CEO Social Preferences and Layoffs*

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Abstract

We study whether CEOs exhibit prosocial preferences in their labor decision-making, using a new dataset on layoffs by U.S. public firms. Reflective of other-regarding concerns, we estimate a large personal cost of firing for CEOs in the form of accelerated long-run mortality. CEO in-office labor decisions further reveal sizable frictions: after plausibly-exogenous CEO changes, new CEOs make more, and shareholder value-increasing, layoffs. CEOs become more reluctant to make layoffs over their tenure as they form more connections inside the firm, consistent with prosocial concerns strengthening with social interactions. This effect is amplified for "painful" layoffs during recessions, of socially and geographically close employees, and during the holiday season.

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1. Introduction

"[You feel shame] when you ask people to leave because you thought the business was going to grow and you were wrong. It ain't their fault. It's your fault. And having to say that 862 times because that's how many people we let go has just been awful for them, but also a deep source of shame for me." – Glenn Kelman, Founder & CEO of Redfin, November 2022

In the standard firm investment problem in finance and macroeconomics, adjustment of human capital is treated akin to adjustment of physical capital, with the firm optimizing over all factor inputs subject to potential adjustment costs. By contrast, CEOs' first-hand responses and viewpoints from various executive surveys reveal that hiring and firing decisions may in fact be different from the purchase, write-down, and divestment of machines in important ways. For example, Martin (2005), surveying 2,000 senior executives and managers worldwide, finds that more than half view hiring and firing as "the toughest decision" in their careers. Hallock (2005) provides additional colorful insight through interviews with senior managers of mostly Fortune 500 firms, with one CEO stating that layoffs are "a human decision. It is hard."[1]

There is, of course, a large prior literature on factor adjustment costs, including adjustment costs with respect to labor. This work has, however, mainly focused on *resource-based* costs. With respect to labor, seminal work highlights adjustment costs arising from new hire training, job advertising and interviewing, and labor-market policies such as severance pay and mandatory advance notices of mass layoffs (Hamermesh 1989).[2]

In this paper, we instead propose a complementary, novel type of "behavioral adjustment costs" firms may face with respect to labor—but not capital—arising from decision-making affecting humans, motivated by the CEO survey evidence above. We link the adjustment cost literature to managerial social preferences for workers, and argue that social-preference considerations can lead to distortions and frictions in firms' labor demand decisions.[3] We study firms' layoff decisions as a natural manifestation of managerial social

[1] We highlight further anecdotal examples from these and other sources in footnote 5 and Section 5.

[2] With respect to capital, prior work emphasizes adjustment costs due to interruptions to production, installation costs, and site cleanup costs after disinvestment (Rothschild 1971, Doms and Dunne 1998, Teisberg 1993).

[3] A large literature in behavioral economics has provided evidence for prosocial behavior, both in the lab

preferences towards employees and examine both a level effect of social preferences, as well as a dynamic perspective analyzing changes in firm decisions over time as managers develop deeper social connections inside the firm.

To study firm and CEO decision-making with respect to layoffs, we assemble a new, comprehensive dataset of layoff announcements over the last two decades by U.S. firms included in Execucomp. Existing work studying the determinants and effects of layoffs oftentimes proxies for layoffs by changes in net employment count (e.g. Schmieder, von Wachter, and Heining 2022, Landier, Nair, and Wulf 2009). As we show later, such proxies tend to be imprecise and indirect. The starting point for our layoff announcement data is the Standard and Poor's (S&P) Capital IQ Key Developments database, specifically the subcategory of "Discontinued Operations/Downsizings." Each key development includes a date, a headline, and a situation summary.

We use a combination of natural language processing (NLP) and hand-coding of these news-like text data to identify layoff announcements and associated layoff characteristics. We specifically identify *involuntary* layoffs as opposed to employee reassignments or voluntary departures such as early retirement, and also collect information on layoff severity and geography, i.e., number of employees laid off as well as layoff site(s). Our final dataset covers more than 12,000 layoff announcements.

We first shed light on personal long-term consequences for CEOs associated with implementing layoffs, and specifically how CEOs' layoff decisions affect their long-run health and mortality. The mortality analysis provides for a direct way to test for firing-induced "disutility costs" that reflect CEOs' intrinsic prosocial concerns. By contrast, a more selfish "social image" mechanism, in which CEOs account for social factors only due to social pressure from other agents such as shareholders or the media, would not easily predict the existence of a true personal cost of firing for CEOs.

The mortality analysis builds on Borgschulte, Guenzel, Liu, and Malmendier (2022), who document significant increases in long-run mortality when CEOs' work environment becomes exogenously more stressful, and uses an earlier layoff dataset from Hallock (1998),

and the field, stronger towards those considered in-group members, and pronounced among experimental subjects who are real-life CEOs (DellaVigna 2009, Chen and Li 2009, Fehr and List 2004). Fehr and List (2004) find evidence that CEOs (from the mill sector in Costa Rica) have more pronounced social preferences than (local) students as gauged by their behavior in standard experimental trust games.

Billger and Hallock (2005), and Farber and Hallock (2009).[4] We find significant mortality effects associated with "painful" layoffs that CEOs make in response to industry distress shocks. We estimate a distress-layoff effect on mortality roughly corresponding to that of a two-year increase in CEO age, which is similar in magnitude to the effect sizes in Borgschulte, Guenzel, Liu, and Malmendier (2022).[5]

Having established a personal firing cost for CEOs reflective of prosocial concerns, we next study whether and how CEOs' prosocial considerations affect their labor decision-making in-office. Here, we proceed in two steps.

First, we document baseline CEO-related frictions in firms' layoff decisions that are detrimental to shareholders. After plausibly-exogenous CEO changes, new CEOs make more layoffs over the next few years relative to unaffected control firms. Moreover, these new-CEO layoffs are accompanied by large, positive announcement returns of more than two percent on average. By contrast, layoff announcements by control firms (as well as the average sample-wide layoff announcement) come with a small, negative announcement return.

Second, turning to the full CEO sample, we study how CEOs' layoff propensity varies over their tenure and as they form more connections inside the firm, as well as various heterogeneities based on when social concerns should theoretically be more or less pronounced.

Consistent with social preferences strengthening with social interactions, long-tenured CEOs make fewer layoffs than short-tenured CEOs. In our preferred and most stringent specification, an interquartile increase in CEO tenure is estimated to reduce the layoff propensity by 11% relative to the baseline annual layoff probability. The negative CEO tenure–layoff relation is not explained by standard firm measures such as size or profitability, year fixed effects, or industry fixed effects. It holds with controls for labor and

[4] We are grateful to Kevin F. Hallock for sharing the data.

[5] Consistent with layoffs having a long-term impact on CEOs, in a 2016 documentary titled "Lonely at the Top: Top-Level Managers at Their Limit," a former executive at Siemens AG recalled that "[l]aying people off is something that took its toll on me." The documentary is available (in German) at youtube.com/watch?v=FcRH3r0nEDE. Consistent with recession-induced layoffs being particularly scarring, one manager in the survey by Martin (2005) responded that "[o]ver the years the toughest decision was letting someone go, not based on their performance, but based on the firm's condition." Similarly, another senior manager interviewed by Hallock (2005) responded that the "goal is to never terminate a good employee."

capital productivity as well as with firm fixed effects, the latter implying that endogenous matching, where long-tenured CEOs prefer companies that generally avoid firing, does not explain the result. It is also robust to controlling for the *CFO*'s tenure—i.e., there is a distinct CEO effect—, and to an instrumental variables (IV) approach for tenure, instrumenting with the fraction of overall tenure realized, as in Graham, Kim, and Leary (2020).

The finding of reduced layoff propensities of longer-tenured CEOs builds on prior work by Pan, Wang, and Weisbach (2016), who first documented the existence of "CEO investment cycles," with investment increasing and disinvestment, using a broader measure of downsizings, decreasing over a CEO's tenure. Our paper differs in that we focus specifically on layoffs as well as in the proposed mechanism. Pan, Wang, and Weisbach (2016) provide evidence that firms' increasing investment in (physical) capital over a CEO's tenure is driven by increasing CEO power as measured by the fraction of the board appointed by the CEO. We find that firms' decreasing layoff propensity over a CEO's tenure is not explained by time-varying CEO power and board co-option. Additionally, the tenure–layoff relation is not explained by CEO entrenchment and holds within and across levels of entrenchment as gauged by the Bebchuk, Cohen, and Ferrell (2009) index.

Further heterogeneity tests corroborate the social-preferences mechanism driving labor decision-making. Over time, CEOs become significantly more averse to "painful" layoffs: layoffs during economic downturns (which signify more pain for those that lose their jobs; Jacobson, LaLonde, and Sullivan 1993), layoffs of socially close (white-collar) employees, layoffs at or near the firm's headquarters, and layoffs during the holiday season. With longer tenure, CEOs become increasingly averse to making layoffs during the holiday season even conditional on making a layoff in a given year. This *within-year layoff timing* is particularly indicative of CEO prosociality as an underlying mechanism and difficult to reconcile with alternative explanations based on some omitted variable that affects both tenure and layoff propensity.

Our paper contributes to several literatures. First, our findings advance the literature on the effects of CEOs' job duties and stress. Bandiera, Lemos, Prat, and Sadun (2018) and Bandiera, Prat, Hansen, and Sadun (2020) document the intense demands and long work hours of CEOs and particularly non-family-firm CEOs. The interviews in Hallock (2005) provide first-hand evidence from high-level managers on the taxing nature of layoff decisions in particular. More directly related to our analysis, Yen and Benham (1986) and Borgschulte, Guenzel, Liu, and Malmendier (2022) provide evidence that plausibly exogenous variation in CEOs' job demands implies significant health consequences in terms of aging and mortality. We extend these prior findings by showing how, in spite of the high-stress top CEOs are under in general, specific decisions such as layoffs have significant long-term adverse effects on CEO health.

Second, our findings shed light on how CEO prosocial concerns influence firms' labor demand choices. Landier, Nair, and Wulf (2009) find that firms are less likely to implement layoffs in divisions located closer to the headquarters. They do, however, not examine how the geographic layoff propensity varies with CEO tenure (nor do they study any other managerial characteristics) and can measure layoffs only indirectly as a decrease in the number of employees in a given division. In contemporaneous work, Keum and Meier (2020) provide evidence that firms (and especially firms with internally promoted and Democratic CEOs) make more layoffs after state-level expansions of unemployment insurance. Two shortcomings of their approach are that, they too, do not measure actual layoffs but changes in firm-wide net employment count and measure unemployment benefit variation in the headquarters' state as opposed to the worker state that determines benefits. Consistent with gender differences in managerial preferences towards workers, Matsa and Miller (2013, 2014) find evidence of fewer employment reductions in female-owned private firms in the U.S. during the Great Recession and firms with a board gender quota in Norway. Consistent with "place attachment," Yonker (2017) finds that following industry distress, establishments in CEOs' hometowns are less likely to see pay or employment reductions. These papers also examine employment changes rather than firing. Our comprehensive data on *actual* layoff announcements help us test for CEO social preferences from a variety of complementary and well-measured angles.

With respect to CEO tenure effects, Pan, Wang, and Weisbach (2016) are the first to document a link with disinvestment (including asset sales, i.e., physical-capital disinvestment), but they do not focus on CEO social preferences as a potential underlying channel. Focusing on manufacturing firms, Bai and Mkrtchyan (2023) find that after the appointment of an external (vs. an internal) CEO, more factories are closed or see employment reductions. We find similar effects of external CEOs on the propensity to make layoffs in our data, including in non-manufacturing firms, and propose social preferences of internal

CEOs with more pre-existing relations as one underlying mechanism. Our findings also connect to Acemoglu, He, and le Maire (2022) finding that CEOs with a business degree pay employees lower wages, as well as to the "social economics and finance paradigm" in Hirshleifer (2020) calling for more work on the "social processes that shape economic thinking and behavior."[6] Broadly speaking, we contribute to the research on nonstandard managerial decision-making (see Malmendier 2018 and Guenzel and Malmendier 2020 for recent surveys).

By focusing on CEO social preferences related to employees, we also provide a complementary angle to prior work on CEO preferences and employees that have, instead, focused on CEO entrenchment. A large literature documents increased managerial slack in response to being protected from job removal due to anti-takeover laws. In particular, the destruction of old plants and the creation of new plants falls, and more entrenched managers take on less risk and pay their employees more (Bertrand and Mullainathan 2003, Giroud and Mueller 2010, Gormley and Matsa 2016, Cronqvist, Heyman, Nilsson, Svaleryd, and Vlachos 2009). Previous work has also studied how entrenchment affects CEO compensation and the composition of observable versus hidden pay (Kuhnen and Zwiebel 2008). Our results are distinct from this prior work as they obtain within and across different levels of CEO entrenchment.

The rest of the paper is structured as follows. Section 2 introduces a simple conceptual framework. Section 3 describes the data. Sections 4 and 5 present our results. Section 6 concludes.

2. Conceptual Framework

To fix ideas, we first discuss a stylized conceptual framework that extends the classical model of firm production decisions to incorporate behavioral labor adjustment costs.

Setup. There are two periods. In both periods, the manager of a firm chooses capital (k) and hires labor (n) to maximize profits. The firm has Cobb-Douglas production with

[6] Our findings also relate Jenter and Lewellen (2015) showing that managerial preferences are influenced by social norms (in the context of retirement choices), Taylor (2010) estimating large personal *board member* disutility costs (which could reflect a distaste for firing) to explain low CEO turnover rates, as well as Cheng, Hong, and Shue (2013) and Cronqvist and Yu (2017) who are also concerned with CEO social preferences but study CEOs' corporate social responsibility rather than labor demand.

capital share $\alpha \in (0,1)$ and labor share $\nu \in (0,1)$, and i.i.d. stochastic productivity shocks a_t (with positive density over the support $[\underline{a}, \bar{a}]$, $\bar{a} > \underline{a} > 0$) realized at the beginning of each period. The firm is a price taker for both rental cost of capital (r) and wages (w) and faces no classical capital or labor adjustment costs, i.e., it can adjust factor inputs at no cost to the firm in both periods. In the absence of classical adjustment costs, we assume decreasing returns to scale ($\alpha + \nu < 1$), to ensure that the solution is not degenerate.

Whereas classical adjustment costs are absent, the firm's manager incurs a behavioral adjustment cost (c_t), i.e., a *personal disutility* cost, when reducing the labor force through layoffs ($\Delta n_t \equiv n_t - n_{t-1} < 0$), given by

$$c_t(\Delta n_t) = \begin{cases} 0 & \Delta n_t \geq 0 \\ \delta_t - \gamma_t \Delta n_t & \Delta n_t < 0. \end{cases}$$

The behavioral adjustment cost includes both a fixed component ($\delta_t > 0$), reflecting heterogeneities in social-preference characteristics across managers, as well as a variable component ($\gamma_t > 0$) that depends on the size of a layoff. The degree of behavioral adjustment costs can also vary over time. In the empirical analysis below, we will, for example, examine time variation that arises from managers forming more connections inside the firm throughout their tenure and from variation in the consequences for affected employees (e.g., layoffs during recessions versus tranquil times).

We assume for simplicity that the manager is aware that she might incur disutility costs from layoffs in the future and that she knows her social-preference parameters γ_t and δ_t ex-ante.[7] Finally, we assume that the firm has no employees at the outset ($n_0 = 0$), such that the first-period behavioral adjustment cost is always zero.

Firm Behavior and Predictions. In period 1, the manager subject to behavioral adjustment costs maximizes

$$\max_{n_t, k_t} a_1 n_1^{\nu} k_1^{\alpha} - w n_1 - r k_1 + E\left[a_2 n_2^{\nu} k_2^{\alpha} - w n_2 - r k_2 - c_2(\Delta n_2)\right]. \tag{1}$$

[7] All our predictions below generalize to the case when the manager is only partially sophisticated or naïve about future disutility costs from conducting layoffs (see Internet Appendix Section I.1 for details).

In period 2, a_2 is realized and the manager maximizes

$$\max_{n_2,k_2} a_2 n_2^{\nu} k_2^{\alpha} - wn_2 - rk_2 - c_2(\Delta n_2). \tag{2}$$

The key result of the framework with respect to layoff decision-making materializes in period 2 after workers have been hired in period 1.

Proposition 1. *Denote the optimal labor decision in period 1 by a standard manager who faces no behavioral labor adjustment costs by n_1^*, and that in period 2 by n_2^*. Then, in period 2:*

(i) [Layoff propensity] A social-preference manager has a lower propensity to make layoffs compared to a standard manager. Specifically, there exists a range of a_2 where $n_2^* < n_1^*$, but where a social-preference manager does not make layoffs.

(ii) [Layoff size] When a_2 is sufficiently small such that the social-preference manager makes a layoff, she lays off fewer employees compared to a standard manager.

(iii) [Heterogeneity in the degree of social preferences] Similar to (i) and (ii), compared to a manager with low social-preference parameters, a manager with high social-preference parameters has a lower propensity to make layoffs and, when making a layoff, lays off fewer employees.

Proof. See Internet Appendix Section I.1. □

In a nutshell, managerial social preferences induce a personal disutility cost of firing. This leads to an inaction region of no layoffs, lowering the manager's layoff propensity. Beyond the no-layoff cutoff, social preferences induce a reduction in layoff size. Finally, the stronger social-preference motives, the more pronounced the effects on layoff propensity and size.

Graphical Illustration. We can convey the main insights of the conceptual framework also graphically using data from the model when solved numerically. Figure 1 displays the change in labor choice in period 2 compared to the chosen period-1 labor level as a function of period-2 productivity, setting the period-1 productivity level and other parameters to the values specified in the figure notes. The figure compares the manager's labor choice when subject to high and low behavioral labor adjustment costs (red and orange line, respectively), and when not subject to behavioral costs (blue line). (Internet Appendix Section I.2 contains further details and figures from the numerical solution.)

When productivity is high, all managers hire additional employees.[8] With medium productivity, the social-preference managers remain at their period-1 labor choice to avoid the layoff disutility cost, whereas the standard manager continuously adjusts labor downward. This result reflects the lower layoff propensity of social-preference managers. When productivity is even lower, all manager types make a layoff, though the size of the workforce reduction is smaller when the manager faces (higher) behavioral labor adjustment costs.

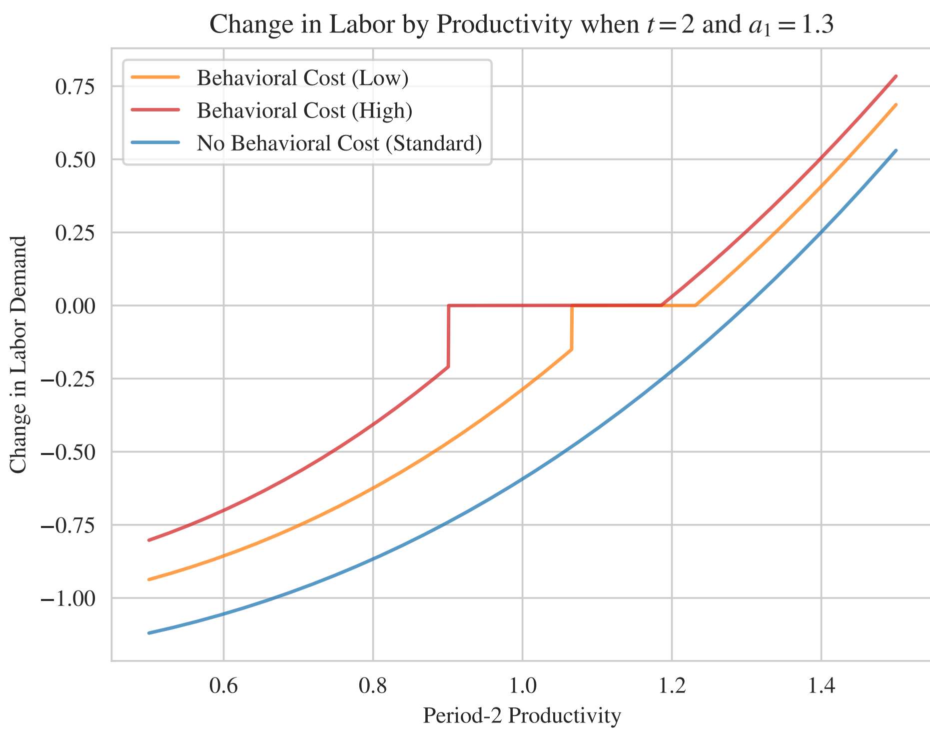


Figure 1. Change in Labor Demand (Period 2 Vs. Period 1)

The figure plots the change in labor demand in period 2 compared to period 1 for different realizations of a_2 both with and without behavioral costs, conditional on the choice of n_1 for $a_1 = 1.3$. The parameters used are $a_t \sim \mathcal{U}$ with $\underline{a} = .5$ and $\bar{a} = 1.5$, $\alpha = 0.2$, $\nu = .4$, $r = 0.2$, $w = 0.5$, $\delta^{high} = 0.005$, $\gamma^{high} = 0.1$, $\delta^{low} = 0.0025$, and $\gamma^{low} = 0.05$.

[8] The social-preference managers increase labor slightly more as in the first period they "shade" hiring in anticipation of possible future layoffs. We fully characterize the period-1 choices under social-preference and standard decision-making in Internet Appendix Section I.1.

3. Data

This section discusses our data and descriptive statistics, with an emphasis on our newly assembled layoff dataset for Execucomp firms since the 2000s. Further details about data sources, data processing, and variable definitions are contained in Internet Appendix Section IV.

3.1 New 2000-2020s Layoff Dataset

The starting point for the construction of our new dataset on layoff announcements since the 2000s is the Standard and Poor's (S&P) Capital IQ Key Developments database, specifically the category of "Potential Red Flags/Distress Indicators" subcategory of "Discontinued Operations/Downsizings." The data begins robustly in 2002 (Edmans, Goncalves-Pinto, Groen-Xu, and Wang 2018; Cohn, Gurun, and Moussawi 2020). Since we rely on Execucomp for details about CEOs (see Section 3.2.1), our data collection focuses on all firms in Execucomp from 2002 to 2020, leading to approximately 18,000 key developments in the relevant category in the database. We restrict our analysis to 02/2020 and earlier, i.e., omit the COVID-19 period.

Each key development entry in the database includes a date, a headline, and a situation summary which is a short news-like text description. The content is based on a variety of sources including news aggregators, stock exchanges, and regulatory websites as well as company websites.

We use a mix of NLP techniques and hand-coding to classify each key development text item as a layoff, closure (e.g., factory, branch, etc.), or neither. Since many closures are likely to result in layoffs, especially when closing entire plants or branches, we treat them as layoff events, *unless* the key development specifically mentions that a closure comes with no layoffs, e.g. due to employee reassignments. More broadly, we specifically identify layoff announcements as opposed to business sales without effects on employees, and in particular involuntary layoffs as opposed to employee reassignments or voluntary departures such as early retirement. We drop any duplicate layoff announcements and also collect the number or percent of employees laid off and layoff locations, up to the city level for U.S. locations and to the country level for foreign layoffs.[9]

We also use NLP techniques to obtain additional detail on the types of employees laid off, in particular, whether a layoff involves blue- or white-collar workers. To identify layoff types, we lemmatize the words of each key development description to identify the 500 most common words in the sample overall, and among those keywords that indicate blue- (e.g., factory, plant), pink- (service-oriented jobs; e.g., retail, store), and white-collar (e.g., corporate, headquarters) layoffs. We then use these keywords to categorize our layoff events as blue-, pink-, or white-collar layoffs and verify that the resulting classifications are sensible using city-level data on occupation frequencies from the 2000 U.S. Census (see Internet Appendix Section IV for additional details).

3.2 Other Data

3.2.1 2000–2020s Firm and CEO Data

We combine the new layoff dataset from Section 3.1 with standard firm and CEO data from CRSP, Compustat, and Execucomp. Data on CEO, CFOs, and their tenure comes from Execucomp. For CEOs, we base the length of tenure on the year the CEO took the position or calculate it using the full Execucomp dataset since 1992. We identify CFOs using Execucomp's classification or following Jiang, Petroni, and Wang (2010) and identifying CFOs by the title. For CFOs, we always calculate tenure based on their Execucomp coverage. Furthermore, to identify exogenous CEO changes, we merge in the new open-source database of CEO turnovers and dismissals by Gentry, Harrison, Quigley, and Boivie (2021), which contains classifications for CEO turnover.

Data on firm characteristics come from Compustat. We use log assets and log employees as proxies for firm size. Firm profitability is measured as operating income before depreciation divided by assets. We lag these variables in all analyses. Stock price data comes from The Center for Research in Security Prices, LLC (CRSP). Cumulative abnormal

[9] Pan, Wang, and Weisbach (2016) use the same data source to create their downsizing announcement measure based on whether a firm is included in the "Seeking to sell/divest" or "Discontinued Operations/Downsizings" categories in a given month. Their downsizing measure is broader and includes asset sales, i.e., physical-capital disinvestment. As described, we construct a pure human-capital-based measure to isolate a social preferences channel and specifically focus on involuntary layoffs that result in unemployment of affected workers (unless they can find a new job at an unrelated firm that is outside the control of the firms of interest making the layoff announcements).

returns are based on the market-adjusted model.[10] Similar to prior work (Opler and Titman 1994; Acharya, Bharath, and Srinivasan 2007; Babina 2020), throughout the paper we define an industry-year as in distress if the median firm's stock price declined by at least 30% in the prior two years or the prior and current year.[11] We also use governance data from the Institutional Shareholder Services (ISS, formerly RiskMetrics), to calculate measures of entrenchment and co-opted directors, described further in Section 5.2.

We refer to this firm panel, covering 2,779 unique firms, as our *2000–2020s firm-layoffs sample*.

3.2.2 1970–1990s Layoff Data and CEO Long-Term Mortality Data

To study long-term CEO health outcomes associated with implementing layoffs, we rely on an earlier layoff dataset from Hallock (1998), Billger and Hallock (2005), and Farber and Hallock (2009). This dataset covers all firms ever listed in the *Fortune 500* between 1970 and 1999 and provides a comprehensive list of layoff announcements collected from the *Wall Street Journal*. The *Wall Street Journal* Index's abstracts are searched by company name and then examined to find layoff announcements.

We intersect this layoff dataset with the mortality dataset from Borgschulte, Guenzel, Liu, and Malmendier (2022), covering all CEOs included in the *Forbes* Executive Compensation Surveys from 1975 to 1991.[12] These surveys are based on corporate proxy statements and include the executives of the largest U.S. firms. All firms with a PERMNO identifier in CRSP are included. The exact dates of CEOs' birth, whether a CEO has died, and the date of death, if the CEO has passed away, were sourced from ancestry.com, newspapers, and obituaries. CEOs who did not pass away by the cutoff date of October 1st, 2017 are censored. We refer to Borgschulte, Guenzel, Liu, and Malmendier (2022) for further details on the dataset construction.

After further merging with Compustat and CRSP control variables, the final dataset, which we refer to as the *CEO long-term mortality sample*, contains 31,917 CEO-year observations from 1,131 CEOs across 658 firms.

[10] For the market return, we use the value-weighted return on the NYSE, AMEX, NASDAQ, and ARCA exchanges.

[11] We find that this definition of distress is even more strongly associated with layoff activity in our comprehensive dataset than an alternative definition based on forward-looking two-year stock price changes.

[12] This is an extension of the data in Gibbons and Murphy (1992).

3.3 Descriptive Statistics

3.3.1 2000–2020s Firm-Layoffs Sample

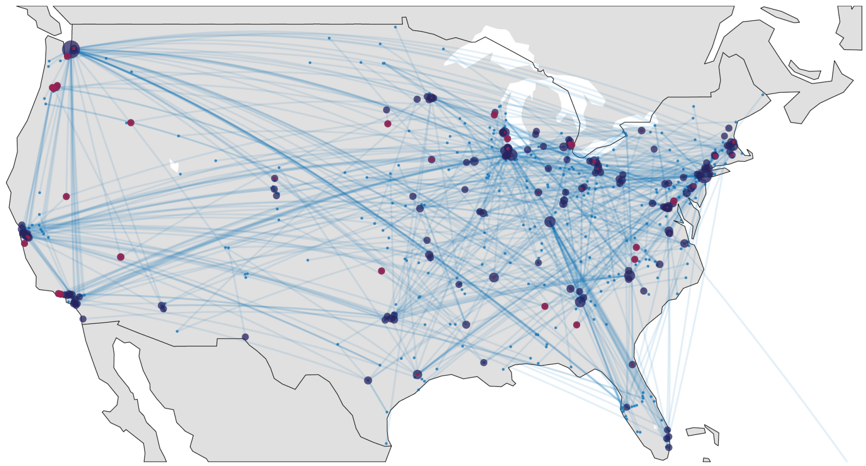
Table 1 Panel a presents summary statistics for the *2000–2020s firm-layoffs sample*. One observation corresponds to a CEO-firm year. The average CEO tenure is 8 years compard to an average CFO tenure of 5 years. Close to 20% of observations are firm-years in industry distress. 13% of CEO-firm years are classified as layoff-years. We require a firm to lay off at least 1% of the workforce or have three separate layoff events to be classified as a layoff-year in the *2000–2020s firm-layoffs sample* (except when we study location-specific or month-specific layoff activity in Tables 7 and 9), to focus on meaningful layoff activity by firms. [13] That said, our results are robust to using a layoff indicator based on any layoff activity in a given year.

Figure 2 shows the geography of layoffs for two years in our sample: 2009 and 2015. The geographic spread of layoffs is substantial, as visible by the lines connecting firms' headquarters (dark blue dots) and layoff locations (light blue dots). Purple dots identify layoffs in the headquarters-city layoffs, which are rare compared to more distant layoffs. Comparing the two maps, general layoff activity across firms in our sample was much higher in 2009 and 2015.

Figure 3a decomposes layoffs across time. The number of layoffs peaks during the Great Recession and is lower than average in recent (pre-COVID-19) years where unemployment has been very low (Petrosky-Nadeau, Valletta, et al. 2019). Figure 3b sheds light on how good of a proxy firms' net employment change from Compustat is for layoff activity. The figure plots the distribution of year-over-year net employment change (in percent) for firm-years with no layoffs in our sample (top figure), as well as firm-years with small, medium, and large (bottom figure) layoff activity. With increasing layoff activity, the firm size distribution shifts to the left, implying both variables are related. Yet, there remains a large dispersion in the employment change distribution within each layoff activity group, including firms shrinking despite no layoffs and growing despite high

[13] For firm-years with fewer than three layoffs and that do not meet the 1% layoff size criterion but have missing information on layoff size for at least one of the layoff events, we manually search on the web and LexisNexis to obtain this information, to ensure a high-quality dataset and precise definitions of variables. We are able to find the layoff size information for about 10% of these layoff events, suggesting that this information is usually included in the key development text when it is publicized.

(a) Layoffs in 2009



(b) Layoffs in 2015

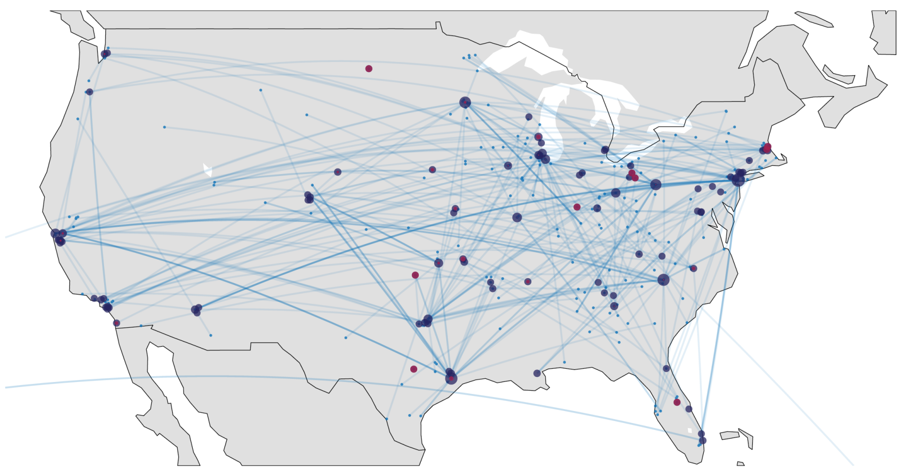
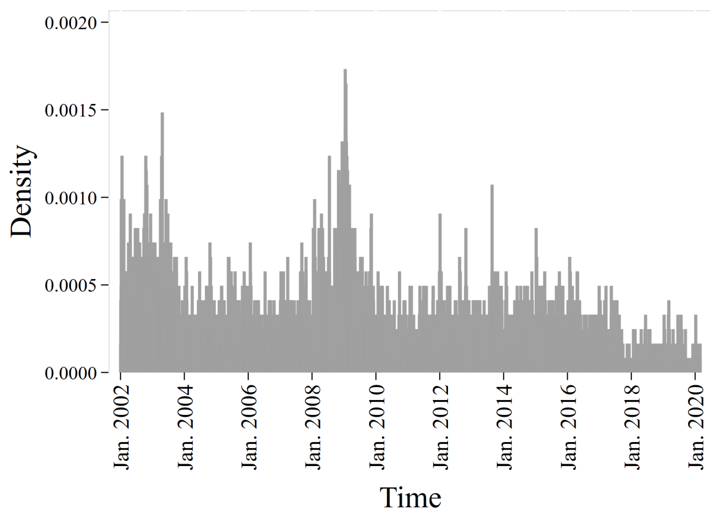


Figure 2. Layoffs Across Space

Lines connect firms' headquarters' and layoff locations. Dark (light) blue dots identify headquarters' (layoff) locations. Purple dots identify headquarters-city layoffs. Panel (a) plots layoffs in 2009. Panel (b) plots layoffs in 2015. Data on layoffs hand-coded using S&P Key Developments data.

(a) Layoffs by Month



(b) Layoffs Versus Net Employment Change

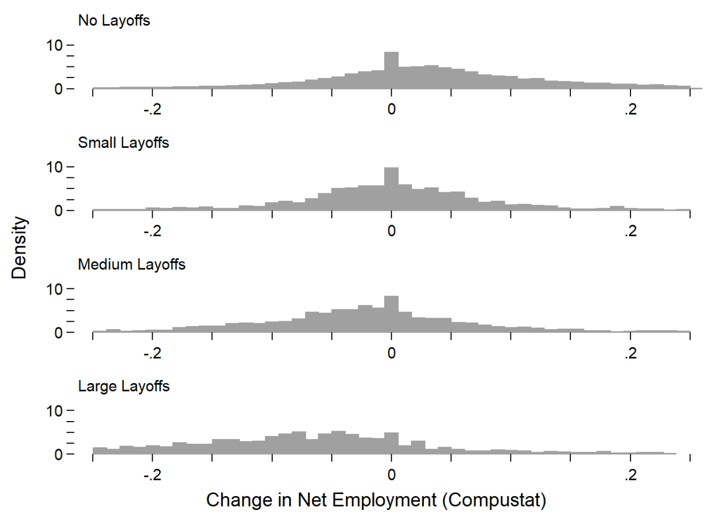


Figure 3. Layoff Events

Panel (a) plots the number of layoffs from our sample by month. Panel (b) plots the distribution of year-over-year net employment change (in percent) for firm-years with no layoffs in our sample (top figure), as well as firm-years with small, medium, and large (bottom figure) layoff activity. Data on layoffs hand-coded using S&P Key Developments data.

layoff activity. Overall, we conclude that changes in the net employment count are not completely uninformative but a highly imprecise proxy of layoffs.

Finally, Figure IA.5 in the Internet Appendix decomposes layoffs by industry. The industries with the most layoff observations are retail trade, which features seasonal labor demand (Anderson 1993), and the manufacturing sector, which has been particularly affected by offshoring and automation (Slaper 2019).[14]

3.3.2 CEO Long-Term Mortality Sample

Table 1 Panel b presents summary statistics for our *CEO lont-term mortality sample*. We present observations at the CEO level. The average year born was 1928, and the average year of death is 2010. 11% of CEOs experienced a distressed layoff and 38% experienced a non-distressed layoff. 43% of CEOs experienced industry distress. Firm size and profitability measures are from the year of appointment. The minimum stock performance, defined as the worst stock performance in any six-month period during a CEO's tenure, is −30% on average in our sample.

4. Personal Cost of Firing for CEOs: Layoffs and CEO Long-Term Mortality

We first examine personal long-term consequences for CEOs associated with implementing layoffs, as a direct way to detect firing-induced "disutilty costs" that reflect CEOs' prosocial concerns. We specifically examine long-run costs in the form of reduced long-term health and accelerated mortality. This builds on recent work by Borgschulte, Guenzel, Liu, and Malmendier (2022), who document adverse aging and mortality outcomes for CEOs arising from more stressful work environments.

Similar to Borgschulte, Guenzel, Liu, and Malmendier (2022), we estimate survival models to detect predictors of CEO mortality in the *CEO long-term mortality sample*. The key variable of interest is whether the CEO implemented a layoff during their tenure. We

[14] Note that these statistics abstract from the distribution of firms within our sample. For example, 40% of firms in our sample are in the manufacturing sector which accounts for about 20% of years with a layoff. Meanwhile, only 8% of firms are in the retail trade sector which accounts for about 25% of years with a layoff.

allow for heterogeneous CEO long-term mortality effects by layoffs implemented during industry distress and those during non-distressed times. Layoffs during economy-wide or industry downturns are particularly painful and damaging for affected workers (Anderson 1993, Martin 2005, Hallock 2005; cf. also footnote 5). Downturns may also frequently force firms to lay off employees for reasons unrelated to their performance (cf. footnote 5). Both aspects suggest particularly high and detectable CEO disutility costs associated with layoffs in times of crisis. We thus estimate:

$$\begin{aligned}\text{Prob}(CEODeath_{i,t}) = \alpha + \beta_1\, DistressLayoff_{i,t} + \beta_2\, NonDistressLayoff_{i,t} \\ + \gamma_1 IndustryDistress + \boldsymbol{X}'_{i,t}\gamma_2 + \varepsilon_{i,t}\end{aligned} \tag{3}$$

where $CEODeath_{i,t}$ is one if CEO i passes away in year t and zero otherwise, $DistressLayoff$, $NonDistressLayoff$, and $IndustryDistress$ are indicator variables for a CEO's cumulative experience of distress layoff, non-distress layoff, and industry distress, respectively. $\boldsymbol{X}$ is a vector of control variables, and we also include fixed effects as discussed below.

In Table 2, we first estimate simple, familiar logit models with an explicit event time control.[15] As in Borgschulte, Guenzel, Liu, and Malmendier (2022), one observation corresponds to a CEO-year and we continue to follow CEOs over time after they leave the CEO position until they pass away or the censoring date is reached. In Column (1), we include our main variables of interest, distress layoff, and non-distress layoff experience, as well as an indicator for lagged distress itself, the CEO's age, firm controls, and a linear year control. We also include HQ state fixed effects as well as industry fixed effects as included in Borgschulte, Guenzel, Liu, and Malmendier (2022). We cluster standard errors at the industry level as this is the level at which distress experience is defined (Abadie, Athey, Imbens, and Wooldridge 2017).

We find a significant adverse effect of distress layoff experience on mortality, consistent with such layoff experiences leaving marks. The coefficient estimate of +0.294, significant at 5%, implies that the mortality effect of distress layoff experience corresponds to that of an increase in age by 1.85 years. This effect is large but of the same magnitude as the mortality effects associated with more stressful job environments documented in Borgschulte, Guenzel, Liu, and Malmendier (2022). By contrast, we find no evidence for

[15] See Efron (1988), Jenter and Kanaan (2015), and Guenzel (2023) for more details and finance applications of this approach.

mortality effects associated with layoffs during non-distressed times. In Column (2), we replace the linear year control with year fixed effects, which makes no difference in the estimation.

One potential confound for the analysis and interpretation of Columns (1) and (2) is that layoff events may simply be a proxy for distress experience that is *generally* worse. In other words, one might be worried about an omitted variable related to industry distress that drives both distress layoffs and mortality. To alleviate this concern, in Column (3), we control for the worst stock performance in any six-month period during the CEO's tenure (up to each given CEO-year). Intuitively, this variable captures the severity of (endogenous) firm distress over the course of a CEO's tenure and introduces variation in "CEO experience" holding fixed whether a CEO has experienced industry distress. With the addition of the minimum stock performance control, we estimate a distress layoff effect on mortality corresponding to a 1.76-year increase in age. That is, the coefficient of interest on distress layoff experience is barely affected. This suggests that our results are not driven simply by "bad distress" but specifically by the effect of distress-induced layoffs.

Robustness. We include several robustness tests in the Internet Appendix. First, we repeat our logit estimations in Table 2 using Cox (1972) hazard models instead. As to be expected given the close link between logit models (with an explicit time control) and hazard models, we find very similar results for the hazard models (Internet Appendix Table IA.1). Second, in Internet Appendix Tables IA.2 and IA.3, we repeat the logit and the hazard models adding a control for CEOs' cumulative tenure, in light of our previous results that longer-tenured CEOs are less likely to initiate layoffs. We omit the CEO tenure control in our preferred specification, in line with Borgschulte, Guenzel, Liu, and Malmendier (2022), since distress (and layoff) experience may themselves affect tenure length. In practice, adding CEO tenure as a control makes little difference. Longer tenure is associated with decreased mortality, suggesting that healthy, resilient CEOs select into serving as CEO for longer. At the same time, we continue to estimate adverse mortality effects of distress layoff experience of very similar magnitude as before, as well as an insignificant effect of non-distress layoff experience on mortality rates.

5. CEOs' Effect on Firms' Layoff Decision-Making

Having established a direct and personal cost of firing for CEOs, indicative of the existence of prosocial concerns of CEOs, this section examines whether and how CEOs' prosocial considerations affect their labor decision-making in-office, using our new, comprehensive layoff dataset, i.e., the *2000–2020s firm-layoffs sample*.

5.1 CEO-Related Frictions in Firms' Layoff Decisions

We first test for baseline CEO-related frictions in firms' labor decisions. We examine how firms' layoff propensity varies around plausibly-exogenous CEO changes, and how the market reacts to layoffs by exogenously appointed CEOs. We use in-office death or sickness of the incumbent CEO to categorize plausibly-exogenous CEO changes. Of course, this approach does not achieve of the gold standard of an "RCT-style" random assignment, but is the standard approach (and arguably most stringent among the feasible options) in the literature (e.g., Fee, Hadlock, and Pierce 2013). We note this approach is not inconsistent with our previous findings in Section 4, since the differential mortality patterns by CEO layoff experience *only* materialize in the long-run *after* CEOs have stepped down (and have retired). Further, we will also show that the identified exogenous CEO departures are not associated with any visible or statistically significant pre-trends in terms of key variables of interest (i.e., layoff propensity).

Stacked Difference-in-Differences Analysis. There are 111 CEOs in our *2000–2020s firm-layoffs sample* who depart due to death or illness as per the Gentry, Harrison, Quigley, and Boivie (2021) database. Since these plausibly-exogenous CEO events happen at different points in time, a standard two-way fixed effects regression approach would result in bias in general (Goodman-Bacon 2021).

Instead, we implement a *stacked difference-in-differences* analysis similar to Gormley and Matsa (2011) and as advocated by Goodman-Bacon (2021). Specifically, for each year with an exogenous CEO change due to death or illness, we construct a cohort of treated firms and untreated firms in the same three-digit SIC industry. We follow these cohorts from five years before to five years after the year of the CEO's death or illness, and restrict the post-period to the first new CEO after the CEO change. As in Gormley and Matsa

(2011), we do not require firms to be in the data for all ten years around the event year. We then aggregate the cohort-event-time data across cohorts into one panel and estimate the following regression:

$$\begin{aligned} Layoff_{j,k,c,t} = \alpha + \alpha_{k,c} + \alpha_{c,t} + \beta_1\, ExogCEOChange_{j,k,c} \\ + \beta_2\, ExogCEOChange_{j,k,c} \times Post_t + \varepsilon_{j,k,c,t} \end{aligned} \tag{4}$$

where j refers to a firm in industry k and a member of cohort c at time t. $Layoff_{j,k,c,t}$ is an indicator for layoff-years as described in Section 3.3 and $ExogCEOChange_{j,k,c}$ identifies treated firms with an exogenous death- or illness-driven CEO departure. $Post_t$ identifies post-treatment years. To reduce the residual variance and improve precision, we also include the firm control variables from Panel a of Table 1 and allow coefficients on the controls to vary between the pre- and post-period (Angrist and Pischke 2009). $\alpha_{k,c}$ are cohort-SIC3-industry fixed effects that account for time-invariant, within-cohort differences between industries. $\alpha_{c,t}$ are cohort-year fixed effects that control for time trends. As a result, the $Post_{c,t}$ indicator is absorbed. We now cluster at the firm level at which "treatment" is assigned (Abadie, Athey, Imbens, and Wooldridge 2017).

Figure 4 presents the stacked difference-in-differences results graphically, slightly modifying Equation (4) by allowing for time-varying coefficients on the interaction term of interest (β_2). (Internet Appendix Table IA.4 contains the table version corresponding to Equation (4).) The figure reveals a sizable increase in firms' layoff propensity following an exogenous CEO change. Prior to the CEO change, treated and control firms are similar with respect to their layoff propensity, consistent with no pre-trends and parallel trends in the couterfactual state being satisfied. The layoff propensity spikes for firms with exogenously replaced CEOs in the year after the CEO transition and remains elevated afterwards.

These results provide direct support for the existence of frictions in firms' layoff decisions associated with incumbent CEOs—the average exogenously replaced CEO served for seven years prior to their departure due to death or sickness.

Checks for Potential Confounds. While the evidence in Figure 4 is consistent with many layoffs needing a "catalyst event" and a disruption in the social connections between CEO and employees, we perform a series of additional tests to assess the plausibility of this interpretation. First, using the data from the pre-period, we find that firm characteristics

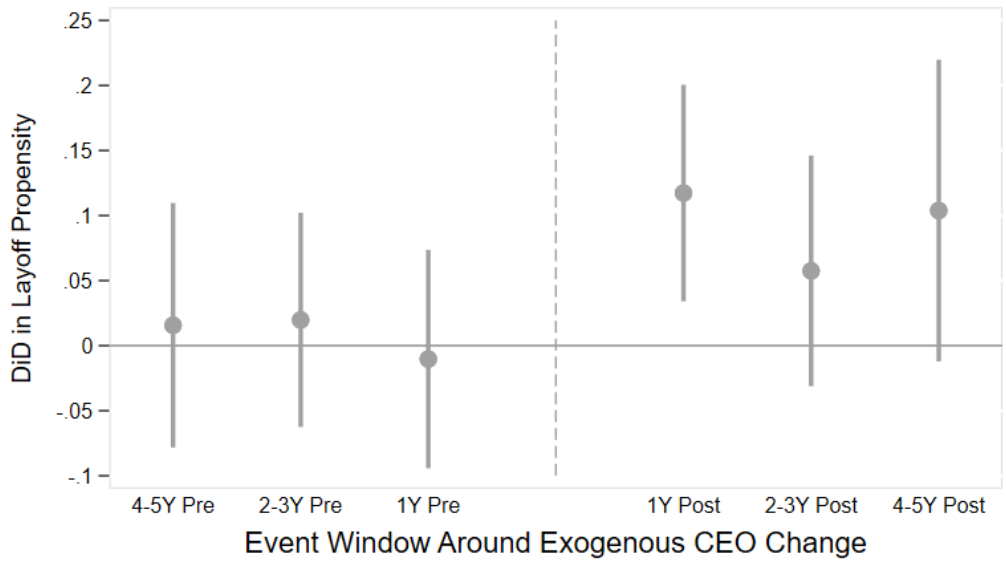


Figure 4. Layoff Propensity Around Exogenous CEO Changes

The figure plots the change in layoff propensity around exogenous CEO departures relative to non-treated firms (stacked difference-in-differences analysis; see Equation (4)). Exogenous CEO changes are defined as those occurring due to CEO death or illness of the incumbent CEO and come from Gentry, Harrison, Quigley, and Boivie (2021). See Section 5.1 for additional details. The figure also plots 95% confidence intervals based on standard errors clustered at the firm level.

such as assets, employees, and profitability do not predict CEO death- and health-related departures. This is further consistent with these CEO events being indeed plausibly exogenous. Second, we do not see evidence that the exogenously replaced CEOs were a superior match for their firm (which could explain a shift in corporate strategy after their departure). The average announcement return of the exogenous CEO departures in our sample is insignificantly *positive* (avg. CAR $= 0.36\%$, $p = 0.51$). Third, we implement a Romer and Romer (2010)–style narrative approach of the layoff announcement descriptions after exogenous CEO turnovers. None of the layoff descriptions mentions a shift in strategy due to a different CEO-firm skill match as a layoff reason. Finally, we implement a placebo test with firm leverage instead of layoff propensity as the outcome of interest and find neither pre- nor post-trends with respect to the financial side of the firm (Figure 5). This finding is consistent with Fee, Hadlock, and Pierce (2013), who similarly do not find significant changes in leverage (as well as book asset growth or ROA) around exogenous CEO turnovers.

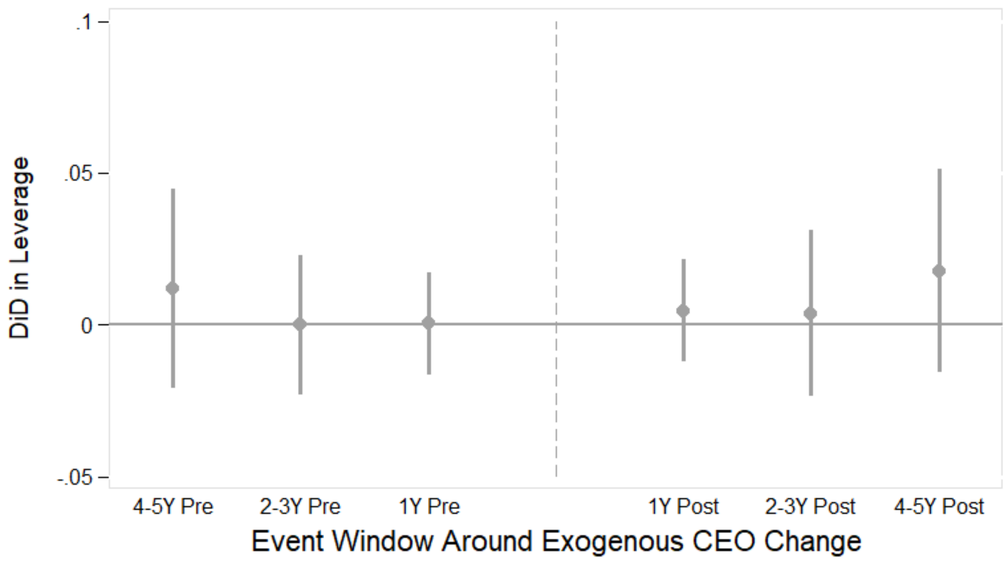


Figure 5. Placebo Test

The figure plots the change in firm leverage (long-term debt over assets) around exogenous CEO departures relative to non-treated firms (stacked difference-in-differences analysis; see Equation (4)). Exogenous CEO changes are defined as those occurring due to CEO death or illness of the incumbent CEO and come from Gentry, Harrison, Quigley, and Boivie (2021). See Section 5.1 for additional details. The figure also plots 95% confidence intervals based on standard errors clustered at the firm level.

Market Reaction to Layoffs After Exogenous CEO Turnovers. To argue that the differential layoff behavior of firms with exogenously replaced CEOs is evidence of frictions prior to the CEO replacement, we also study how investors react to layoffs made by the newly appointed CEOs. Across our entire sample, the average layoff announcement comes with a slight negative market reaction of -0.3% (unreported). Figure 6 plots average layoff announcement returns for the difference-in-differences sample from Figure 4 in the post-period, separately for the control firms (i.e., firms with no exogenous CEO change) and treated firms (i.e., firms with a new, exogenously appointed CEO).

Layoff announcements in the post-period period by control firms trigger a slight negative market reaction on average, similar to the full sample mean. By contrast, layoff

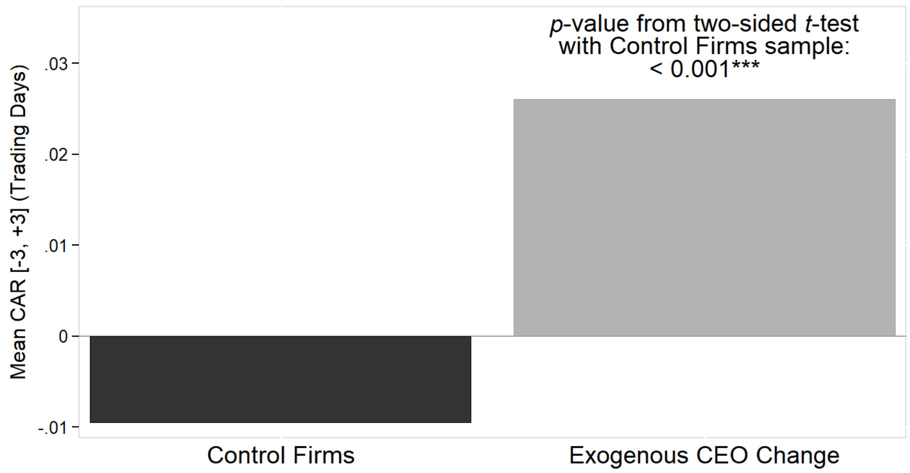


Figure 6. Layoff Announcement Returns After Exogenous CEO Changes

announcements by treated firms trigger a pronounced positive reaction on average (CAR $= +2.61\%$). The difference in average layoff announcement returns between control and treated firms is highly statistically significant (p-value < 0.001). We can also reject that the announcement return samples have the same median or are from the same distribution at 1% (unreported).

Overall, the evidence in Figures 4 to 6 is consistent with the existence of sizable, CEO-driven frictions in firms' layoff decisions that are detrimental to shareholder value. The evidence is consistent with incumbent CEOs having developed more pronounced social concerns towards workers than exogenously appointed CEOs (i.e., social connections being eliminated, and γ_t and δ_t in the conceptual framework in Section 2 decreasing or being zero, upon CEO replacements), leading to a lower propensity to make layoffs of incumbent CEOs compared to new CEOs (Proposition 1(i) and (iii)).

5.2 Layoffs and CEO Tenure

If the frictions documented in the previous section indeed arise because of more pronounced prosocial concerns of incumbent relative to new CEOs, mapping to the conceptual framework as behavioral adjustment costs (γ_t and δ_t) increasing with CEO tenure,[16] then Proposition 1 predicts that firms' layoff activity should decrease over the course of a CEO's tenure.

Layoff Propensity and CEO Tenure. We first examine the prediction that pronounced behavioral adjustment costs in long-tenured CEOs induce a lower propensity to make layoffs (Proposition 1(i), (iii)). To estimate the relationship between a firm's layoff propensity and CEO tenure, we run the following regression:

$$Layoff_{i,j,t} = \alpha_j + \alpha_t + \beta\, CEOTenure_{i,j,t} + \boldsymbol{X}'_{i,j,t}\gamma + \varepsilon_{i,j,t} \tag{5}$$

for CEO i at the helm at firm j in year t. $Layoff_{i,j,t}$ is an indicator for layoff-years as described in Section 3.3 and $CEOTenure_{i,j,t}$ is accumulated tenure of the CEO measured in years. α_j and α_t are firm and year fixed effects, though below we also estimate models with no or less granular fixed effects. We continue to cluster standard errors at the firm level.

Column (1) of Table 3 finds a strongly negative raw association between layoff propensity and CEO tenure. In Column (2), this relation persists when including lagged firm profitability and an indicator for industry-wide distress, as well as measures of firm size, year fixed effects, location fixed effects, and Fama and French (1997) 49-industry fixed effects (using SIC-3 industry fixed effects produces very similar results).[17]

The layoff–CEO tenure relationship also survives when we add firm fixed effects in Column (3). That is, we do not pick up an effect where firms with long-serving CEOs have a preference (firm culture) for long-term relationships with employees at all hierarchy levels. This interpretation is strengthened in Column (4) when we include, in addition, the CFO's tenure at the firm. While CEO and CFO tenure are meaningfully correlated ($\rho = 0.20$, $p-$value < 0.001), the coefficient on CEO tenure is almost unchanged, suggesting that there is a distinct CEO effect in this setting. In terms of magnitudes, Column (4) estimates

[16] As Levitt and List (2007) discuss, social preferences are expected to be less pronounced among strangers, and more pronounced in the presence of social relations. Consistent with this, Bandiera, Barankay, and Rasul (2005) find that social preferences among (low-ranking) co-workers are stronger when relationships are stronger as measured by friendship networks.

[17] The coefficients on the added control variables in Column (2) all make intuitive sense. More profitable firms are less likely to announce layoffs, whereas larger firms as measured by the number of employees or total assets are more likely to do so. Industry distress makes layoffs substantially more likely, in line with the evidence in Figure 3.

an interquartile increase in CEO tenure to reduce the layoff propensity by 1.5 percentage points, or by 11% relative to the baseline probability of a layoff of 13% (see Table 1). Figure 7 visualizes the relationship between layoff propensity and CEO tenure graphically, plotting the raw relation on the left and the residualized relation (based on Column (4)) on the right.

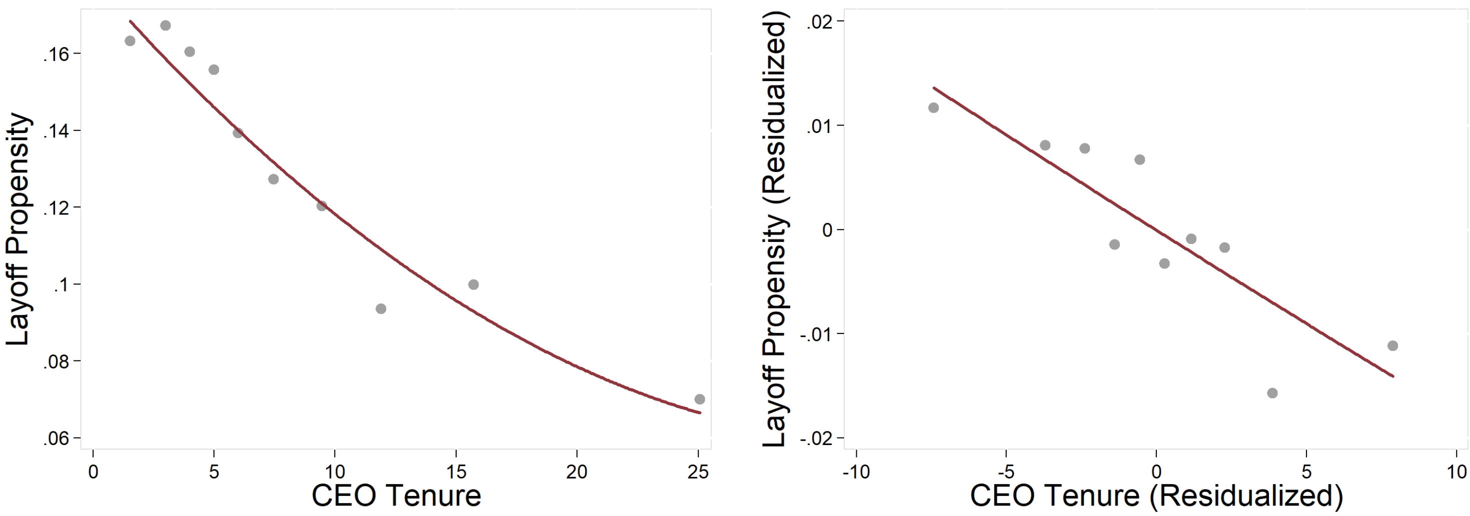


Figure 7. Layoff Propensity and CEO Tenure

The figure shows binned scatterplots of the relation between firms' layoff propensity and CEO tenure. The left figure plots the raw data. The right figure plots the relationship after residualizing on the controls and fixed effects from Column (4) of Table 3.

Comparison With Existing Work. The result in Table 3 builds on previous influential findings by Pan, Wang, and Weisbach (2016), who were the first to document "investment and disinvestment cycles" over the course of a CEO's tenure. In particular, these authors document a reduction in firms' *downsizing* probability with increasing CEO tenure. Like us, they use the Key Developments database to identify downsizings.

A first difference is that their downsizing definition is broader than our layoff definition and includes "non-dismissal" decisions, such as sales of business segments to other entities without effects on employees, as well as employee reassignments. A second difference is that Pan, Wang, and Weisbach (2016) focus on agency explanations for the

CEO investment cycle, specifically showing that patterns in CEOs' investment in *physical* capital are driven by variation in CEO power. By contrast, we focus on social preferences explanations for CEOs' decisions regarding *human* capital and also show below that variation in CEO power does *not* drive their labor-related decisions.

Robustness and Extensions. In Internet Appendix Section II, we include a detailed discussion of several tests we perform to confirm the robustness of the CEO tenure–layoff link. We summarize these tests here briefly. *(i) Additional controls:* The link between layoff propensity and CEO tenure is unchanged when we add additional for employment growth, investment opportunities, and debt maturity (Table IA.5). Thus, the relation is unlikely to be driven by loan covenants or changes in the marginal products of labor or capital. *(ii) Testing for "fixed" CEO differences:* The CEO tenure–layoff link is also not due to "fixed" CEO differences in the propensity to lay off workers, with short-tenured CEOs (in the sense of CEOs with a short *total* tenure) being more layoff-prone, and long-tenured CEOs being less layoff-prone independent of the cumulated tenure up to a certain point (Figure IA.6). *(iii) Time-varying fixed effects:* Our results are robust to state-year and industry-year fixed effects both separately and together as well as together with firm fixed effects (Table IA.6). This suggests our results are not driven by time-varying state or industry trends. *(iv) First year effect:* Our results are robust to dropping the first year of CEOs' tenure, thus we do not simply pick up that CEOs may be hired for the express purpose of undertaking layoffs or that they may face less judgment for layoffs in an initial window (Table IA.7). *(v) IV approach:* Finally, we use an IV approach following Graham, Kim, and Leary (2020) and Altonji and Shakotko (1987) to account for average tenure effects. Using the fraction of a CEO's overall tenure realized until a given point in time as the instrument for the cumulative realized tenure at that time, we confirm that the layoff propensity effects arise indeed *through* a CEO's tenure (Table IA.8).

Mechanism—CEO Power and Co-Opted Directors? As alluded to above, Pan, Wang, and Weisbach (2016) find that with respect to firm investment in *physical assets*, the positive effect of CEO tenure on investment is largely driven by increasing CEO power, in particular the fraction of the board appointed by the incumbent CEO. Motivating the CEO power channel, directors appointed during a CEO's tenure have been picked, at least to some extent, under the CEO's influence, which empire-desiring CEOs may be able to increasingly use to their advantage over their tenure. This idea was first formalized in

Hermalin and Weisbach (1998) (see also Coles, Daniel, and Naveen 2014).

To test the possibility of a mechanism related to CEO power in combination with empire building, we construct a measure of the percent of new directors appointed during a CEO's tenure using data from the Institutional Shareholder Services (ISS). The ISS data covers S&P 1500 firms since 1996 (robustly since 1998) and includes the directors in each year for each firm and the year they became a director.[18] We also create indicator variables for CEO–president and CEO–chairman/woman duality as further measures of CEO power.

In Table 4, we perform "horse race" regressions, as done in the investment rate regressions in Pan, Wang, and Weisbach (2016), with both CEO tenure and the CEO power measures as independent variables. As noted in this prior work, CEO tenure and the fraction of co-opted directors are by construction highly correlated. The first two columns in Table 4 include industry and location fixed effects, and the latter two include firm fixed effects. In Columns (1) and (3), we include only the new CEO power variables, the percent of co-opted directors as well as the duality measures, without including CEO tenure. In this case, we observe a negative link between new directors appointed with layoff probability, implying that increasing CEO power could indeed drive the findings. The duality measures are economically and statistically insignificant. However, when we add CEO tenure in Columns (2) and (4), it is the CEO tenure effect that dominates and retains its sign and economic magnitude.

The fact that the CEO tenure effect remains stable with the added board co-option and duality measures implies that increasing CEO power of empire-desiring CEOs is unlikely to be a primary mechanism of our findings.

Mechanism—CEO Entrenchment? Previous work has found that when CEOs become more protected during their tenure, they shy away from difficult decisions, such as closing plants and negotiating wages, and instead "enjoy the quiet life" (Bertrand and Mullainathan 2003). CEOs also reduce riskiness, for example via risk-reducing acquisitions, even if this negatively affects the stock price (Gormley and Matsa 2016). Thus, increasing CEO entrenchment could be one channel for the CEO tenure–layoff relation.

We investigate the influence of entrenchment in detail in Internet Appendix Section II,

[18] As with the Execucomp data, if no year is listed for the director's first year we use their first year in the data as the start year of their directorship. We also rely on the process of Coles, Daniel, and Naveen (2014) to match the ISS data between the current and legacy samples.

supplementing our dataset with the entrenchment index (E-index) of Bebchuk, Cohen, and Ferrell (2009). We find that the effect of CEO tenure on layoff propensity is *not* confined to CEO-years in the high entrenchment regime. Instead, it is of similar magnitude across entrenchment levels (Table IA.9), which does not support classical entrenchment as being a primary driver of the previous findings.

Layoff Size and CEO Tenure. Our detailed layoff data allow us to also take into account the number of employees laid off. In principle, it could be that layoff announcements of new CEOs—who are presumably still less familiar with many parts of the firm—are more frequent but involve fewer employees per layoff, without the *layoff size* actually changing over the CEO's tenure. By contrast, Proposition 1 (i), (ii), and (iii) jointly predict that social-preference considerations will not solely reduce the layoff propensity but also reduce the layoff size (when defining layoff size as zero in the case of no layoffs).

In Table 5, we replace the layoff indicator from Table 3 with the *fraction of employees laid off* in a given year, defined as zero for non-layoff years. The inclusion of controls and fixed effects is the same as before. We indeed find that CEO tenure also strongly predicts the layoff size. As in Table 3, the CEO tenure coefficient is significant at the 1% level across specifications. Using the more stringent specifications with firm fixed effects, an increase in CEO tenure from the 10th to the 90th percentile is associated with a layoff size effect size about three-quarters as large as that corresponding to industry distress.

5.3 Heterogeneity

In a final step, we study heterogeneity in the effect of CEOs on layoff decisions, guided by the predictions of our conceptual framework in Section 2 as to when prosocial concerns of CEOs for workers should be particuarly pronounced.

5.3.1 Heterogeneity in Consequences of Job Loss

We first focus on heterogeneity in the effect of CEO tenure on layoff propensity by how painful job losses are for workers.

Layoffs During Recessions. Our mortality evidence in Section 4 shows that CEOs' disutility costs of implementing layoffs are particularly large for layoffs during crisis times. Consistent with prosocial concerns being particularly pronounced for "pain–inducing" layoffs during recessions, prior work also shows that the long-term adverse effects of job loss are particularly severe for workers displaced during downturns compared to boom times (Jacobson, LaLonde, and Sullivan 1993).

Combined with the evidence from the previous sections consistent with CEOs' prosocial concerns intensifying as they form more connections over time, we predict that CEOs' tenure-induced prosocial concerns for workers are particularly pronounced in recession times. In the conceptual framework in Section 2, this corresponds to a steeper increase in the behavioral cost components γ_t and δ_t with CEO tenure during recessions.

Table 6 presents the results. The effect of CEO tenure on layoff propensity is approximately twice as large in periods of recessions compared to tranquil times. This holds true across columns, including when we interact all control variables with the distress indicator (Columns (3) and (4)). These results reinforce the social preferences interpretation of the CEO tenure effect from Table 3 and, consistent with theory, indicate heterogeneity in the degree of prosocial concerns based on how bleak the job loss implications for workers are.

Layoffs Around the Holiday Season. A second differentiator in how pain-inducing layoffs are is the time of year (rather than time during the business cycle) when workers are laid off. The interviews with top managers in Hallock (2005) highlight several responses implying reluctance to implement layoffs around the holidays.[19] Similar to the recession evidence above, this predicts that CEOs' tenure-driven prosocial considerations for workers are intensified around the holiday season. (We also observe in the data that December is, *in general*, the month with the lowest probability of firms announcing a layoff, as shown in Figure IA.7 of the Internet Appendix.)

We explore the conjecture regarding layoffs during the holiday season and CEO tenure in Table 7 and find strong support for it. In Columns (1) and (2), we first examine how the unconditional probability of a December layoff depends on the CEO's accumulated tenure. The results are similar with and without firm fixed effects, and imply a reduction in the probability of a December layoff of around 0.5 percentage points for an interquartile tenure shift, which is 25% of the baseline unconditional probability.

In Columns (3) and (4), we examine how the occurrence of December layoffs varies with CEO tenure conditional on the firm announcing a layoff in a given year. Here, an

[19] For example, one senior manager noted that they "didn't want to have layoffs in December for emotional reasons...[not] at Christmas."

interquartile tenure increase is estimated to lower the inclination of a December layoff by about 2.9 percentage points, or 25% relative to the conditional baseline probability. These conditional results are particularly indicative of intensifying prosocial considerations, as they imply a within-year layoff timing, i.e., a *choice* to avoid holiday layoffs that becomes more important to CEOs as they form more connections inside the firm throughout their tenure.

We also note that decreased layoff activity of long-tenured CEOs in December is *not* predicted by a channel where CEOs learn over time to strategically release bad news. Chava and Paradkar (2016) find that investors appear *more* distracted during the December holiday season. Additionally, December layoffs announcements do *not* come with worse announcement returns in the data (unreported; if anything, the point estimate goes in the opposite direction).

Finally, to further buttress these results, Table IA.10 of the Internet Appendix repeats the conditional regressions from Columns (3) and (4) when extending the "layoff year window." We include, in addition, CEO-firm-years with a layoff in the first quarter, or first and second quarter, of the subsequent year, thus taking into account both forward and backward layoff timing. We find very similar results.

5.3.2 Heterogeneity in Intensity of Social Interactions

We next focus on heterogeneity based on the intensity of social interactions between CEOs and employees. The conceptual framework captures this when allowing the variable behavioral cost component to depend on the degree and type of social interactions.[20]

Layoffs of White-Collar Employees. A first way to measure heterogeneity in the intensity of social connections is to examine managers' and employees' social proximity, leveraging our classifications of layoffs as blue-, pink-, and white-collar layoffs (see Section 3.1). The literature on other-regarding preferences shows that social preferences tend to be more pronounced for in-group compared to out-group members (Chen and Li 2009). For top-level managers, we thus expect that with increasing tenure they become particularly prosocial towards white-collar employees.[21]

[20] Formally, we can apply Proposition 1(iii) while distinguishing high closeness/contact employees, x_H, and distant employees, x_L, with $c_t(x_L, x_H) = \delta_t + \gamma_{L,t} x_L + \gamma_{H,t} x_H$ where $\gamma_{L,t} < \gamma_{H,t}$.

[21] The anecdotal evidence from the practitioners-oriented book by Martin (2005) is consistent with this

Table 8 shows the results for the relationship between CEO tenure and layoffs of white-collar employees. Columns (1) and (2) show that as CEOs' tenure increases, the probability of white-collar layoffs significantly drops. An interquartile increase in tenure is associated with a 24% drop relative to the baseline white-collar layoff probability of 3.2%, which is roughly double the estimated decrease from the baseline probability in Table 3 using all layoff types.

Columns (3) and (4) of Table 8 estimate the effect of tenure on a white-collar layoff conditional on the CEO-firm-year being a year with layoffs (of any type of employees). Also conditionally, white-collar layoffs become less likely as the CEO remains at the top for longer. For example, in column (4) with firm fixed effects, an interquartile increase in tenure is associated with a 19% reduction (relative to the baseline) that a firm-year with layoff activity involves white-collar layoffs.

Layoffs Close to Firm's Headquarters. A second way to capture heterogeneity in social interactions is through the geographic rather than social proximity of affected employees, leveraging the geographic detail of our layoff dataset.[22]

Table 9 shows the results. Column (1) shows that CEO tenure predicts less layoff activity in the state of the firm's HQ. An interquartile increase in tenure reduces the likelihood of an HQ-state layoff by 0.6 percentage points, or 15% relative to the baseline probability of an HQ-state layoff of 4%. The remaining columns increase the level of "layoff closeness" and focus on layoff propensity in the same city as the corporate HQ. Column (2) shows that longer CEO tenure is also associated with fewer HQ-city layoffs. Here, an interquartile tenure increase is associated with a 0.38 percentage point reduction in same-city HQ, or 21% relative to the baseline probability of just 1.8%.

Columns (3) and (4) show that HQ-city layoffs are less likely with increasing tenure, again conditional on the CEO-firm-year being a year with layoffs (Column (3)) or a year with HQ-state layoffs (Column (4)). In Column (3), conditional on a layoff-year,

hypothesis with one respondent saying, "[a]lways, the most difficult decisions are those that affect families of people that have become friends."

[22] In line with geography-based differences in social preferences, Landier, Nair, and Wulf (2009) find that firms are less likely to implement layoffs in divisions that are located closer to the headquarters (HQ). Landier, Nair, and Wulf (2009) do, however, not examine how the geographic layoff propensity varies with CEO tenure, nor do they study any other managerial characteristics. Furthermore, Landier, Nair, and Wulf (2009) do not have actual layoff data and measure layoffs only indirectly as a decrease in the number of employees in a given division.

an interquartile tenure increase is associated with a 1.4 percentage point reduction in layoff propensity or 13% relative to the baseline conditional probability of an HQ-city layoff of 11%. In the most narrow layoff closeness specification in Column (4), conditional on a layoff-year occurring in the HQ-state, an interquartile tenure increase is associated with a 3.7 percentage point reduction in layoff propensity or 8% relative to the baseline conditional probability of an HQ-city layoff of 45%. We note that standard errors increase substantially in this most narrowly defined subsample in Column (4), and while the point estimate is economically significant, it is statistically insignificant ($p = 0.118$).[23]

Overall, the results in Tables 8 and 9 are consistent with a social-preference-based explanation and increasing social considerations of longer-tenured CEOs in particular with respect to socially and geographically close employees.

Internally Versus Externally Hired CEO. We also investigate the effect of the CEO being hired internally or externally as an additional source of variation in the intensity of social connections between CEO and employees in Table 10. Related to this test, Bai and Mkrtchyan (2023) show for manufacturing firms that under external CEOs, more factories are closed or see employment reductions. We build on their evidence, focusing on a broader set of firms and layoff decisions specifically, and suggest prosocial concerns of internal CEOs with more pre-existing relations as one underlying mechanism.

One data limitation is that the variable JOINED_CO in Execucomp to identify when a given CEO joined the firm (in any position) is oftentimes missing (cf. Landier, Sauvagnat, Sraer, and Thesmar 2013). This results in a more than two-thirds reduction in sample size. Nonetheless, we observe a strong negative internal CEO effect on layoff propensity, including in the specifications with firm fixed effects which partially (albeit imperfectly) reduce endogeneity concerns. Firms' layoff propensity is lower by 20–30% relative to the baseline when it is run by a CEO who is internally hired and thus has existing within-firm ties.[24] Consistent with the CEO mortality results in Table 4 and the heterogeneity results of CEO tenure by economic conditions in Table 6, the point estimates on the interaction

[23] All columns in Table 9 include industry and location fixed effects. We estimate similar economic magnitudes when we include firm fixed effects instead, though we lose power in both conditional specifications in Columns (3) and (4).

[24] In unreported tests, we restrict the sample to non-manufacturing firms, i.e., sectors not studies in Bai and Mkrtchyan (2023). We estimate a large internal-CEO effect on reduced layoff propensity of up to 40% for firms outside of manufacturing.

term between internal CEO hire and the distress indicator in Table 10 are negative and economically meaningful, though we note that they are not statistically significant.

6. Conclusion

This paper offers a new interpretation of frictions in firms' labor demand choices and examines the impact of CEO prosocial concerns on firms' labor adjustment. We establish a number of results to argue that top-level managers exhibit prosocial concerns for workers, with this being economically important factor in managers' hiring and firing decisions. First, CEOs responsible for "painful" layoffs during recessions incur a large, personal health cost of firing detectable even in the long run, in the form of accelerated long-term mortality rates. Second, consistent with baseline CEO-related frictions in firms' labor-related decisions, exogenous CEO changes trigger more layoffs that come with large, positive market announcement returns and are thus good news for shareholders. Third, consistent with a channel where by CEO prosocial concerns deepen through social interactions, and building on prior work by Pan, Wang, and Weisbach (2016), long-tenured CEOs implement fewer layoffs than new CEOs. Finally, this effect is amplified when we expect prosocial considerations to have a larger influence, as gauged by heterogeneity in the consequences of job loss and the intensity of social interactions between CEOs and employees.

Our findings suggest several avenues for further investigation. Further research may analyze the types of employees accumulated before a layoff, the types of workers laid off, as well as these workers' subsequent career paths, e.g., using matched employer-employee data. Exploring heterogeneity in employee types would further speak to the nature of managerial prosocial concerns.

Additionally, our findings have new corporate governance implications. Along similar lines as Cheng, Hong, and Shue (2013), our results suggest that *if* the aim is to maximize shareholder value, a broad range of managerial activities needs to be monitored. Monitoring activities should, of course, be concerned with traditional CEO pet projects and perks (see, e.g., Yermack 2006, Décaire and Sosyura 2022), but may also need to extend to decisions that are influenced by managers' social preferences.

Finally, it is also conceivable that from an *ex-ante* perspective, more talented workers might be more attracted to more social firms, which could ultimately be firm value-increasing in the long run (cf. Agrawal and Matsa 2013), and further showcases that accounting for the variation in managerial social preferences for employees opens up a series of new research opportunities.

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Tables

Table 1. Summary Statistics

Panel (a) shows summary statistics for all CEO-firm-year observations used in Column (1) of Table 3. Data on layoffs hand-coded using S&P Key Developments data. CEO and CFO tenure based on Execucomp data. Firm size and profitability measures from Compustat data. Industry distress measure based on data from CRSP. More details about the data are in Section 3 and Appendix-Section IV. Panel (b) shows summary statistics for all CEOs used in Table 2. Mortality and tenure data is from Borgschulte, Guenzel, Liu, and Malmendier (2022). Layoff data is from Hallock (1998), Billger and Hallock (2005), and Farber and Hallock (2009). Firm size and profitability measures from Compustat data. Industry distress measure and minimum stock performance based on data from CRSP. More details about the data are in Section 3.

(a) 2000–2020s Firm-Layoffs Sample (Sections 3.1 and 3.2.1)

	N	Mean	SD	P25	Median	P75
Layoff	34,683	0.13	0.34	0.00	0.00	0.00
CEO Tenure	34,683	8.12	6.94	3.00	6.00	11.00
CFO Tenure	32,433	4.64	3.55	2.00	4.00	6.00
Industry Distress	34,683	0.19	0.39	0.00	0.00	0.00
Firm Size (Ln Assets)	34,683	7.68	1.85	6.39	7.57	8.86
Firm Size (Ln Employees)	34,683	1.44	1.77	0.26	1.46	2.62
Firm Profitability	34,683	0.11	0.11	0.06	0.11	0.17

(b) CEO Long-Term Mortality Sample (Section 3.2.2)

	N	Mean	SD	P25	Median	P75
Age Appointed CEO	1,131	53.49	6.45	49.00	54.00	58.00
Year Born	1,131	1928.12	8.50	1922.00	1928.00	1934.00
Year Dead/Censored	1,131	2010.33	9.58	2004.83	2015.00	2017.75
Ever Distressed Layoff	1,131	0.11	0.32	0.00	0.00	0.00
Ever Non-Distressed Layoff	1,131	0.38	0.49	0.00	0.00	1.00
Ever Industry Distress	1,131	0.43	0.50	0.00	0.00	1.00
Firm Size (Ln Assets)	1,131	7.35	1.66	6.33	7.38	8.42
Firm Size (Ln Employees)	1,131	9.61	1.40	8.78	9.67	10.56
Firm Profitability	1,131	0.14	0.07	0.09	0.13	0.18
Minimum Stock Performance	1,131	0.70	0.15	0.60	0.71	0.80

Table 2. Layoffs and CEO Long-Term Mortality

CEO mortality and tenure data is from Borgschulte, Guenzel, Liu, and Malmendier (2022). Industry distress measure and minimum stock performance based on CRSP stock data. Layoff data is from Hallock (1998), Billger and Hallock (2005), and Farber and Hallock (2009). Firm characteristics are from Compustat data. More details about the data are in Section 3. Standard errors, clustered by industry, are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)
Distress Layoff	0.294**	0.296**	0.287**
	(0.137)	(0.138)	(0.139)
Non-Distress Layoff	−0.031	−0.038	−0.052
	(0.098)	(0.098)	(0.099)
Industry Distress	0.149	0.156	0.132
	(0.110)	(0.111)	(0.118)
CEO Age	0.159***	0.161***	0.163***
	(0.010)	(0.010)	(0.010)
Firm Size (Ln Assets)	−0.137*	−0.134*	−0.130*
	(0.078)	(0.079)	(0.078)
Firm Size (Ln Employees)	0.064	0.061	0.067
	(0.074)	(0.075)	(0.075)
Firm Profitability	0.669	0.628	0.808
	(0.688)	(0.697)	(0.728)
Year	0.009		
	(0.009)		
Minimum Stock Performance			−0.326
			(0.349)
Year FE	No	Yes	Yes
State FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	31,917	31,917	31,917

Table 3. Layoff Propensity and CEO Tenure

Data on layoffs hand-coded using S&P Key Developments data. CEO and CFO tenure based on Execucomp data, divided by 100 in the regressions for ease of exposition. Firm characteristics are from Compustat data and lagged. Industry distress is based on CRSP stock data. Standard errors, clustered by firm, are shown in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

	(1)	(2)	(3)	(4)
CEO Tenure / 100	-0.427^{***}	-0.269^{***}	-0.187^{***}	-0.181^{***}
	(0.034)	(0.029)	(0.039)	(0.041)
Industry Distress		0.057^{***}	0.046^{***}	0.040^{***}
		(0.007)	(0.007)	(0.007)
Firm Size (Ln Assets)		0.029^{***}	0.028^{***}	0.029^{***}
		(0.003)	(0.007)	(0.007)
Firm Size (Ln Employees)		0.026^{***}	0.050^{***}	0.055^{***}
		(0.003)	(0.008)	(0.008)
Firm Profitability		-0.280^{***}	-0.251^{***}	-0.255^{***}
		(0.023)	(0.030)	(0.032)
CFO Tenure / 100				-0.096
				(0.071)
Year FE	No	Yes	Yes	Yes
State FE	No	Yes	No	No
Industry FE	No	Yes	No	No
Firm FE	No	No	Yes	Yes
Observations	34,683	34,683	34,565	32,301

Table 4. Layoff Propensity and CEO Tenure—CEO Power

Data on layoffs hand-coded using S&P Key Developments data. CEO tenure based on Execucomp data, divided by 100 in the regressions for ease of exposition. Firm characteristics are from Compustat data and lagged. Industry distress is based on CRSP stock data. % of new directors is between 0 and 1 and is calculated using ISS data and Execucomp data as the percent of directors appointed in the years following the CEOs appointment. Standard errors, clustered by firm, are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)
CEO Tenure / 100		-0.407^{***}		-0.213^{***}
		(0.053)		(0.081)
% of New Directors	-0.039^{***}	0.030^{**}	-0.015	0.017
	(0.010)	(0.013)	(0.012)	(0.018)
CEO and Chairman/woman	0.001	0.008	-0.001	0.002
	(0.007)	(0.007)	(0.008)	(0.008)
CEO and President	-0.005	-0.007	0.006	0.004
	(0.006)	(0.006)	(0.007)	(0.007)
Industry Distress	0.059^{***}	0.059^{***}	0.045^{***}	0.045^{***}
	(0.009)	(0.009)	(0.009)	(0.009)
Firm Size (Ln Assets)	0.036^{***}	0.033^{***}	0.030^{***}	0.030^{***}
	(0.004)	(0.004)	(0.010)	(0.010)
Firm Size (Ln Employees)	0.025^{***}	0.026^{***}	0.066^{***}	0.067^{***}
	(0.003)	(0.003)	(0.011)	(0.011)
Firm Profitability	-0.266^{***}	-0.268^{***}	-0.321^{***}	-0.320^{***}
	(0.037)	(0.037)	(0.049)	(0.049)
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	No	No
Industry FE	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes
Observations	23,621	23,621	23,425	23,425

Table 5. Layoffs and CEO Tenure—Fraction of Employees Laid Off

Data on layoffs hand-coded using S&P Key Developments data. CEO and CFO tenure based on Execucomp data, divided by 100 in the regressions for ease of exposition. Firm characteristics are from Compustat data and lagged. Industry distress is based on CRSP stock data. Standard errors, clustered by firm, are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)
CEO Tenure / 100	-0.027^{***}	-0.019^{***}	-0.017^{***}	-0.016^{***}
	(0.003)	(0.003)	(0.004)	(0.004)
Industry Distress		0.007^{***}	0.006^{***}	0.006^{***}
		(0.001)	(0.001)	(0.001)
Firm Size (Ln Assets)		0.002^{***}	0.002^{***}	0.003^{***}
		(0.000)	(0.001)	(0.001)
Firm Size (Ln Employees)		0.001^{**}	0.003^{***}	0.003^{***}
		(0.000)	(0.001)	(0.001)
Firm Profitability		-0.021^{***}	-0.019^{***}	-0.021^{***}
		(0.002)	(0.004)	(0.004)
CFO Tenure / 100				-0.010^{*}
				(0.006)
Year FE	No	Yes	Yes	Yes
State FE	No	Yes	No	No
Industry FE	No	Yes	No	No
Firm FE	No	No	Yes	Yes
Observations	33,251	33,251	33,130	30,941

Table 6. Layoff Propensity and CEO Tenure—Recession Periods

Data on layoffs hand-coded using S&P Key Developments data. CEO tenure based on Execucomp data, divided by 100 in the regressions for ease of exposition. Firm characteristics are from Compustat data and lagged. Industry distress is based on CRSP stock data. Standard errors, clustered by firm, are shown in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

	(1)	(2)	(3)	(4)
CEO Tenure / 100	-0.229^{***}	-0.141^{***}	-0.239^{***}	-0.150^{***}
	(0.029)	(0.039)	(0.028)	(0.039)
Industry Distress	0.074^{***}	0.067^{***}	0.018	0.005
	(0.010)	(0.010)	(0.030)	(0.031)
CEO Tenure × Industry Distress	-0.221^{***}	-0.261^{***}	-0.170^{**}	-0.222^{***}
	(0.078)	(0.075)	(0.079)	(0.076)
Controls	Yes	Yes	Yes	Yes
Control Interactions	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	No	No	No
Industry FE	Yes	No	No	No
Firm FE	No	Yes	Yes	Yes
Observations	34,683	34,565	34,683	34,565

Table 7. Layoff Propensity and CEO Tenure—Layoffs Around Holiday Season (December)

Data on layoffs hand-coded using S&P Key Developments data. CEO tenure based on Execucomp data, divided by 100 in the regressions for ease of exposition. Firm characteristics are from Compustat data and lagged. Industry distress is based on CRSP stock data. Standard errors, clustered by firm, are shown in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

	Full Sample		Layoff-Years	
	(1)	(2)	(3)	(4)
CEO Tenure / 100	-0.066^{***}	-0.064^{***}	-0.319^{***}	-0.407^{***}
	(0.009)	(0.015)	(0.072)	(0.129)
Industry Distress	0.009^{***}	0.006^{*}	0.027^{**}	0.040^{**}
	(0.003)	(0.003)	(0.013)	(0.017)
Firm Size (Ln Assets)	0.007^{***}	0.004^{*}	0.009	0.018
	(0.001)	(0.002)	(0.006)	(0.021)
Firm Size (Ln Employees)	0.006^{***}	0.010^{***}	0.008	0.010
	(0.001)	(0.002)	(0.006)	(0.021)
Firm Profitability	-0.045^{***}	-0.027^{***}	-0.068	0.010
	(0.008)	(0.009)	(0.050)	(0.085)
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes
Observations	34,683	34,565	5,722	5,174

Table 8. Layoff Propensity and CEO Tenure—Layoffs of White-Collar Employees

Data on layoffs hand-coded using S&P Key Developments data. CEO tenure based on Execucomp data, divided by 100 in the regressions for ease of exposition. Firm characteristics are from Compustat data and lagged. Industry distress is based on CRSP stock data. Standard errors, clustered by firm, are shown in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

	Full Sample		Layoff-Years	
	(1)	(2)	(3)	(4)
CEO Tenure / 100	-0.091^{***}	-0.099^{***}	-0.272^{***}	-0.400^{***}
	(0.014)	(0.020)	(0.092)	(0.152)
Industry Distress	0.018^{***}	0.014^{***}	0.024	0.011
	(0.004)	(0.004)	(0.015)	(0.018)
Firm Size (Ln Assets)	0.013^{***}	0.009^{***}	0.021^{***}	-0.009
	(0.001)	(0.003)	(0.008)	(0.026)
Firm Size (Ln Employees)	0.010^{***}	0.014^{***}	0.015^{*}	0.040
	(0.001)	(0.003)	(0.008)	(0.028)
Firm Profitability	-0.061^{***}	-0.036^{***}	-0.044	0.028
	(0.011)	(0.014)	(0.069)	(0.114)
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes
Observations	34,683	34,565	5,722	5,174

Table 9. Layoff Propensity and CEO Tenure—Geographic Proximity of Layoffs

Data on layoffs hand-coded using S&P Key Developments data. CEO tenure based on Execucomp data, divided by 100 in the regressions for ease of exposition. Firm characteristics are from Compustat data and lagged. Industry distress is based on CRSP stock data Standard errors, clustered by firm, are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	HQ-State Layoff	HQ-City Layoff		
	(1)	(2)	(3)	(4)
CEO Tenure / 100	-0.079^{***}	-0.048^{***}	-0.179^{**}	-0.458
	(0.015)	(0.011)	(0.089)	(0.293)
Industry Distress	0.013^{***}	0.008^{***}	0.019	0.031
	(0.004)	(0.003)	(0.012)	(0.038)
Firm Size (Ln Assets)	0.014^{***}	0.007^{***}	0.018^{***}	0.012
	(0.002)	(0.001)	(0.007)	(0.021)
Firm Size (Ln Employees)	0.010^{***}	0.004^{***}	-0.006	-0.008
	(0.001)	(0.001)	(0.007)	(0.024)
Firm Profitability	-0.087^{***}	-0.042^{***}	-0.044	0.016
	(0.013)	(0.009)	(0.058)	(0.209)
Sample	Full	Full	Layoff-Years	HQ-State Layoff-Years
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	34,683	34,683	5,722	1,406

Table 10. Layoff Propensity and Internally Versus Externally Hired CEO

Data on layoffs hand-coded using S&P Key Developments data. CEO tenure based on Execucomp data, divided by 100 in the regressions for ease of exposition. Firm characteristics are from Compustat data and lagged. Industry distress is based on CRSP stock data. Externally hired CEOs are CEOs who assume the CEO position within one year of joining the firm, as identified through the variables BECAMECEO and JOINED_CO in Execucomp. Standard errors, clustered by firm, are shown in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

	(1)	(2)	(3)	(4)
Internal CEO	-0.029^{***}	-0.023^{**}	-0.048^{**}	-0.040^{**}
	(0.010)	(0.010)	(0.019)	(0.019)
Industry Distress	0.060^{***}	0.078^{***}	0.046^{***}	0.066^{***}
	(0.013)	(0.018)	(0.013)	(0.018)
Internal CEO / 100 × Industry Distress		-0.028		-0.031
		(0.020)		(0.021)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	No	No
Industry FE	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes
Observations	10,952	10,952	10,872	10,872

Internet Appendix

CEO Social Preferences and Layoffs

Marius Guenzel Clint Hamilton Ulrike Malmendier

I. Conceptual Framework: Proofs and Numerical Results

I.1 Proofs

We prove a stronger version of Proposition 1 in which we include the case where the social-preference manager only partially anticipates, or does not anticipate, future disutility costs from layoffs (partial sophistication and naïvité, respectively):

$$\max_{n_t,k_t} a_1 n_1^{\nu} k_1^{\alpha} - wn_1 - rk_1 + E\left[a_2 n_2^{\nu} k_2^{\alpha} - wn_2 - rk_2 - \widehat{\mu} c_2(\Delta n_2)\right] \tag{IA.1}$$

where $\widehat{\mu} = 0$ denotes a naïve manager and $\widehat{\mu} \in (0, 1]$ a manager (partially) sophisticated regarding the behavioral costs.

We first prove the following ancillary proposition:

Proposition IA.1. *In period 1, a social-preference manager chooses the same or a lower level of labor compared to a standard manager who faces no behavioral labor adjustment costs.*

Proof of Proposition IA.1. Part (i) of Proposition IA.1 is trivial. If the manager maximizes under the assumption behavioral labor adjustment costs do not exist, they will maximize the same objective function as a standard manager who does not face behavioral adjustment costs.

For part (ii), we show that the marginal value of labor for the sophisticated behavioral manager is uniformly lower than for the standard manager, from which it follows that they will choose a (weakly) lower choice for labor. The marginal value in the first period will be equal for all choices of n_1, so what we need to show is that the marginal value of n_1 in expectation for period 2 is always less than or equal to one. The expected value in period 2 can be written as

$$\int_{\underline{a}}^{\hat{a}} \frac{1}{\bar{a}-\underline{a}} a(n^*_{\text{layoff}})^{\nu} k_t^{\alpha} - wn^*_{\text{layoff}} - rk^*_{\text{layoff}} - \delta + \gamma(n^*_{\text{layoff}} - n_1) da +$$
$$\int_{\hat{a}}^{\hat{\hat{a}}} \frac{1}{\bar{a}-\underline{a}} a n_1^{\nu} \left(\left(\frac{rn_1^{-\nu}}{a\alpha} \right)^{\frac{1}{\alpha-1}} \right)^{\alpha} - wn_1 - r \left(\frac{rn_1^{-\nu}}{a\alpha} \right)^{\frac{1}{\alpha-1}} da +$$
$$\int_{\hat{\hat{a}}}^{\bar{a}} \frac{1}{\bar{a}-\underline{a}} a(n^*_{\text{layoff}})^{\nu} k_t^{\alpha} - wn^*_{\text{standard}} - rk^*_{\text{standard}} - \delta da,$$

where $\hat{a}$ is the minimal value of a for which bunching occurs and $\hat{\hat{a}}$ is the value of a where the standard manager chooses n_1. n_1 does not enter the third term and the first term is decreasing in n_1. The derivative of the second term with respect to n must be weakly negative since n_1 is, by construction greater than the optimal choice n for $a \in [\hat{a}, \hat{\hat{a}})$. If the derivative was positive that would imply that the optimal value of n is greater than n_1 ,which is not true by construction, or that the function is not concave, as there would be a second local optimum. Thus, the derivative of the second term with respect to n must be negative and we can conclude

$$\frac{d}{dn} \left(\int_{\underline{a}}^{\hat{a}} \frac{1}{\bar{a}-\underline{a}} a(n^*_{\text{layoff}})^{\nu} k_t^{\alpha} - wn^*_{\text{layoff}} - rk^*_{\text{layoff}} - \delta + \gamma(n^*_{\text{layoff}} - n_1) da + \right.$$
$$\int_{\hat{a}}^{\hat{\hat{a}}} \frac{1}{\bar{a}-\underline{a}} a n_1^{\nu} \left(\left(\frac{rn_1^{-\nu}}{a\alpha} \right)^{\frac{1}{\alpha-1}} \right)^{\alpha} - wn_1 - r \left(\frac{rn_1^{-\nu}}{a\alpha} \right)^{\frac{1}{\alpha-1}} da +$$
$$\left. \int_{\hat{\hat{a}}}^{\bar{a}} \frac{1}{\bar{a}-\underline{a}} a(n^*_{\text{layoff}})^{\nu} k_t^{\alpha} - wn^*_{\text{standard}} - rk^*_{\text{standard}} - \delta da \right) \leq 0.$$

It could be that $\underline{a} = \hat{a} = \hat{\hat{a}}$, therefore we can only conclude that this is a weak inequality. Thus the marginal value of n is weakly lower for the behavioral manager for all n than the standard manager. Therefore the manager will choose a weakly lower value of n for all realizations of a_1. Partial naïvete simply implies smaller δ and γ values, but this does not affect anything in the above proof. Therefore, the statement holds for fully and partially sophisticated managers. □

We then turn to the proof of Proposition 1.

Proof of Proposition 1. For readability, we now refer to n_2^* as n^*_{standard}, and the chosen level of labor in period 1 as n_1. When unspecified, $t = 2$.

Equation 2 yields two first order conditions for optimality when $n_2 \geq n_1$, i.e., when there are no behavioral adjustment costs:

$$n_2 = \left(\frac{wk_2^{-\alpha}}{a_2\nu}\right)^{\frac{1}{\nu-1}} \tag{IA.2}$$

and

$$k_2 = \left(\frac{rn_2^{-\nu}}{a_2\alpha}\right)^{\frac{1}{\alpha-1}}. \tag{IA.3}$$

Next we substitute equation IA.3 into equation IA.2 and solve for n to obtain

$$n^*_{\text{standard}} = n^*_{\text{behavioral, } n_2>n_1} = \left(\frac{w}{a\nu}\right)^{-\frac{(\alpha-1)}{\alpha+\nu-1}} \left(\frac{r}{a_2\alpha}\right)^{\frac{\alpha}{\alpha+\nu-1}}. \tag{IA.4}$$

Note that if $n^*_{\text{standard}} \geq n_1$, behavioral adjustment costs do not bind and $n^*_{\text{standard}} = n^*_{\text{behavioral}}$. If behavioral adjustment costs are relevant, then the first order condition for labor is

$$n_2 = \left(\frac{(w-\gamma)k_2^{-\alpha}}{a_2\nu}\right)^{\frac{1}{\nu-1}}. \tag{IA.5}$$

This yields the optimal labor choice of

$$n^*_{\text{behavioral, } n_2<n_1} = \left(\frac{w-\gamma}{a\nu}\right)^{-\frac{(\alpha-1)}{\alpha+\nu-1}} \left(\frac{r}{a_2\alpha}\right)^{\frac{\alpha}{\alpha+\nu-1}}. \tag{IA.6}$$

In either case, we can then substitute the optimal choice for labor into equation IA.3 to obtain the optimal choice for k,

$$k^* = \left(\frac{r(n_2^*)^{-\nu}}{a_2\alpha}\right)^{\frac{1}{\alpha-1}}. \tag{IA.7}$$

Note that the production function is concave by construction so the second order conditions for optimality are satisfied.

If $n^*_{\text{standard}} \geq n_1$ then

$$n^*_{\text{standard}} = n^*_{\text{behavioral}} = \left(\frac{w}{a\nu}\right)^{-\frac{(\alpha-1)}{\alpha+\nu-1}} \left(\frac{r}{a_2\alpha}\right)^{\frac{\alpha}{\alpha+\nu-1}}. \tag{IA.8}$$

This is because this solution dominates the solutions with a lower n even when the behavioral adjustment costs are not considered. If $n^*_{\text{standard}} < n_1$, then we must consider both the interior and boundary solution. Let

$$n^*_{\text{layoff}} = \left(\frac{w-\gamma}{a\nu}\right)^{-\frac{(\alpha-1)}{\alpha+\nu-1}} \left(\frac{r}{a\alpha}\right)^{\frac{\alpha}{\alpha+\nu-1}},$$

$$k^*_{\text{layoff}} = \left(\frac{r(n^*_{\text{layoff}})^{-\nu}}{a\alpha}\right)^{\frac{1}{\alpha-1}}$$

$$n^*_{\text{bunch}} = n_1,$$

and

$$k^*_{\text{bunch}} = \left(\frac{r(n^*_{\text{bunch}})^{-\nu}}{a\alpha}\right)^{\frac{1}{\alpha-1}}.$$

n^*_{layoff} is the interior optimal labor choice when behavioral costs apply. The optimal labor choice is at the bunching point when profit there exceeds the profit for the interior solution.

$$a_t(n^*_{\text{bunch}})^{\nu}(k^*_{\text{bunch}})^{\alpha} - wn^*_{\text{bunch}} - rk^*_{\text{bunch}} >$$
$$a_t(n^*_{\text{layoff}})^{\nu}(k^*_{\text{layoff}})^{\alpha} - wn^*_{\text{layoff}} - rk^*_{\text{layoff}} - \delta + \gamma(n^*_{\text{layoff}} - n_1).$$

There is guaranteed to be a zone where bunching occurs as long as $\gamma > 0$ and $-\frac{(\alpha-1)}{\alpha+\nu-1} < 0$ which are both true under the assumptions made. To guarantee bunching, we also need n_1 to be greater n^*_{standard} for $a = \underline{a}$. This is because the marginal utility of labor will be discontinuous around the value of a_2 such that $n_1 = n^*_{\text{standard}}$. As a result, the optimal solution when costs do not apply will be below n_1 while he optimal solution when costs do apply will be above n_1 for some values of a. Mathematically, we know that

$$\left(\frac{w-\gamma}{a\nu}\right)^{-\frac{(\alpha-1)}{\alpha+\nu-1}}\left(\frac{r}{a\alpha}\right)^{\frac{\alpha}{\alpha+\nu-1}} > \left(\frac{w}{a\nu}\right)^{-\frac{(\alpha-1)}{\alpha+\nu-1}}\left(\frac{r}{a\alpha}\right)^{\frac{\alpha}{\alpha+\nu-1}}.$$

Since $\lim_{a\to 0}\left(\frac{w-\gamma}{a\nu}\right)^{-\frac{(\alpha-1)}{\alpha+\nu-1}}\left(\frac{r}{a\alpha}\right)^{\frac{\alpha}{\alpha+\nu-1}} = 0$ and $\lim_{a\to\infty}\left(\frac{w-\gamma}{a\nu}\right)^{-\frac{(\alpha-1)}{\alpha+\nu-1}}\left(\frac{r}{a\alpha}\right)^{\frac{\alpha}{\alpha+\nu-1}} = \infty$, there exists some $a^{\dagger}$ such that $\left(\frac{w-\gamma}{a\nu}\right)^{-\frac{(\alpha-1)}{\alpha+\nu-1}}\left(\frac{r}{a\alpha}\right)^{\frac{\alpha}{\alpha+\nu-1}} = n_1$ by the intermediate value theorem. By similar logic, there exists some $a^{\dagger\dagger}$ such that $\left(\frac{w-\gamma}{a\nu}\right)^{-\frac{(\alpha-1)}{\alpha+\nu-1}}\left(\frac{r}{a\alpha}\right)^{\frac{\alpha}{\alpha+\nu-1}} = n_1$. By the inequality above, it must be the case that $a^{\dagger} > a^{\dagger\dagger}$. Additionally, the manger will never choose $n_1 > n^*_{\text{standard}}$ for $a = \bar{a}$ in period 1, and we have assumed n_1 to be greater than n^*_{standard} for $a = \underline{a}$. Thus, $a^{\dagger\dagger} > \underline{a}$ and bunching is guaranteed to occur for all values of a_2 on the nondegenerate interval $(a^{\dagger\dagger}, a^{\dagger})$ though it may, and likely will, feature bunching on a larger interval.[IA.1] This proves point (i) of Proposition 1.

For point (ii) of Proposition 1, we have that

$$n^*_{\text{layoff}} = \left(\frac{w-\gamma}{a\nu}\right)^{-\frac{(\alpha-1)}{\alpha+\nu-1}}\left(\frac{r}{a\alpha}\right)^{\frac{\alpha}{\alpha+\nu-1}} > \left(\frac{w}{a\nu}\right)^{-\frac{(\alpha-1)}{\alpha+\nu-1}}\left(\frac{r}{a\alpha}\right)^{\frac{\alpha}{\alpha+\nu-1}} = n^*_{\text{standard}}.$$

Furthermore, from Proposition IA.1, the choice of n_1 is weakly smaller for the behavioral manager compared to the standard manager without behavioral adjustment costs. Additionally, we can note that the optimal choice of n_2 is independent of n_1 for the standard manager. This is to say that $n_{2,\text{standard}} < n_{2,\text{layoff}}$ and $n_{1,\text{behavioral}} \leq n_{1,\text{standard}}$. This implies

$$n_{2,\text{standard}} - n_{1,\text{standard}} < n_{2,\text{layoff}} - n_{1,\text{behavioral}},$$

[IA.1] If $a^{\dagger\dagger} < \underline{a}$, then bunching will occur more precisely on the interval $[a^{\dagger\dagger}, a^{\dagger})$.

which proves point (ii) that if a behavioral manager makes a layoff in period 2, the layoff size is reduced compared to that of a standard manager without behavioral adjustment costs.

For part, (iii) we prove that an increase in either cost will weakly monotonically reduce layoff size and likelihood. Suppose that the fixed cost δ increases by $\epsilon > 0$. It is clear that conditional on hiring or layoffs the optimal choice based on the first order conditions, which the fixed cost does not enter, will be the same when the manager undertakes one of these actions with fixed cost δ or $\delta + \varepsilon$. Note that when $n^*_{\text{standard}} < n_1$ then, bunching occurs when

$$\begin{aligned}&a_t(n^*_{\text{bunch}})^{\nu}(k^*_{\text{bunch}})^{\alpha} - wn^*_{\text{bunch}} - rk^*_{\text{bunch}} > \\ &a_t(n^*_{\text{layoff}})^{\nu}(k^*_{\text{layoff}})^{\alpha} - wn^*_{\text{layoff}} - rk^*_{\text{layoff}} - \delta + \gamma(n^*_{\text{layoff}} - n_1),\end{aligned}$$

or

$$\begin{aligned}&a_t(n^*_{\text{bunch}})^{\nu}(k^*_{\text{bunch}})^{\alpha} - wn^*_{\text{bunch}} - rk^*_{\text{bunch}} > \\ &a_t(n^*_{\text{layoff}})^{\nu}(k^*_{\text{layoff}})^{\alpha} - wn^*_{\text{layoff}} - rk^*_{\text{layoff}} - \delta - \epsilon + \gamma(n^*_{\text{layoff}} - n_1),\end{aligned}$$

, respectively, where n^*_{layoff} is the interior optimal labor choice when behavioral costs apply and $n^*_{\text{bunch}} = n_1$. Note that if there is bunching in the low fixed cost case there must be bunching in the high fixed cost case.

Next note that k_{layoff} is an implicit (continuous) function of n^*_{layoff} and let,

$$f(n^*_{\text{layoff}}) = a_t(n^*_{\text{layoff}})^{\nu}(k^*_{\text{layoff}})^{\alpha} - wn^*_{\text{layoff}} - rk^*_{\text{layoff}} - \delta + \gamma(n^*_{\text{layoff}} - n_1).$$

Since f is the combination of the sum and products of continuous functions over the relevant domain it is a continuous function of n. For values of a such that n^*_{layoff} satisfies the criterion,

$$\begin{aligned}&a_t(n^*_{\text{bunch}})^{\nu}(k^*_{\text{bunch}})^{\alpha} - wn^*_{\text{bunch}} - rk^*_{\text{bunch}} + \epsilon > \\ &f(n^*_{\text{layoff}}) > \\ &a_t(n^*_{\text{bunch}})^{\nu}(k^*_{\text{bunch}})^{\alpha} - wn^*_{\text{bunch}} - rk^*_{\text{bunch}},\end{aligned}$$

there are layoffs only in the low behavioral cost case and no change in labor in the high behavioral cost case. In conclusion, an increase in the fixed cost of layoffs will weakly decrease layoff probability.

Next suppose that we have variable behavioral cost of layoffs γ and γ' where $\gamma' > \gamma > 0$. If $n^*_{\text{standard}} > n_1$, the FOC implies that there is no effect. Let ${n^*_{\text{layoff}}}'$ be the optimal interior solution for labor when there is a layoff when the variable cost is γ' and n^*_{layoff} be the optimal interior solution for labor when there is a layoff when the variable cost is γ.

Next we note that

$$n^*_{\text{layoff}}{}' = \left(\frac{w-\gamma'}{a\nu}\right)^{-\frac{(\alpha-1)}{\alpha+\nu-1}} \left(\frac{r}{a\alpha}\right)^{\frac{\alpha}{\alpha+\nu-1}} > \left(\frac{w-\gamma}{a\nu}\right)^{-\frac{(\alpha-1)}{\alpha+\nu-1}} \left(\frac{r}{a\alpha}\right)^{\frac{\alpha}{\alpha+\nu-1}} = n^*_{\text{layoff}},$$

since $-\frac{(\alpha-1)}{\alpha+\nu-1} < 0$ and we assume $w > \gamma'$. This inequality states that in the case of a layoff the labor force will always be bigger under the larger variable behavioral cost. Note that regardless of the variable cost size the utility of bunching is the same

$$a_t(n^*_{\text{bunch}})^\nu (k^*_{\text{bunch}})^\alpha - wn^*_{\text{bunch}} - rk^*_{\text{bunch}}.$$

We also note that the utility for all realizations a_2 is higher when the variable cost is lower. If $n_{\text{standard}^*} \leq n_1$, bunching occurs if $n_{\text{layoff}^*} \geq n_1$ in the low variable cost case and if $n_{\text{layoff}^*}{}' \geq n_1$ in the high cost case. Since $n_{\text{layoff}^*}{}' > n_{\text{layoff}^*}$, we can conclude that in all cases where $n_{\text{layoff}^*} > n_1$, then under the high cost regime there will also be bunching. If $n_{\text{layoff}^*}{}' > n_1 > n_{\text{layoff}^*}$, there will definitely be no bunching in the high cost case and will be either bunching or a reduction in the labor force in the low cost case. Thus, we only need to focus on the remaining case where $n_{\text{layoff}^*} < n_{\text{layoff}^*}{}' < n_1$. In this case,

$$\begin{aligned}
&a_t(n^*_{\text{layoff}}{}')^\nu (k'_{\text{layoff}}{}^*)^\alpha - wn^*_{\text{layoff}}{}' - rk^*_{\text{layoff}}{}' - \delta + \gamma'(n^*_{\text{layoff}}{}' - n_1) < \\
&a_t(n^*_{\text{layoff}}{}')^\nu (k'_{\text{layoff}}{}^*)^\alpha - wn^*_{\text{layoff}}{}' - rk^*_{\text{layoff}}{}' - \delta + \gamma(n^*_{\text{layoff}}{}' - n_1) \geq \\
&a_t(n^*_{\text{layoff}})^\nu (k_{\text{layoff}}{}^*)^\alpha - wn^*_{\text{layoff}} - rk^*_{\text{layoff}} - \delta + \gamma(n^*_{\text{layoff}} - n_1),
\end{aligned}$$

where the first inequality holds since $n^*_{\text{layoff}}{}' - n_1 < 0$ and the second inequality holds by the definition of optimality. Similar to above this implies that no layoff bunching will occur in the high cost case whenever it occurs in the low cost case. It may be that there is no layoff, in the high cost case and a layoff in the low cost case. In the case that both are layoffs, we have already shown that there is a smaller workforce reduction in the high cost case. This proves that for an increase in either γ or δ there is a weakly monotonic decrease in layoff propensity and size. $\square$

I.2 Numerical Results

The parameters used are $a_t \sim \mathcal{U}$ with $\underline{a} = .5$ and $\bar{a} = 1.5$, $\alpha = 0.2$, $\nu = .4$, $r = 0.2$, $w = 0.5$, $\delta^{high} = 0.005$, $\gamma^{high} = 0.1$, $\delta^{low} = 0.0025$, and $\gamma^{low} = 0.05$. That is, we choose the capital share to be half the size of the labor share and the rental cost of a unit of capital to be less than the cost of unit of labor.

In Internet Appendix Figure IA.1, we plot the optimal choice of labor in period 1 both when behavioral costs are present (in period 2) and when they are not. As a result of the possible behavioral costs in period 2, the labor choice of the behavioral managers in period 1 is uniformly below the optimal choice of labor in the standard model (except for the lowest realization of productivity when the choices are identical).

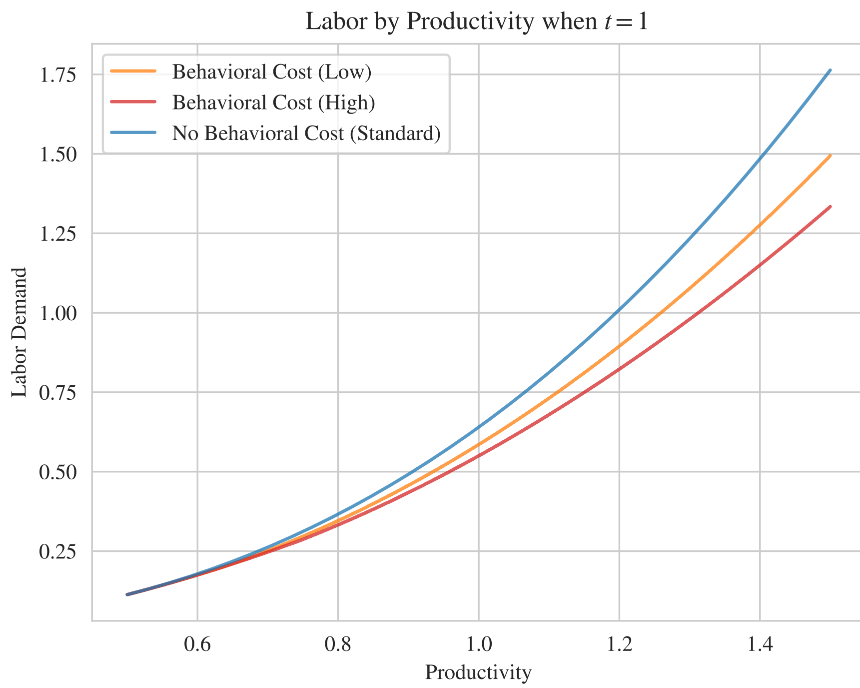

Figure IA.1. Labor Demand in Period 1

The figure plots the manager's labor demand in period 1 for different realizations of a_1. The parameters used are $a_t \sim \mathcal{U}$ with $\underline{a} = .5$ and $\bar{a} = 1.5$, $\alpha = 0.2$, $\nu = .4$, $r = 0.2$, $w = 0.5$, $\delta^{high} = 0.005$, $\gamma^{high} = 0.1$, $\delta^{low} = 0.0025$, and $\gamma^{low} = 0.05$.

Internet Appendix Figure IA.2 displays the optimal total expected payout in period

1 for both the case with and without behavioral costs in period 2. In alignment with the choice of labor, when the realization of productivity is high, more value is forgone by the managers subject to behavioral costs shading the choice for labor; however, the difference in value decreases as the realized productivity shock is lower. The high behavioral cost manager's value function is lowest throughout followed by the low behavioral cost manager.

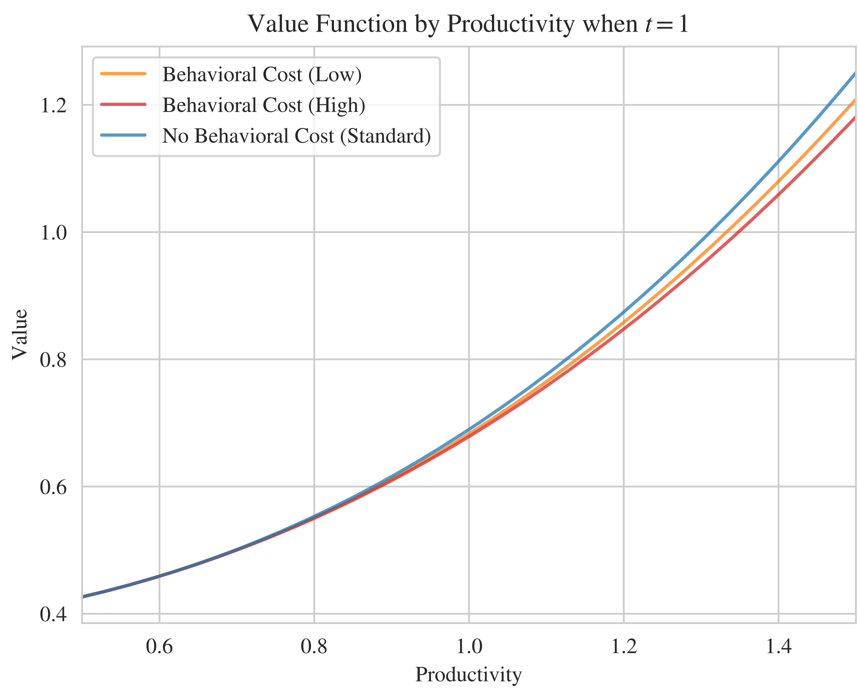

Figure IA.2. Value Function in Period 1

The figure plots the expected present total payoff in period 1 for different realizations of a_1. The parameters used are $a_t \sim \mathcal{U}$ with $\underline{a} = .5$ and $\bar{a} = 1.5$, $\alpha = 0.2$, $\nu = .4$, $r = 0.2$, $w = 0.5$, $\delta^{high} = 0.005$, $\gamma^{high} = 0.1$, $\delta^{low} = 0.0025$, and $\gamma^{low} = 0.05$.

Internet Appendix Figure IA.3 plots the labor choices in period 2. When productivity is high and behavioral managers hire, their hiring choice is identical to that of a standard manager. (This is because there are no future periods, and thus no incentives to shade hiring in anticipation of future layoffs.) However, when productivity is low, behavioral managers are reluctant to choose a low level of labor (due to their reluctance to fire), visible in the flat labor regions as well as the higher labor demand relative to the standard manager in the left region of the figure.

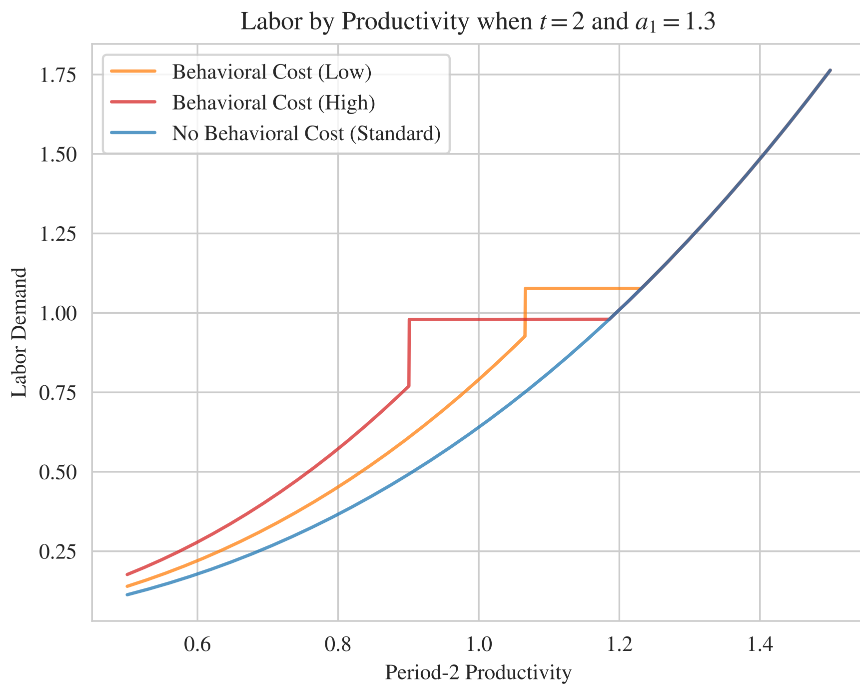

Figure IA.3. Labor Demand in Period 2

The figure plots the labor demand in period 2 for different realizations of a_2 both with and without behavioral costs, conditional on the choice of n_1 for $a_1 = 1.3$. The parameters used are $a_t \sim \mathcal{U}$ with $\underline{a} = .5$ and $\bar{a} = 1.5$, $\alpha = 0.2$, $\nu = .4$, $r = 0.2$, $w = 0.5$, $\delta^{high} = 0.005$, $\gamma^{high} = 0.1$, $\delta^{low} = 0.0025$, and $\gamma^{low} = 0.05$.

Finally, Internet Appendix Figure IA.4 generalizes to the case of a naïve social-preference manager. The insights are the same as those for the case of the sophisticated social-preference manager shown in the main text in Figure 1.

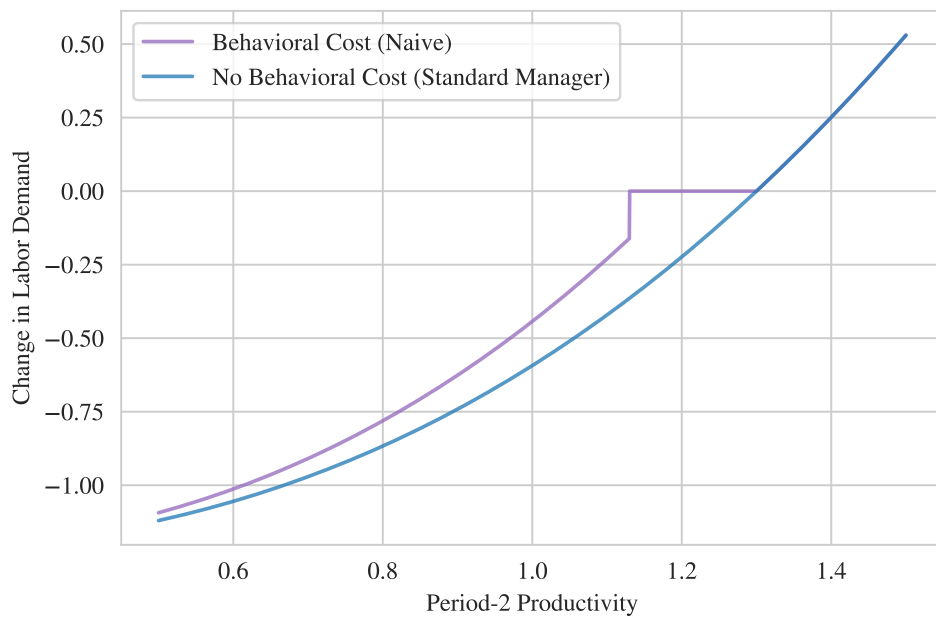

Figure IA.4. Change in Labor Demand (Period 2 Vs. Period 1) — Naïve Vs. Standard Manager

The figure plots the change in labor demand in period 2 compared to period 1 for different realizations of a_2 both with and without behavioral costs, conditional on the choice of n_1 for $a_1 = 1.3$. The parameters used are $a_t \sim \mathcal{U}$ with $\underline{a} = .5$ and $\bar{a} = 1.5$, $\alpha = 0.2$, $\nu = .4$, $r = 0.2$, $w = 0.5$, $\delta^{high} = 0.005$, $\gamma^{high} = 0.1$, $\delta^{low} = 0.0025$, and $\gamma^{low} = 0.05$.

II. Additional Discussion of Robustness and Mechanism Tests

This section summarizes the results of select figures and tables included in Internet Appendix Section III that serve as robustness tests for the results in Section 5.2, and presents further details on CEO entrenchment as a possible underlying channel.

Additional Controls. As a first robustness check, we extend our previous set of control variables with measures of physical or human capital investment opportunities, to address potential concerns that CEO tenure and layoffs may be correlated with these variables. We consider two measures of capital productivity: lagged market-to-book ratio (Jovanovic and Rousseau 2002) and a more complex definition of Q from Livdan and Nezlobin (2021). As a measure of worker productivity, we use lagged net employment growth, based on Bilal, Engbom, Mongey, and Violante (2022). As a measure of debt maturity, we use the long-term debt (debt with maturity greater than two years) as a percentage of total debt following Chen, Xu, and Yang (2021). More details about the calculation of these variables are contained in Appendix Section IV.

Internet Appendix Table IA.5 presents the results when including these additional control variables. Columns (1) and (2) replicate Column (2) of Table 3, augmented with the employment growth and market-to-book ratio or Q measures. Similarly, Columns (3) and (4) replicate Column (3) of Table 3. We find that, as expected, firms with higher labor and capital productivity or higher debt maturity are less likely to implement layoffs. At the same time, the size and statistical significance of the coefficient on CEO tenure remains unaffected with the additional controls. Thus, measures of the marginal products of labor and capital, closely related to investment opportunities, or debt maturity do not appear to affect or drive our results.

Fixed CEO Differences? One possibility is that the results in Table 3 are due to fixed CEO differences in the propensity to lay off workers, with short-tenured CEOs (in the sense of CEOs with a short *total* tenure) being more layoff-prone, and long-tenured CEOs being less layoff-prone independent of the cumulated tenure up to a certain point.

We investigate this possibility in Figure IA.6 of the Internet Appendix. Similar to Figure 7, we plot layoff probabilities by CEO tenure, but split the sample into three subgroups based on CEO's overall tenure length with the firm (short overall tenure of up to five years, medium tenure up to ten years, and long tenure of more than ten years). This split results in comparable subsample sizes in terms of the number of CEOs in each group ($N = 1,578$, $N = 1,426$, and $N = 1,674$, respectively).

Inconsistent with the idea of fixed CEO differences, we observe similar layoff patterns over CEOs' tenure cycle across the three subgroups. The finding of a within-tenure effect even for long-tenured CEOs is supported in additional unreported tests, in which we interact the main effect of CEO tenure from Table 3 with indicator variables for CEO subgroups based on overall tenure length, and continue to find strong tenure effects for long-tenured CEOs that are of similar economic magnitude as those reported in Table 3.

IV Approach. To further account for average tenure effects and to isolate effects arising *through* the tenure of CEOs, we follow Graham, Kim, and Leary (2020) and Altonji and Shakotko (1987) and also implement an instrumental variables (IV) approach as follows. As these authors note, it is not possible to include CEO-firm-pair fixed effects in the estimation in Table 3, since tenure and year fixed are collinear within a CEO-firm pair. Instead, we implement their proposed IV approach and use a CEO's *proportion* of overall tenure realized as an instrument for cumulated tenure up to that point. Specifically, we use $CEOTenureProp \equiv (Tenure_{i,j,t} - \overline{Tenure_{i,j}}) / \max_t Tenure_{i,j,t}$ as the instrument for CEO tenure, $Tenure_{i,j,t}$. Intuitively, this instrument purges the estimation of differences in average tenure across CEO-firm pairs.

Table IA.8 shows the results of this IV approach, implementing the two-stage versions of Columns (2) and (3) of Table 3, i.e., the specifications with either industry and location fixed effects or with firm fixed effects. Unsurprisingly, for both specifications, the first stage relation between CEO tenure and tenure proportion is strong, with the F-statistic well above 10. Additionally, in both specifications, the coefficient on instrumented CEO tenure is strongly negative, and similar to magnitude to the coefficients found in Table 3. These results lend additional support to the idea that the documented layoff–CEO tenure relation is not simply driven by cross-CEO differences.

CEO Entrenchment. The entrenchment index of Bebchuk, Cohen, and Ferrell (2009) emphasizes six key governance provisions capturing entrenchment: staggered boards, limits to shareholder bylaw amendments, poison pills, golden parachutes, and supermajority requirements for mergers and charter amendments. Since 2007, this data is collected by ISS, but restricted to the first four measures listed above.[IA.2] Therefore, we construct a partial E-index using the ISS data for the four available variables. The index ranges from 0 to 4 and increases by one for each provision, and is available for approximately two-thirds of our observations from our *2000–2020s firm-layoffs sample*.

Table IA.9 analyzes how the relationship between layoff propensity and CEO tenure varies with the level of entrenchment. We first focus on low entrenchment (defined as E-index ≤ 2) versus high entrenchment (E-index > 2). This simple split identifies about 25% of CEO-firm-years as low entrenchment years, and the remaining 75% as high entrenchment years. As revealed in Columns (1) and (2), which as before include either industry and location or firm fixed effects, the effect of CEO tenure on layoff propensity is *not* confined to CEO-years in the high entrenchment regime. Instead, the layoff–CEO tenure association is pronounced in both entrenchment regimes, and the magnitudes are similar in both regimes, as well as similar to the magnitudes estimated in Table 3.

[IA.2] The primary source of data in Bebchuk, Cohen, and Ferrell (2009) is the Investor Responsibility Research Center (IRRC). However, the IRRC stopped producing this data after 2006.

These patterns are unchanged in Columns (3) and (4), which split the high-entrenchment subsample further up into two separate categories (E-index = 3, approx. 67% of CEO-firm-years) (E-index = 4, approx. 7% of CEO-firm-years). In both columns, the effect of CEO tenure on layoff propensity is similarly pronounced in the highest-entrenchment regime as it is in the medium- and low-entrenchment regimes.

Overall, the evidence in Table IA.9 does not support classical entrenchment as being a primary driver of the previous findings.

III. Additional Figures and Tables

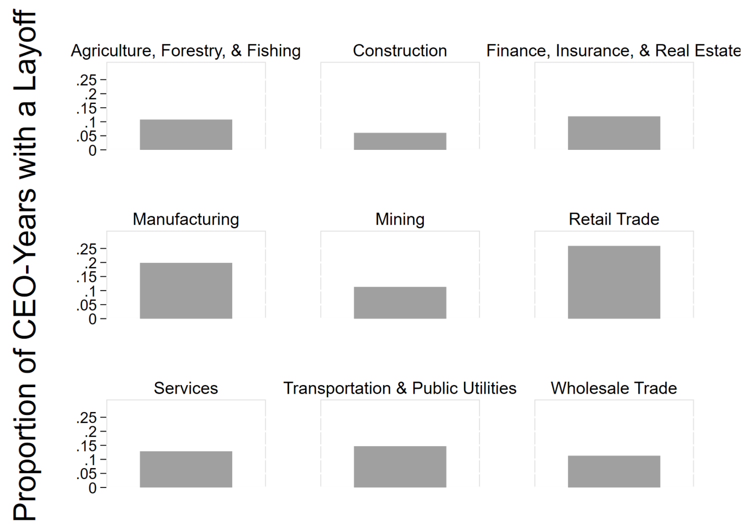

Figure IA.5. Layoffs by Industry

The figure plots the distribution of layoffs from our sample by industry classification based on SIC code. Data on layoffs hand-coded using S&P Key Developments data. SIC codes are provided by Compustat.

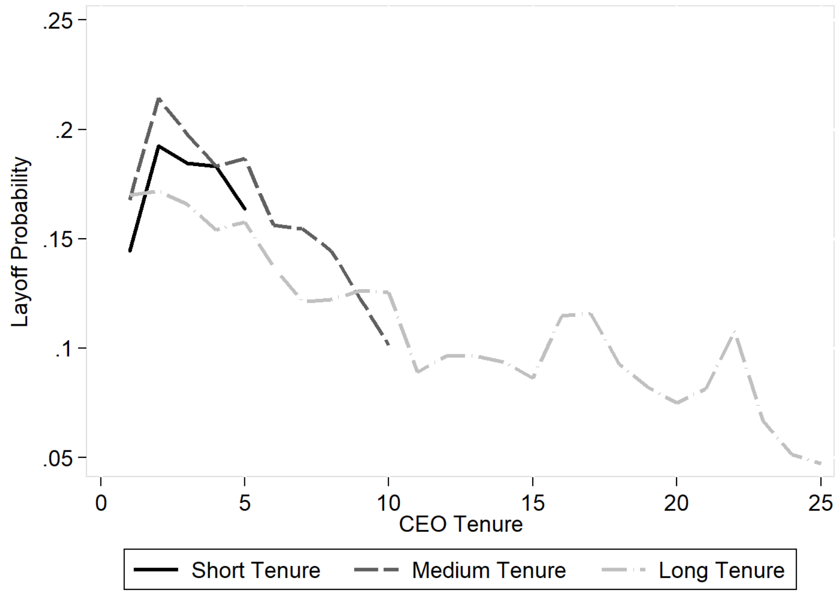

Figure IA.6. Layoff Propensity and Tenure—Fixed CEO Differences?

Layoff propensity by year of tenure plotted for three different CEO types based on overall/total tenure. Short tenure is up to five years. Medium tenure is more than five and up to ten years. Long tenure is more than ten years. Data on layoffs hand-coded using S&P Key Developments data. CEO tenure based on Execucomp data.

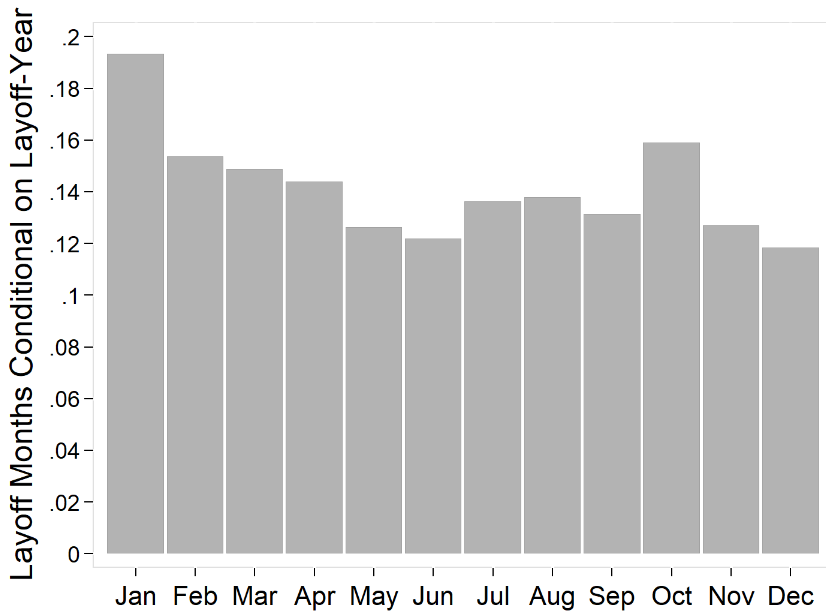

Figure IA.7. Layoffs By Month of the Year

This figure plots the probability of making at least one layoff announcement by month conditional on making at least one layoff announcement in a given year. Data on layoffs hand-coded using S&P Key Developments data.

Table IA.1. Layoffs and CEO Mortality—Stratified Cox Hazard Model

This table shows hazard ratios estimated from a Cox (1972) proportional hazards model. Mortality and tenure data is from Borgschulte, Guenzel, Liu, and Malmendier (2022). Industry distress measure and minimum stock performance based on data from CRSP. Layoff data is from Hallock (1998), Billger and Hallock (2005), and Farber and Hallock (2009). The dependent variable is an indicator that equals one if the CEO dies in a given year. The main independent variable of interest is "Distress Layoff" which is equal to one in year t if prior to or in year t, a CEO has undertaken a layoff during industry-wide distress, defined by the lagged industry distress variable. Age is CEO age. Firm size and profitability measures from Compustat data. We include time-invariant measures of firm size (assets and employees), as of the first year that the CEO has assumed the top position. Minimum stock performance defined as the worst stock performance in any six-month period during the CEO's tenure. More details about the data are in Section 3. Survival models are stratified by firms' industry affiliation. Standard errors, clustered by industry, are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)
Distress Layoff	0.292**	0.287**	0.283**
	(0.138)	(0.135)	(0.135)
Non-Distress Layoff	−0.103	−0.106	−0.112
	(0.094)	(0.092)	(0.094)
Industry Distress	0.088	0.097	0.087
	(0.115)	(0.114)	(0.122)
CEO Age	0.136***	0.138***	0.139***
	(0.009)	(0.009)	(0.009)
Firm Size (Ln Assets)	0.004	0.005	0.006
	(0.073)	(0.071)	(0.071)
Firm Size (Ln Employees)	−0.035	−0.038	−0.035
	(0.070)	(0.070)	(0.072)
Firm Profitability	0.651	0.591	0.667
	(0.697)	(0.700)	(0.725)
Year	−0.007		
	(0.009)		
Minimum Stock Performance			−0.145
			(0.332)
Year FE	No	Yes	Yes
State FE	Yes	Yes	Yes
Observations	31,917	31,917	31,917

Table IA.2. Layoffs and CEO Mortality—CEO Tenure Control

This table shows coefficients from a logit model controlling for the passage of time (Efron 1988). Mortality and tenure data is from Borgschulte, Guenzel, Liu, and Malmendier (2022). Industry distress measure and minimum stock performance based on data from CRSP. Layoff data is from Hallock (1998), Billger and Hallock (2005), and Farber and Hallock (2009). The dependent variable is an indicator that equals one if the CEO dies in a given year. The main independent variable of interest is "Distress Layoff" which is equal to one in year t if prior to or in year t, a CEO has undertaken a layoff during industry-wide distress, defined by the lagged industry distress variable. Age is CEO age. Firm size and profitability measures from Compustat data. We include time-invariant measures of firm size (assets and employees), as of the first year that the CEO has assumed the top position. Minimum stock performance defined as the worst stock performance in any six-month period during the CEO's tenure. More details about the data are in Section 3. Standard errors, clustered by industry, are shown in parentheses. Standard errors, clustered by industry, are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)
Distress Layoff	0.305**	0.308**	0.295**
	(0.139)	(0.140)	(0.142)
Non-Distress Layoff	0.034	0.023	0.007
	(0.105)	(0.105)	(0.106)
Industry Distress	0.196*	0.200*	0.166
	(0.119)	(0.120)	(0.126)
Cumulative CEO Tenure	−0.027*	−0.026*	−0.030**
	(0.014)	(0.014)	(0.014)
CEO Age	0.148***	0.151***	0.152***
	(0.010)	(0.011)	(0.011)
Firm Size (Ln Assets)	−0.158**	−0.154**	−0.152**
	(0.076)	(0.077)	(0.076)
Firm Size (Ln Employees)	0.058	0.057	0.067
	(0.075)	(0.076)	(0.075)
Firm Profitability	0.487	0.454	0.726
	(0.704)	(0.715)	(0.735)
Year	0.007		
	(0.010)		
Minimum Stock Performance			−0.536*
			(0.325)
Year FE	No	Yes	Yes
State FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	31,917	31,917	31,917

Table IA.3. Layoffs and CEO Mortality—Stratified Cox Hazard Model With Tenure Control

This table shows hazard ratios estimated from a Cox (1972) proportional hazards model. Mortality and tenure data is from Borgschulte, Guenzel, Liu, and Malmendier (2022). Industry distress measure and minimum stock performance based on data from CRSP. Layoff data is from Hallock (1998), Billger and Hallock (2005), and Farber and Hallock (2009). The dependent variable is an indicator that equals one if the CEO dies in a given year. The main independent variable of interest is "Distress Layoff" which is equal to one in year t if prior to or in year t, a CEO has undertaken a layoff during industry-wide distress, defined by the lagged industry distress variable. Age is CEO age. Firm size and profitability measures from Compustat data. We include time-invariant measures of firm size (assets and employees), as of the first year that the CEO has assumed the top position. Minimum stock performance defined as the worst stock performance in any six-month period during the CEO's tenure. More details about the data are in Section 3. Survival models are stratified by firms' industry affiliation. Standard errors, clustered by industry, are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)
Distress Layoff	0.313**	0.306**	0.296**
	(0.139)	(0.136)	(0.137)
Non-Distress Layoff	0.006	0.001	−0.014
	(0.104)	(0.103)	(0.104)
Industry Distress	0.161	0.171	0.142
	(0.127)	(0.126)	(0.133)
Cumulative CEO Tenure	−0.044***	−0.043***	−0.047***
	(0.015)	(0.015)	(0.015)
CEO Age	0.118***	0.121***	0.122***
	(0.010)	(0.010)	(0.010)
Firm Size (Ln Assets)	−0.023	−0.023	−0.021
	(0.071)	(0.069)	(0.069)
Firm Size (Ln Employees)	−0.046	−0.047	−0.039
	(0.072)	(0.072)	(0.072)
Firm Profitability	0.430	0.370	0.604
	(0.738)	(0.742)	(0.751)
Year	−0.010		
	(0.009)		
Minimum Stock Performance			−0.484
			(0.309)
Year FE	No	Yes	Yes
State FE	Yes	Yes	Yes
Observations	31,917	31,917	31,917

Table IA.4. Layoff Propensity Around Exogenous CEO Changes

This table shows the results of the stacked difference-in-differences analysis estimating the change in layoff propensity around exogenous CEO departures relative to non-treated firms (see Equation (4)). Exogenous CEO changes are defined as those occuring due to CEO death or illness of the incumbent CEO and come from Gentry, Harrison, Quigley, and Boivie (2021). See the text in Section 5.1 for additional details. Standard errors, clustered by firm, are shown in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

	(1)	(2)
Treat	−0.007	0.001
	(0.031)	(0.020)
T minus 5	−0.028	
	(0.053)	
T minus 4	0.053	
	(0.059)	
T minus 3	0.006	
	(0.051)	
T minus 2	0.032	
	(0.047)	
T minus 1	−0.010	
	(0.043)	
T plus 1	0.117***	
	(0.042)	
T plus 2	0.082	
	(0.060)	
T plus 3	0.031	
	(0.051)	
T plus 4	0.103	
	(0.068)	
T plus 5	0.105	
	(0.074)	
Treat × Post		0.080***
		(0.031)
Controls	Yes	Yes
Cohort-Year FE	Yes	Yes
Cohort-Industry FE	Yes	Yes
Observations	38,709	38,709

Table IA.5. Layoff Propensity and CEO Tenure—Additional Controls

Data on layoffs hand-coded using S&P Key Developments data. CEO tenure based on Execucomp data, divided by 100 in the regressions for ease of exposition. Firm characteristics are from Compustat data and lagged. Industry distress is based on CRSP stock data. Employment growth, Market-to-Book, and Q are all calculated using data from Compustat and, in the case of Market-to-Book and Q, CRSP, and lagged. Standard errors, clustered by firm, are shown in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

	(1)	(2)	(3)	(4)
CEO Tenure / 100	−0.270***	−0.257***	−0.174***	−0.165***
	(0.036)	(0.036)	(0.050)	(0.050)
Industry Distress	0.059***	0.061***	0.051***	0.051***
	(0.009)	(0.009)	(0.009)	(0.009)
Firm Size (Ln Assets)	0.033***	0.039***	0.026***	0.035***
	(0.003)	(0.004)	(0.009)	(0.009)
Firm Size (Ln Employees)	0.022***	0.017***	0.054***	0.050***
	(0.003)	(0.003)	(0.009)	(0.010)
Firm Profitability	−0.261***	−0.291***	−0.204***	−0.252***
	(0.032)	(0.031)	(0.045)	(0.044)
Debt Maturity	−0.028***	−0.027***	−0.012	−0.011
	(0.009)	(0.009)	(0.009)	(0.009)
Employment Growth	−0.075***	−0.068***	−0.045***	−0.044***
	(0.012)	(0.012)	(0.012)	(0.012)
Market-to-Book	−0.009***		−0.015***	
	(0.002)		(0.004)	
Q		−0.002***		−0.002***
		(0.000)		(0.001)
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	No	No
Industry FE	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes
Observations	24,243	23,768	24,046	23,574

Table IA.6. Layoff Propensity and CEO Tenure—Time-Varying Fixed Effects

Data on layoffs hand-coded using S&P Key Developments data. CEO tenure based on Execucomp data, divided by 100 in the regressions for ease of exposition. Firm characteristics are from Compustat data and lagged. Industry distress is based on CRSP stock data. Standard errors, clustered by firm, are shown in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

	(1)	(2)	(3)	(4)
CEO Tenure / 100	-0.267^{***}	-0.266^{***}	-0.265^{***}	-0.173^{***}
	(0.030)	(0.029)	(0.030)	(0.041)
Firm Size (Ln Assets)	0.030^{***}	0.029^{***}	0.029^{***}	0.024^{***}
	(0.003)	(0.003)	(0.003)	(0.007)
Firm Size (Ln Employees)	0.026^{***}	0.027^{***}	0.027^{***}	0.053^{***}
	(0.003)	(0.003)	(0.003)	(0.008)
Firm Profitability	-0.279^{***}	-0.283^{***}	-0.285^{***}	-0.239^{***}
	(0.024)	(0.024)	(0.024)	(0.031)
Industry Distress	0.054^{***}			
	(0.008)			
State FE	No	Yes	No	No
State-Year FE	Yes	No	Yes	Yes
Industry FE	Yes	No	No	No
Industry-Year FE	No	Yes	Yes	Yes
Firm FE	No	No	No	Yes
Observations	34,610	34,671	34,597	34,477

Table IA.7. Layoffs and CEO Tenure—Drop First CEO-Year

Data on layoffs hand-coded using S&P Key Developments data. CEO and CFO tenure based on Execucomp data, divided by 100 in the regressions for ease of exposition. Firm characteristics are from Compustat data and lagged. Industry distress is based on CRSP stock data. Standard errors, clustered by firm, are shown in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

	(1)	(2)	(3)	(4)
CEO Tenure / 100	-0.454^{***}	-0.295^{***}	-0.229^{***}	-0.220^{***}
	(0.035)	(0.030)	(0.041)	(0.044)
Industry Distress		0.059^{***}	0.046^{***}	0.040^{***}
		(0.007)	(0.007)	(0.008)
Firm Size (Ln Assets)		0.030^{***}	0.029^{***}	0.029^{***}
		(0.003)	(0.007)	(0.007)
Firm Size (Ln Employees)		0.026^{***}	0.049^{***}	0.054^{***}
		(0.003)	(0.008)	(0.008)
Firm Profitability		-0.267^{***}	-0.241^{***}	-0.244^{***}
		(0.024)	(0.030)	(0.033)
CFO Tenure / 100				-0.054
				(0.074)
Year FE	No	Yes	Yes	Yes
State FE	No	Yes	No	No
Industry FE	No	Yes	No	No
Firm FE	No	No	Yes	Yes
Observations	31,595	31,595	31,469	29,465

Table IA.8. Layoff Propensity and CEO Tenure—IV Approach

Data on layoffs hand-coded using S&P Key Developments data. CEO tenure based on Execucomp data, divided by 100 in the regressions for ease of exposition. Firm characteristics are from Compustat data and lagged. Industry distress is based on CRSP stock data. Standard errors, clustered by firm, are shown in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

	1st Stage	2nd Stage	1st Stage	2nd Stage
	(1)	(2)	(3)	(4)
CEO Tenure Proportion	0.128***		0.139***	
	(0.002)		(0.002)	
CEO $\widehat{\text{Tenure}}$ / 100		−0.182***		−0.233***
		(0.069)		(0.057)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	No	No
Industry FE	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes
Observations	34,683	34,683	33,130	33,130

Table IA.9. Layoff Propensity and CEO Tenure—CEO Entrenchment

Data on layoffs hand-coded using S&P Key Developments data. CEO tenure based on Execucomp data, divided by 100 in the regressions for ease of exposition. Firm characteristics are from Compustat data and lagged. Industry distress is based on CRSP stock data. Data for the E-index comes from ISS and is defined as the count of four key governance provisions (staggered boards, limits to shareholder bylaw amendments, poison pills, and golden parachutes) which the firm has implemented. Standard errors, clustered by firm, are shown in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

	(1)	(2)	(3)	(4)
CEO Tenure / 100 × E-Index ≤ 2	-0.337^{***}	-0.191^{***}	-0.337^{***}	-0.189^{***}
	(0.056)	(0.064)	(0.056)	(0.064)
CEO Tenure / 100 × E-Index > 2	-0.193^{***}	-0.174^{***}		
	(0.038)	(0.052)		
CEO Tenure / 100 × E-Index = 3			-0.180^{***}	-0.164^{***}
			(0.039)	(0.052)
CEO Tenure / 100 × E-Index = 4			-0.303^{***}	-0.259^{**}
			(0.116)	(0.131)
E-Index > 2	−0.016	0.008		
	(0.010)	(0.011)		
E-Index = 3			−0.016	0.008
			(0.010)	(0.011)
E-Index = 4			−0.012	0.008
			(0.017)	(0.019)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes
Observations	23,323	23,241	23,323	23,241

Table IA.10. Layoff Propensity and CEO Tenure—Layoffs Around Holiday Season With Extended Layoff-Year Window

Dependent variable is equal to one for years with a layoff in December and zero otherwise. Regressions use the layoff-year sample from Columns (3) and (4) of Table 7, extended by CEO-firm-years for which there is a layoff in Q1 (Q1 or Q2) of the following year. Data on layoffs hand-coded using S&P Key Developments data. CEO tenure based on Execucomp data, divided by 100 in the regressions for ease of exposition. Firm characteristics are from Compustat data and lagged. Industry distress is based on CRSP stock data. Standard errors, clustered by firm, are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Layoff-Years + Q1		Layoff-Years + Q1 + Q2	
	(1)	(2)	(3)	(4)
CEO Tenure / 100	-0.271^{***}	-0.298^{***}	-0.249^{***}	-0.261^{**}
	(0.061)	(0.112)	(0.057)	(0.106)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes
Observations	6,585	6,144	7,133	6,787

IV. Data Appendix

IV.1 Key Developments Data

This section provides more details about the Standard and Poor's (S&P) Capital IQ Key Developments database and our data collection. Although there are some observations from the years before, the data collection is generally not considered to be robust until 2002 (Edmans, Goncalves-Pinto, Groen-Xu, and Wang 2018; Cohn, Gurun, and Moussawi 2020. Many of the events entered in 2000 and 2001 were entered in 2002 or later. The data was downloaded on January 28, 2022. Therefore our sample period covers from 2002 to 2021. The database covers more than 250,000 companies worldwide, but since we rely on Execucomp for details about CEOs, we collect only key developments for firms in Execucomp in the 2002 to 2021 period. Layoff announcements are located in the Key Developments database under the category of "Potential Red Flags/Distress Indicators" subcategory of "Discontinued Operations/Downsizings". Sometimes layoff related announcements may be referenced in other categories, such as "Labor-related Announcements" which covers union related announcements; however, we found this to be highly atypical in reviewing the data. There are approximately 18,000 key developments in this subcategory for firms in our sample.

Each key development entry includes the announcement date, the date entered into the database, the last date the entry was modified, a short headline, a situation summary, a type, a source, a company role, and other identifiers. We only use dates, headlines, and the situation summaries. The headlines are typically a phrase and the summaries are generally between one sentence and a small paragraph. To the best of our knowledge, the content is written by S&P employees based on a variety of sources which, according to S&P, may include "news aggregators, stock exchanges and regulatory websites as well as company websites." The data was raw text and therefore required significant programmatic processing and reviewing described below. We classify each key development as a layoff, a closure, or irrelevant. If a key development specifies a layoff and a closure, then it is classified as a layoff. In general, closures are also likely tied to (unspecified) layoffs. For example, in some cases, we see the announcement of a closure followed by a duplicate announcement which specifies an associated layoff. Duplicate layoffs/closures are noted when possible.[IA.3] Since most key developments are announcements, for consistency we focus on layoff announcements in our data; therefore, a key development which details a previously announced layoff would be coded as a duplicate. When available we collect the number of people laid off or percent (of total employees) laid off.[IA.4] Additionally, we

[IA.3] In some cases, the summary will note that the announced layoff was part of an earlier announcement or the execution of an alternative announcement. Alternatively, a duplicate may be obvious from context. For example, if it is specified a certain factory is being shut down.

[IA.4] If only the percent of a subset of workers being laid off is referenced, this number is not collected since collect layoff/closure location(s) up to the city level for US layoffs and at the country level for non-US layoffs. We also take note of layoffs which are specified as global, international, or similarly described.

To increase the speed of hand-collection, we prepopulated some variables algorithmically. First, the headline and the situation summary were lemmatized which standardizes verbs and nouns. For example, "cutting" would be reduced to "cut" and "jobs" would be reduced to "job". Layoffs were identified if there was a headline or sentence in the summary which includes a layoff related verb and occupation related noun. Layoffs were identified with low confidence if only a one of the two is present. If the key development was not classified as a layoff but contained a closure word, then it was classified as a closure. Other observations or observations which included words indicating uncertainty in layoff/closure related sentences were classified as neither. Layoff numbers and percentages were identified with high confidence if the number was included in a common pattern using layoff verbs and occupation nouns. For example, "cut its workforce by 5%" or "cut x% of its workforce" would fit common patterns. If no numbers in this pattern were available or more than one number in a pattern was found, the number/percent was coded with low confidence. We focus on US companies and therefore collect the location up to the city level for US locations and to the country level for foreign layoffs. We identify foreign locations at the country level. Foreign countries are identified by looking for country names or large global cities. Locations in the United States are identified up to the city level when available. States are identified by name or abbreviation. US cities are identified by name in the case of large cities or coming before a comma and state name (i.e., "city, state"). Layoffs are identified as global if they include a related word (e.g., global, international, etc.).

We recognize that this algorithm is imperfect and cannot identify duplicates; therefore, after this prepopulation, all entries were read and all data points were entered/reviewed by a research assistant or coauthor. Low confidence layoffs and numbers were highlighted during the hand collection process to call extra attention to these data points. Instructions specified layoffs as when "when it is clear people lost their jobs". Our measure focuses on human capital. Thus, business sales, including exits via sales, where no jobs were lost and temporary furloughs were specifically noted to not be coded as layoffs. Duplicates were specified as when an "observation is believed to be a duplicate of a previous observation". The instructions did not request manual review (e.g., by using a search engine) with the solitary exception of identifying locations. This could apply to cities where the state was not specified and could easily be identified by using a search engine to search for the city name and company name. Alternatively, sometimes non-city locations, for example, business complexes may be specified and the city can be easily identified using a search engine.

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we only have the number of total employees at the firm in Compustat.

To provide more detail on the classification of layoff events into blue-, pink-, and white-collar layoffs, we count how many words from each category appear in the layoff description. If a description does not contain any blue-collar or pink-collar words and at least one white-collar word, we classify it as a white-collar layoff. The reason is that if a blue- or pink-collar word appears in the description, it is almost certainly not a white-collar layoff since these would typically not discuss factories or retail stores. We classify the remaining layoffs that contain at least one blue-collar word or pink-collar word as the type that it contains more words from, defaulting to blue-collar in the case of a tie.

As mentioned in the main text, to verify our approach we leverage the data on the locations of layoffs. We use occupation data for cities from the 2000 US Census.[IA.5] We construct a proxy for the percent of predominantly blue-collar occupations, white-collar occupations, and pink-collar occupations. There are 13 broad categories, and we designate "Management, business, and financial operations occupations" and "Professional and related occupations" as white-collar, "Construction, extraction, and maintenance occupations" and "Production occupations" as blue-collar, and "Personal care and service occupations" and "Sales and related occupations" as pink-collar.

For classified layoffs for which local demographic information on occupations is available, the layoff type as determined using our text-based approach, is positively and statistically significantly associated with the city-level Census data. That is, layoffs we classify as blue-(pink-, white-) collar positively predict a higher percent of the employed population in the city being in the blue-(pink-, white-) collar occupation category, as well as a higher likelihood that the city is among the top 25% of cities in the sample with the largest share of blue-(pink-, white-) collar employees.

IV.2 CEO Long-Term Mortality Sample Variables

Death. Based on hand-collected mortality data from Borgschulte, Guenzel, Liu, and Malmendier (2022). Censored at a cutoff date of October 1st, 2017.

Layoff. Layoffs are based on data from Hallock (1998), Billger and Hallock (2005), and Farber and Hallock (2009). This dataset provides a comprehensive list of layoff announcements collected from the *Wall Street Journal*.

Age. Based on hand-collected birth data from Borgschulte, Guenzel, Liu, and Malmendier (2022).

Industry Distress. The variable used in our analysis is equal to one if the CEO has experienced industry distress, as defined below in Section IV.3.

Firm Size, Assets. We measure assets as total assets from Compustat, variable code AT. We use assets as of the first year that the CEO has assumed the top position.

[IA.5] More precisely we used data on "Places." Data is obtained from Social Explorer.

Firm Size, Employees. We measure employees as total employment from Compustat, variable code EMP. We use employees as of the first year that the CEO has assumed the top position.

Firm Profitability. Firm profitability is measured as $\frac{OIDBP}{AT}$. We use profitability as of the first year that the CEO has assumed the top position.

Minimum Stock Performance. Minimum stock performance is defined as the worst stock performance in any six-month period during a CEO's tenure.

IV.3 2000–2020s Firm-Layoffs Sample Variables

Layoff. We classify a CEO-Firm pair year as a layoff if there are three separate layoff events or at least 1% of the workforce is laid off. Some layoff events directly note the percent of the workforce laid off. In other cases, the percent of the workforce laid off is based off of the number of employees laid off collected from the key development data divided by the total employment from Compustat. For our analyses focusing on location- or month-specific layoffs, we define a layoff as any layoff event in the relevant time period.

CEO Tenure. We identify CEOs using ExecuComp's classification, where the CEOANN variable has value "CEO". CEO tenure is calculated using the "BECAMECEO" variable as the starting year when it is available. Otherwise we attempt to calculate it using the Execucomp panel which starts in 1992.

CFO Tenure. We identify CFOs using ExecuComp's classification, where the CFOANN variable has value "CFO." If there are two such individuals in a year, then we choose the one whose title includes some variation of CFO (e.g., "Chief Financial Officer"). If there is no CFO noted in Execucomp, we identify them by examining the text of their title following Jiang, Petroni, and Wang (2010). We look for titles in the following order: CFO, chief financial officer, treasurer, controller, finance, and vice president-finance. If more than one person in a year has the the same title then the person with the higher age is chosen as the CFO.

Industry Distress. An industry-year is defined as in distress if the median firm's stock price declined by at least 30% in the prior two years prior or the prior and current year. As in Babina (2020), we (i) use SIC3 industry classes, (ii) restrict to single-segment CRSP/Compustat firms, i. e., drop firms with multiple segments in the Compustat Business Segment Database (CBSD), (iii) drop firms if the reported single-segment sales differ from those in Compustat by more than 5%, (iv) restrict to firms with sales of at least \$20m, and (v) exclude industry-years with fewer than four firms. We use firms' modal SIC code across CRSP, Compustat, and CBSD, and the latter in case of a tie.

Firm Size, Assets. We measure assets as total assets from Compustat, variable code AT.

Firm Size, Employees. We measure employees as total employment from Compustat, variable code EMP.

Firm Profitability. Firm profitability is measured as $\frac{OIDBP}{AT}$. $OIDBP$ is operating income before depreciation and AT is total assets, both from Compustat.

Market-to-Book Ratio. The market to book ratio is defined as $\frac{PRCC\_F \cdot CSHO}{AT}$. $PRCC\_F$ is the annual closing stock price from CRSP. $CSHO$ is the number of common shares outstanding from CRSP. AT is total assets from Compustat.

Tobin's Q. Our measure of Q is defined as $\frac{DLC+DLTT+PRCC\_F \cdot CSHO}{PPEGT}$. DLC is debt in current liabilities from Compustat. $DLTT$ is long-term debt from Compustat. $PPEGT$ is gross property, plant and equipment from Compustat. We use the variable winsorized one-period lagged. We winsorize Q at the 95th percentile as this measure is substantially more right-skewed than market-to-book, though our results do not depend on this winsorizing approach.

Employment Growth. Employment growth is defined as $\frac{EMP_t - EMP_{t-1}}{EMP_{t-1}}$. EMP is total employment from Compustat.

Debt Maturity. Debt maturity is defined as $\frac{DLTT-DD2}{DLC+DLTT}$, which is the fraction of total debt maturing in more than two years. $DD2$ is the fraction of debt maturing in 2 years.