-0.177*
	(0.0334)	(0.0310)	(0.0337)	(0.0354)	(0.0409)	(0.0946)
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 managers 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 clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A9: Substitutability of MBB Experience and Age—Robustness

	CEO Age			
	(1)	(2)	(3)	(4)
MBB Inflows	1.183***	0.0739***	0.0722***	0.139***
	(0.275)	(0.0190)	(0.0253)	(0.0348)
MBB Experience	-3.122***	-3.354***	-3.313***	-3.377***
	(0.426)	(0.382)	(0.375)	(0.635)
MBB Inflows × MBB Experience	-1.512**	-0.0763**	-0.104**	-0.800**
	(0.734)	(0.0315)	(0.0405)	(0.365)
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 > 3	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 managers 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. 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; Column (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 clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A10: 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 4.2), 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 A11: CEO Appointment of Former Coworker and Job Mobility (Any Sector Switch)

	Sector 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 sectors. *Treat* is an indicator for having worked alongside a future CEO. *Post* is an indicator for periods following the CEO appointment. All fixed effects refer to the position the individual worked in alongside the future CEO. Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A12: 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. All fixed effects refer to the position the individual worked in alongside the future CEO. Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A13: 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. All fixed effects refer to the position the individual worked in alongside the future CEO. Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A14: 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. All fixed effects refer to the position the individual worked in alongside the future CEO. Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A15: 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. All fixed effects refer to the position the individual worked in alongside the future CEO. Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A16: 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. All fixed effects refer to the position the individual worked in alongside the future CEO. Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A17: 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. All fixed effects refer to the position the individual worked in alongside the future CEO. Standard errors clustered at the firm level in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A18: Effects on Individuals at Seniority above Future CEO

	Any Firm	Upward	Lateral	Downward	Any Sector
	(1)	(2)	(3)	(4)	(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. All fixed effects refer to the position the individual worked in alongside the future CEO. Standard errors clustered at the firm level in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A19: Time Variation in Effect of CEO Appointment of Former Coworker and Job Mobility (5-Year Bins)

	Any Firm	Upward	Lateral	Downward	Any Sector
	(1)	(2)	(3)	(4)	(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 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. All fixed effects refer to the position the individual worked in alongside the future CEO. Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A20: 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. All fixed effects refer to the position the individual worked in alongside the future CEO. Standard errors clustered at the firm level in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A21: 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. All fixed effects refer to the position the individual worked in alongside the future CEO. Standard errors clustered at the firm level in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A22: Heterogeneity by Size Quartile of Current Firm

	Any Firm	Upward	Lateral	Downward	Any Sector
	(1)	(2)	(3)	(4)	(5)
Quintile = 2	0.036***	0.007***	0.010***	0.019***	0.018***
	(0.002)	(0.0006)	(0.0007)	(0.001)	(0.002)
Quintile = 3	0.051***	0.008***	0.011***	0.032***	0.032***
	(0.002)	(0.0009)	(0.0009)	(0.002)	(0.002)
Quintile = 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 × Quintile = 2	0.007***	0.007***	0.004***	-0.005***	-0.002
	(0.002)	(0.0008)	(0.0010)	(0.001)	(0.002)
Treat × Post × Quintile = 3	0.003	0.008***	0.003***	-0.008***	-0.004
	(0.003)	(0.001)	(0.001)	(0.002)	(0.003)
Treat × Post × Quintile = 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. All fixed effects refer to the position the individual worked in alongside the future CEO. Standard errors clustered at the firm level in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A23: 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 towards 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. All fixed effects refer to the position the individual worked in alongside the future CEO. Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A24: 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. All fixed effects refer to the position the individual worked in alongside the future CEO. Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A25: 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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 A28.

D.1 Correlational Evidence

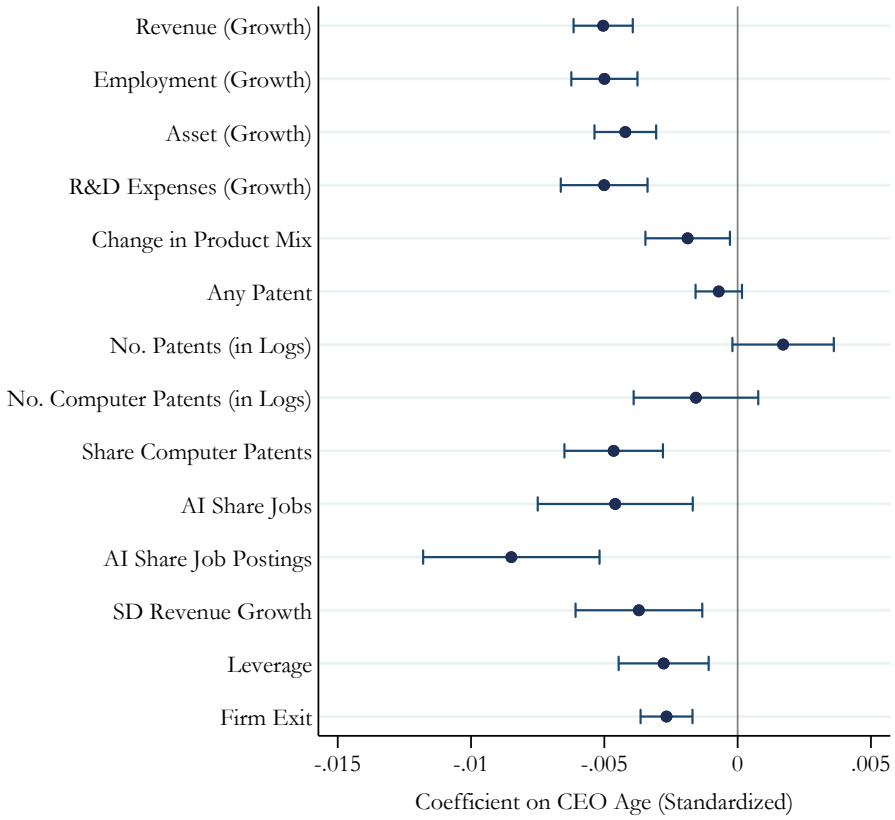
Motivated by upper echelons theory (Hambrick and Mason, 1984), a vast body of research explores the role of executive characteristics in determining company outcomes (Bertrand and Schoar, 2003). This literature has established a negative the association between CEO age and reduced levels of business dynamism and firm risk. Our analysis revisits this relationship, yielding results in line with previous research. Figure A26 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.[44] 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.

[44] 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.

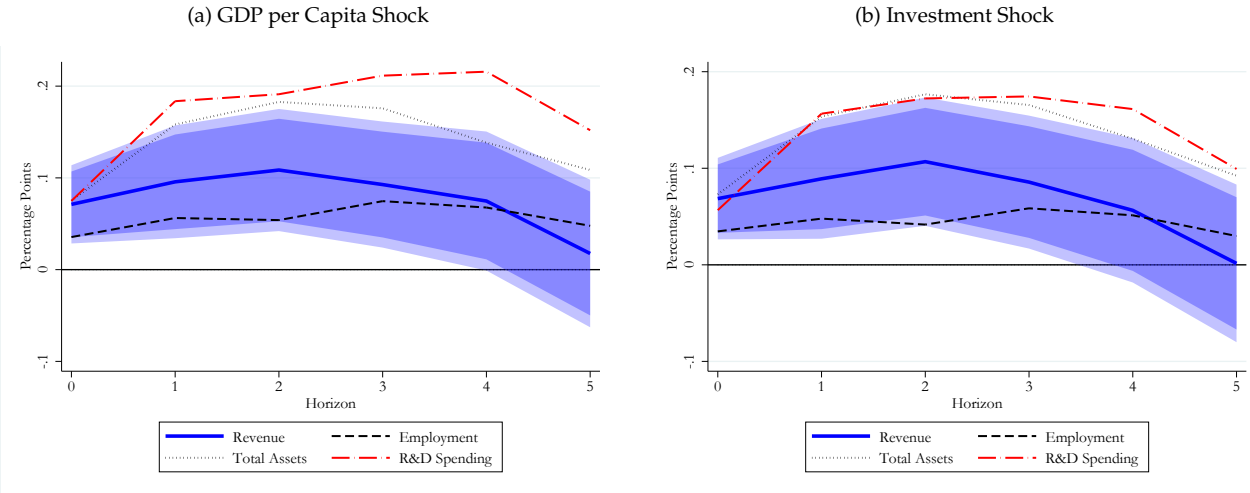
Appendix Figure A26: Correlations of CEO Age and Firm-Level Outcomes



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 A27: 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 A27 presents results from local projections using the shock series from Angeletos et al. (2020). Panel (a) shows the

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 4.1). 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 t. We then estimate the following equation for a time-varying firm outcome v_{jt}

$$v_{jt} = \nu_{wj} + \phi_{it} + X_{jt} + \epsilon_{jt}, \tag{24}$$

where ν_{wj} are firm-by-CEO fixed effects and ϕ_{it} denote NAICS-4-year fixed effects. The vector of controls, X_{jt}, includes the natural logarithm of the number of employees and firm age, both obtained from employment history data, as well as the CEO's tenure at the firm. The coefficients of interest are the estimated firm-by-CEO fixed effects $\hat{v}_{wj}$, 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 on the match-specific firm outcomes $\hat{v}_{wj}$, leveraging our plausibly exogenous measure of demand for more experienced CEOs as an instrument. Specifically, we run the following regression

$$\hat{v}_{wj} = \beta \widehat{Age}_{jt} + \gamma_{mt} + \phi_{it} + \epsilon_{jt}, \tag{25}$$

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

Appendix Table A26: 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 25. The dependent variables are the firm-by-CEO fixed effects $\hat{v}_{wj}$, which we estimate as described in Equation 25 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 sector. 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 sector and MSA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

regression described by Equation 1, we control for time-varying characteristics at the level of metro areas and NAICS-4 sectors.

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 A26. While we find no significant coefficient for employment growth (column 1), we detect a negative effect for R&D expenditure growth. However, 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.[45]

[45]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 A27, 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 A27: 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 Equation 25. The dependent variables are the firm-by-CEO fixed effects $\hat{v}_{wj}$, which we estimate as described in Equation 25 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 sector. 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 sector and MSA level. We compute the between-variance $\hat{\sigma}^2_{\hat{\beta}}$ 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 $\sqrt{\hat{\sigma}^2_{\hat{\beta}} + (1 + \frac{1}{R})\hat{\sigma}^2}$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A28: 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

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 this approach 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 irrelevant for our purposes. Nevertheless, as we show in the below, 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.

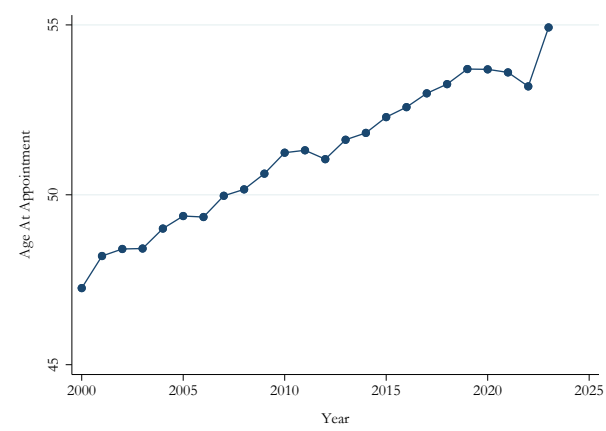
First, as shown in Figure A28, CEO age at appointment increases by almost eight years over the sample period (Panel a). Second, when decomposing total work experience into tenure accumulated before and after joining the firm where the individual became CEO, we find that the increase is entirely driven 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 A29 reproduces Figure A10, 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%).

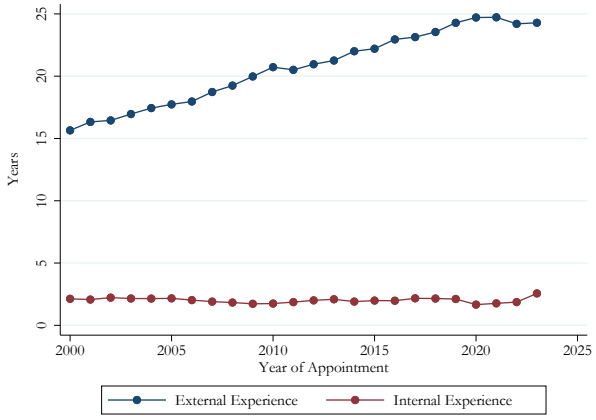
Sample Composition: Another potential concern relates to BoardEx's inclusion criteria. In particular, once an individual becomes CEO of a large firm, BoardEx might retrospectively add their entire employment history, including prior CEO appointments at smaller firms. This could mechanically generate 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 A6 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 A30. Reassuringly, albeit being overly conservative, excluding this group of CEOs leaves the pattern unchanged.

Appendix Figure A28: CEO Age At Appointment Over Time, Alternative Data Preparation

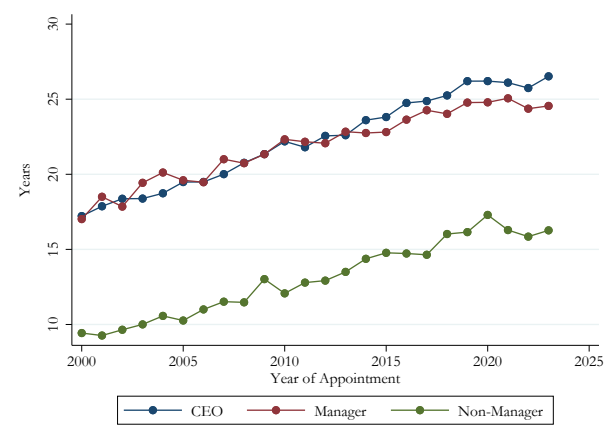
(a) Age



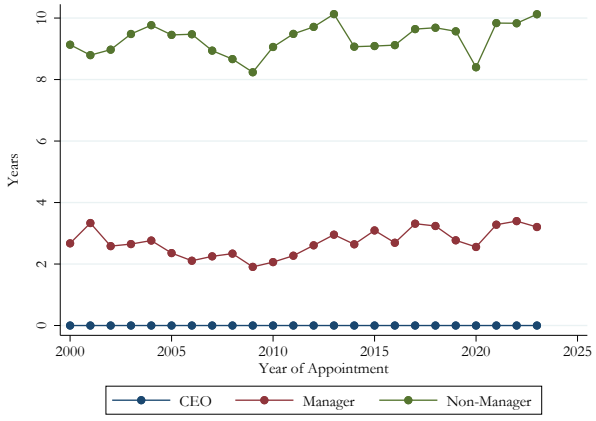
(b) External vs. Internal Work Experience



(c) External Experience, by Seniority of First Position

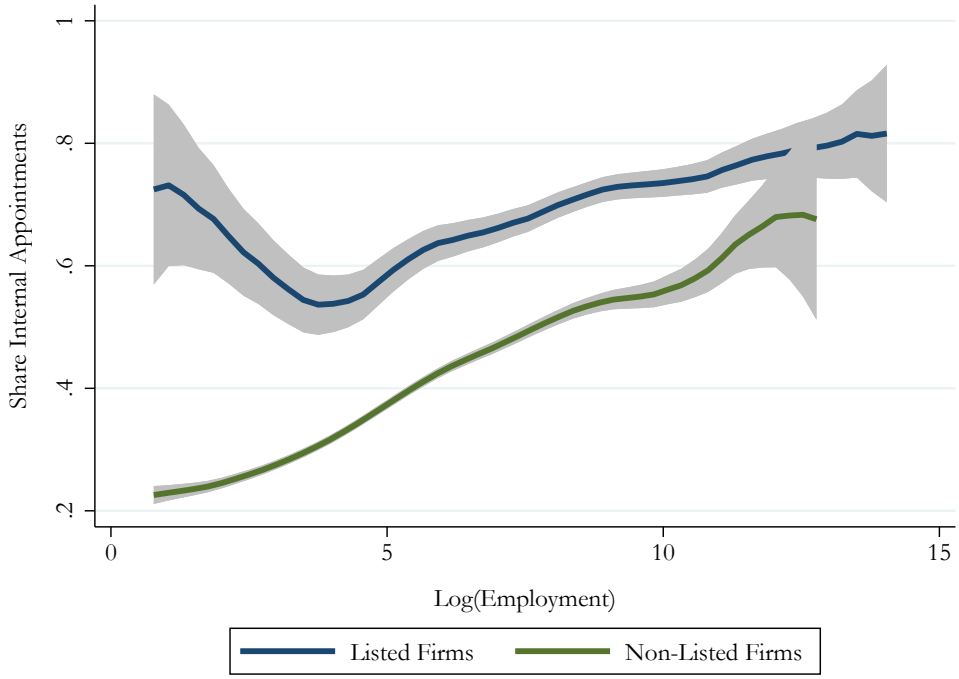


(d) Internal Experience, by Seniority of First Position



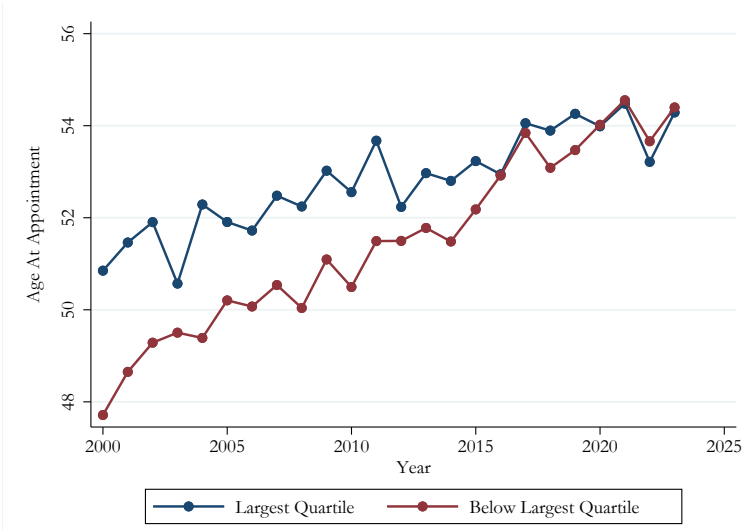
Notes: Panel (a) shows the average age at appointment of CEOs in the United States over time. Panel (b) plots the average external vs. internal work experience prior to appointment. Panels (c) and (d) show the average years of external and internal experience, respectively, stratified by the seniority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

Appendix Figure A29: 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 A10. Point estimates are shown alongside 95% confidence intervals.

Appendix Figure A30: 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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