Prosociality and Layoffs*

Marius Guenzel† Clint Hamilton‡ Ulrike Malmendier§

February 11, 2025

Abstract

Many managers describe layoffs as the hardest and most painful decisions of their careers; yet, standard economic models treat human and physical capital adjustments alike. We provide a new set of facts about frictions in layoff decisions, using a novel dataset of layoffs by U.S. public firms constructed with NLP techniques, and propose prosocial considerations of the CEO as a unifying explanation. First, firing decisions have large adverse health effects on CEOs, with distress-induced layoffs estimated to reduce CEO lifespan by 1.85 years, accounting for the direct effects of distress. Second, CEOs become more reluctant to make layoffs over their tenure as they form more connections inside the firm. Third, their increasing reluctance to lay off employees intensifies when layoffs are more painful for employees, such as during recessions or the holiday season, or more painful for managers to witness, such as when they affect socially or geographically close employees. Fourth, the documented layoff reluctance is substantially more pronounced among CEOs with higher empathy-related traits. We also show that long-tenured CEOs are more likely to cut R&D spending during recessions, offsetting forgone savings from layoffs. Our results imply the need to adjust models of managerial decision-making for a "human" component of layoff avoidance.

Keywords: Layoffs, CEOs, Managerial Prosocial Concerns, CEO Job Demands
JEL Codes: G30, M12, M50, D91

---

* For helpful comments and suggestions, we thank our discussants Cláudia Custódio, Paul Décaire, David Matsa, Ernst Maug, Morten Sørensen, and David Yermack, conference and seminar participants at the 2023 AFA Annual Meeting, the 2023 RCFS Winter Conference, the 2023 Drexel Annual Corporate Governance Conference, the 2023 Erasmus Corporate Governance Conference, the 2023 SITE Psychology and Economics Conference, the 2023 JCF SI Conference on Ownership and Corporate Social and Sustainable Policies, the Fall 2023 NBER Behavioral Finance Meeting, the 2024 Adam Smith Conference, the Banque de France, University of Chicago, Havard University, Tilburg University, UC Berkeley, and Wharton, as well as Dan Garrett, Vincent Glode, Ashley Litwin, Dmitry Livdan, Karin Li, Amir Kermani, Bernardo Maciel, Andrew Perry, Rob Stambaugh, Luke Taylor, Johan Walden, Minghao Yang, and Yao Zeng. We thank Kevin F. Hallock for sharing data. We thank Tim Zhang for outstanding research assistance and research assistants at UC Berkeley and the University of Pennsylvania for help with data collection. Guenzel gratefully acknowledges financial support from Analytics at Wharton. All errors are our own.

†University of Pennsylvania. mguenzel@wharton.upenn.edu.
‡UC Berkeley. cth@berkeley.edu.
§UC Berkeley, NBER, and CEPR. ulrike@berkeley.edu.

1. Introduction

In the standard firm investment model, the adjustment of human capital is treated akin to the adjustment of physical capital: every period, the firm optimizes over all factor inputs subject to potential adjustment costs. In practice, CEOs describe their personal experiences with hiring and firing in rather different terms. In a worldwide survey of 2,000 senior executives, 60% state that hiring and firing was "the toughest decision" in their careers (Martin 2005). Similarly, the senior managers of Fortune 500 firms interviewed in Hallock (2005) express that the "entire layoff process is gut wrenching" because it is "a human decision." It is also common to find a CEO describing the impact on them personally as "something that took a heavy toll on me ... something I don't ever want to do again."[1] These first-hand accounts depict hiring and firing decisions as different in nature from the purchase, write-down, and divestment of machines.

Prior work on the frictions in human capital choices has highlighted "classical" adjustment costs in hiring and firing that arise 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 propose a complementary, novel type of "behavioral adjustment costs" firms may face with respect to labor—but not capital—that arises from decision-making affecting humans. The proposed channel builds on prior evidence on managerial prosociality towards workers, both from the laboratory and the field.[3] While previous studies have linked CEO prosocial attitudes to CEOs' corporate social responsibility (Cheng et al. 2023; Cronqvist and Yu 2017), we focus on the context of mass layoffs, where CEO decisions can negatively affect the lives of many employees.

We assemble a new, comprehensive dataset covering layoff announcements by S&P 1500 firms (and other firms in Execucomp) over the last two decades. Existing

[1] Quote from a former executive at Siemens AG in the 2016 documentary titled "Lonely at the Top: Top-Level Managers at Their Limit," available (in German) at youtube.com/watch?v=FcRH3r0nEDE.

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

[3] Chen and Li (2009) find prosocial behavior to be strong towards in-group members, and Fehr and List (2004) find it to be pronounced among experimental subjects who are real-life CEOs. Relatedly, Taylor (2010) estimates large personal disutility costs of board member from firing CEOs (which could reflect a distaste for firing) to explain low CEO turnover rates.

work typically proxies for layoffs by changes in net employment count (e.g., Landier et al. 2009, Schmieder et al. 2022). We utilize the data on "Discontinued Operations and Downsizings" in the S&P Capital IQ Key Developments database and use a combination of natural language processing (NLP) and hand-coding of these news-like text data to identify actual layoffs and their characteristics. Unlike existing datasets, our data allows us to distinguish *involuntary* layoffs from employee reassignments or voluntary departures, such as early retirement. We also collect information on layoff severity and geography, i. e., the numbers of employees laid off and layoff sites. Our final dataset covers more than 12,000 layoff announcements.

We utilize the data to perform several empirical tests regarding the effects and determinants of layoff decisions. Our tests are guided by a simple theoretical framework that allows for CEOs to experience a reduction in their utility from the act of firing workers. The proposed underpinning for the disutility cost comes from the psychology literature on *empathy*, which is the affective response to other people's (actual or inferred) emotional state (Decety and Jackson 2004)—in this case a CEO's affective response to workers' distress from losing their job. Empathy has been shown to grow over time as attachment to others increases ("friends-vs-strangers") and to depend on the perceived closeness or similarity to others ("self-other overlap"), see Meyer et al. (2013), Morelli et al. (2015). Motivated by these characteristics, the framework predicts that CEOs' layoff propensity is decreasing (i) in CEOs' tenure (as they become more attached to their workforce over time), (ii) in the disutility of workers from a layoff (e.g., around Christmas and in recessions), and (iii) in workers' geographical and social closeness to the CEO, as defined below.

In the first part of our empirical analysis, we estimate the personal health costs of firing for CEOs. We document a significant reduction in the longevity of CEOs who implement layoffs in response to industry distress shocks. The estimated effect size is large, roughly corresponding to that of a two-year increase in CEO age, and is robust to controlling for the direct effect of industry distress (cf. Borgschulte et al. (2023)) as well as firm performance. By contrast, layoff decisions that were not necessitated by an industry distress shock have no significant mortality effect.

The estimated health costs are consistent with the proposed prosociality channel as well as other mechanisms that make firing particularly stressful, above and beyond the effects of the industry distress itself. The estimation results are, instead,

hard to reconcile with models under which CEOs avoid layoffs (in non-distress times) solely in response to social pressure from the media or stakeholders, or due to social-image concerns, but do not experience direct disutility costs from firing. That is, preferences that reflect social considerations, but no actual stress induced by the act of firing are harder to reconcile with CEOs physically suffering when they implement layoff decisions.

In the second part of the analysis, we test for changes in CEOs' proclivity to implement layoffs over the course of their tenure as they develop deeper social connections inside the firm. We proceed in three steps.

In the first step, we contrast the firing decisions of newly appointed CEOs to those of incumbent CEOs in the same industry. We utilize plausibly-exogenous CEO changes due to the death or the illness of the incumbent CEO, which have been previously used as an instrument for CEO turnover (e.g., Fee et al. 2013). Comparing treated firms (with exogenous turnover) to untreated firms in the same industries over the five years before and the five years after treatment, we estimate a significant 8.7 percentage points (pp) increase in the propensity to lay off employees. These additional 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. This result suggests frictions in firing among CEOs who have been leading their company for some time, to the detriment of shareholders.

Second, turning to the full CEO sample, we show that CEOs' propensity to make layoffs is strongly declining over their tenure. An interquartile increase in CEO tenure (from 3 to 11 years) predicts a reduction in layoff propensity of 11% (1.5 pp) relative to the baseline annual layoff probability of 13%. The negative tenure-layoff relation is not explained by firm size (e.g., assets and employment), profitability, labor and capital productivity, year fixed effects, industry fixed effects, or firm fixed effects. The latter implies that endogenous matching, where long-tenured CEOs prefer companies that generally avoid firing, does not explain the result. The finding is also robust to controlling for the *CFO*'s tenure. That is, there is a distinct tenure effect for CEOs but not for any C-Suite manager.

Unlike in the first approach (death- and illness-induced turnover), however, we do not have plausibly exogenous variation in the tenure length of a given

CEO. In order to address remaining concerns about possible confounds of the estimated tenure-layoff link, we implement the instrumental variables (IV) approach first proposed by Altonji and Shakotko (1987) and also applied by Graham et al. (2020). Specifically, we instrument the tenure variable with the proportion of total tenure completed. As discussed in Graham et al. (2020), the proportion of tenure completed is (a) correlated with tenure, but (b) orthogonal to fixed individual CEO characteristics or CEO-firm match quality, which affects tenure length, since all CEOs start having completed none of their tenure and finish having completed all of it. The instrument addresses remaining concerns that the estimated decline in layoff propensity might reflect different "types" of CEOs (with long versus short tenure) having different layoff propensities for other reasons, as well as concerns about long-tenured CEOs experiencing different economic circumstances, which also lead to different layoff propensities. We show that all results replicate using instrumented tenure.

As a third step, we also show that internally hired CEOs are significantly less likely to lay off employees than externally hired CEOs, consistent with the tenure-layoff relation being driven by the CEO's attachment to firm employees.

The estimated decline in layoff propensity with CEO tenure is distinct from prior work on "CEO investment cycles" (Pan et al. 2016), which documents increasing investment in physical and human capital over a CEO's tenure. The increasing investment in physical capital appears to be explained by increasing CEO power, but, notably, the same pattern does not hold for human capital investment. In fact, the decrease in layoff propensity is not explained by any of the existing measures of CEO power and entrenchment, including time-varying board co-option, CEO duality, the Bebchuk et al. (2009) index and others.

In summary, the results of this second set of analyses indicate that CEOs' layoff propensity decreases with the length of their tenure and attachment to the firm. The results are consistent with increasing prosociality in response to deepening connections inside the firm. Other stressors associated with firing, such as lawsuits by employees, could also explain the first set of results on adverse CEO health effects, but are less likely to become more severe over a CEO's tenure.

In the third set of analyses, we implement several heterogeneity tests guided by theoretical predictions about when managerial prosocial concerns should be more or less pronounced. One prediction is that layoff decisions become more costly

to the manager when their effect on employees is more severe. Examples include layoffs during economic downturns, which have more adverse consequences for those who lose their jobs than layoffs at other times (Jacobson et al. 1993), and layoffs during the holiday season. We show that, over their tenure, CEOs become more averse to these "painful" layoffs and are significantly less likely to implement them, both unconditionally and conditionally on making a layoff in a given year. The within-year layoff timing is particularly difficult to reconcile with alternative explanations of the tenure-layoff link. The results are also robust to using the instrumented tenure variable.

In an auxiliary analysis, we ask how longer-tenured CEOs manage to avoid layoffs during times of economic distress financially, i. e., how they recoup the financial burden of continuing to pay the corresponding wages during an economic downturn. We show that the reduction in layoffs appears to come at the expense of other firm activities, such as investment in research and development (R&D). That is, longer-tenured CEOs reduce R&D spending during recessions, when financing constraints are more likely to bind, while also avoiding layoffs.

For another set of heterogeneity tests motivated by our framework, we identify layoffs that might be more painful for the CEO to witness, holding constant workers' disutility. One such type of variation is geographical closeness. We compare layoffs at or near the firm's headquarters to layoffs at sites that are further away. Layoffs at geographically distant sites might affect CEOs less since they are not witnessing the effects of the layoff and are also less likely to know the laid-off employees personally. Another type of variation is in social closeness. We build on evidence of "familiarity" or "similarity" affecting the degree of prosociality (Chen and Li 2009, Meyer et al. 2013), and compare CEOs' proclivity to lay off socially close white-collar workers with their proclivity to lay off blue-collar workers. In both cases, we find that the tenure-induced increase in the reluctance to lay off workers is driven by (geographically or socially) close employees. As before, all results are robust to instrumenting the explanatory tenure variable using the approach of Altonji and Shakotko (1987) and Graham et al. (2020).

The analyses thus far have provided three sets of facts about frictions in layoff decisions: a link to adverse CEO health outcomes, a link to CEOs' tenure and attachment to their firm, and the specific avoidance of more painful layoff during distress and holiday seasons as well as among socially or geographically close

employees. All of these results are consistent with a "human" component of layoff avoidance that could reflect empathy towards employees. As an additional piece of evidence in support of the proposed interpretation, we turn to prior work that has directly assessed personality characteristics among U.S. CEOs, and established a link between variation in empathy-related managerial attributes and CEO behavior. Specifically, Kaplan et al. (2012) use detailed personality assessments of U.S. CEO candidates to identify key characteristics. They find that managerial overconfidence (resoluteness) on the one hand and empathy on the other hand are primary distinguishing factors of CEOs (Kaplan et al. 2012, p. 975). Corroborating the distinction between overconfident and empathetic CEO types, Kaplan et al. (2022) find that the *Longholder* measure, the most widely used measure of managerial overconfidence, predicts significantly lower managerial scores on empathy-related attributes.[4] Motivated by this evidence, we use the *Longholder* measure to empirically distinguish between less empathetic ($Longholder = 1$) and more empathetic ($Longholder = 0$) CEOs. We find that the declining layoff propensity of CEOs over the course of their tenure is driven by non-overconfident, more empathetic CEOs.

Overall, a psychological underpinning of prosociality arising from managers' empathetic concern for employees is consistent with all of our empirical evidence. Our analysis uncovers new evidence on a human dimension in layoff decisions that suggests the need to adjust existing models of the firm's optimization problem. These findings contribute to the "social economics" paradigm (Hirshleifer 2020), which calls for more work on the "social processes that shape economic thinking and behavior."

Literature. Our paper makes four main contributions to the literature.

First, we advance the literature on the effects of CEOs' job duties and stressful job environments. Bandiera et al. (2018) and Bandiera et al. (2020) document the intense demands and long work hours of CEOs, especially non-family-firm CEOs. Bertrand and Mullainathan (2003) and Cronqvist et al. (2009) provide evidence on more labor-friendly policies such as higher employee pay when managers are more able to "enjoy the quiet life." The interviews in Hallock (2005) provide first-hand evidence from senior managers on the taxing nature of layoff decisions in particular.

[4] The *Longholder* measure was first introduced by Malmendier and Tate (2005) and identifies managers as overconfident if they fail to diversify and exercise own-firm stock options until the last year of their duration.

Most directly related to our result on layoffs and CEO mortality, Borgschulte et al. (2023) provide evidence that plausibly exogenous variation in CEOs' job demands, including from industry crises, implies significant health consequences in terms of aging and mortality. In a related vein, Kárpáti and Renneboog (2023) find increased use of antidepressants by employees of Dutch firms, including by higher-paid individuals, when their firm faced financing difficulties during the Great Recession. We extend the prior work by providing direct empirical evidence that layoffs are a major contributing factor to the demanding nature and adverse health effects of the CEO role and by showing, in turn, a direct effect of those consequences on layoff decision-making.

Our paper also integrates a mechanism for those effects based on managerial prosocial concerns for workers.[5] As such, this paper contributes to the research on nonstandard managerial decision-making (see Malmendier (2018) and Guenzel and Malmendier (2020) for recent surveys).

Second, we contribute to the literature on CEO effects, and in particular tenure effects, on firm investment. Pan et al. (2016) document a link between CEO tenure and disinvestment, including asset sales. We instead focus on labor decision-making and on managerial prosocial concerns as an underlying channel. Correspondingly, while the prior work uses the S&P Capital IQ data to extract downsizing announcements, we use the subset of the data that identifies layoffs and construct a pure human-capital measure. We specifically focus on involuntary layoffs that result in the unemployment of affected workers.

Bai and Mkrtchyan (2023) analyze a sample of manufacturing firms and find that, after the appointment of an external (as opposed to an internal) CEO, more factories are closed or see employment reductions. In our data, which includes non-manufacturing firms, external CEOs have a higher propensity to make layoffs. Collectively, our findings suggest that one significant underlying mechanism involves internal CEOs having more extensive or deeper pre-existing relations with employees.

Third, our findings add to the literature on social considerations in (corporate)

[5] Our finding of a direct link between layoffs and health for top-level managers responsible for these decisions complements other work focusing on the effects of layoffs on dismissed employees, both in terms of subsequent labor market outcomes (Jacobson et al. 1993) as well as health and other outcomes, such as mortality (Sullivan and Von Wachter 2009, Roelfs et al. 2011), alcoholism (Deb et al. 2011), and depression (Kuhn et al. 2009).

finance. Prior work generally does not study actual layoffs but instead changes in firms' employment count (which, as we show in Section 3, is often a weak proxy for layoff activity). Landier et al. (2009) find that divisions located closer to firms' headquarters are less likely to experience significant employment reductions. We link the geographic variation in layoff propensity to managers' attachment to their firm and employees as measured by their tenure. Other related work includes Matsa and Miller (2013, 2014), who argue for gender differences in managerial preferences towards workers, as they document fewer employment reductions in female-owned private firms in the U.S. during the Great Recession and in firms with a board gender quota in Norway. Consistent with a role for geographical closeness, Yonker (2017) finds that following industry distress, establishments in CEOs' hometowns are less likely to see pay or employment reductions. Keum and Meier (2023) find smaller firm-wide net employment growth rates after state-level expansions of unemployment insurance, which help mitigate the economic impact of job loss. This pattern is pronounced in firms with internally promoted and Democratic CEOs. Complementary to our approach of assembling a dataset on actual layoffs, Bertheau et al. (2022) field a large-scale survey of private firms in Denmark that elicits underlying reasons for firms' labor decision-making, specifically during the COVID-19 crisis. Additionally, using survey data from one large U.S. firm, Hoffman and Tadelis (2021) provide evidence that managerial interpersonal skills (as assessed by employees) are associated with lower rates of employee turnover.

Finally, our findings also relate to the broader literature on managers' social considerations. Acemoglu et al. (2022) finds that managers' inclination to share profits with employees varies with managers' exposure to business-school, shareholder-value-oriented education.[6] Jenter and Lewellen (2015) shows that managerial preferences are influenced by social norms (in the context of retirement choices). Taylor (2010) estimates large personal board member disutility costs (which could reflect a distaste for firing) to explain low CEO turnover rates. Additionally, Cheng et al. (2023) and Cronqvist and Yu (2017) also study CEO prosocial attitudes but link them to CEOs' corporate social responsibility rather than labor demand.

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

[6] We did not find a significant relation between CEOs having an MBA and their propensity to lay off employees.

results. Section 7 concludes.

2. Conceptual Framework

2.1 Framework and Testable Predictions

To fix ideas, we first sketch a stylized conceptual framework that extends the classical model of firm production decisions to incorporate managerial prosociality. Details and proofs are in Appendix-Section A.

Setup. We consider a simple three-period framework. In period 0, labor is exogenously chosen as if by a previous manager of the firm. Then, in periods $t \in \{1, 2\}$, the manager of a firm chooses capital k_t and labor n_t to generate profits π_t. The firm faces i.i.d. stochastic shocks to cash on hand, c_t at the beginning of each period, upon which the manager makes the capital and labor choices subject to spending choices not exceeding cash on hand. Layoffs are reductions in employment ($n_2 < n_1$), with worker i's period-2 utility in employment status $s \in \{emp, unemp\}$, $u^s_{2,i}$, being higher if employed than unemployed, $u^{emp}_{2,i} > u^{unemp}_{2,i}$.

A standard manager's objective is to maximize total profits, $\max_{n_t,k_t} \pi_1(n_1, k_1) + \pi_2(n_2, k_2)$, whereas a prosocial manager also weights the outcomes for incumbent employees:

$$\max_{n_1,k_1} \pi(n_1, k_1) + \mathrm{E}_1 \left[\max_{n_2,k_2} \pi(n_2, k_2) + \underbrace{\int_0^{n_1} f_{2,i}\left(s_{2,1}\right) \, \mathrm{d}i}_{\text{prosociality}} \right], \tag{1}$$

where $f_{2,i}\left(s_{2,1}\right)$ captures the effect of the employment status of a period-1 employee i in period 2 on the manager's utility. We define

$$f_{2,i}(s_{2,i}) = \mathbb{1}\left\{s_{2,i} = \text{unemp}\right\} \alpha_{2,i} \cdot \left(u^{\text{unemp}}_{2,i} - u^{\text{emp}}_{2,i}\right),$$

where $\alpha_{2,i} > 0$ specifies the extent of the manager's prosociality towards employee i in the spirit of Becker (1981), Bandiera et al. (2005), and Hjort (2014). Layoffs thus imply a *personal disutility* cost $c = \int_{n_2}^{n_1} \alpha_{2,i} \left(u^{emp}_{2,i} - u^{unemp}_{2,i}\right) \mathrm{d}i$ for a prosocial

manager, who assigns positive weight to dismissed employees' utility loss.[7]

Our formulation of prosociality implies that the manager puts weight only on employees who have been working at the firm for one period. While broader formulations are conceivable, e. g., with weights on job candidates or other stakeholder groups, defining current employees as the "reference group" is in line with managers' employee-centered survey responses and quotes. Specifically, layoff-induced adjustment costs occur only in period 2, as $\alpha_1 = 0$ since the workers' employment under the current manager starts in period 1.

This stylized framework allows us to illustrate the key predictions arising from managerial prosociality regarding labor decision-making.

Prediction 1. *After their initial period at the firm, prosocial managers incur a direct disutility cost from layoffs.*

Prediction 1 closely follows from the framework's setup, but it is worth noting for a few reasons. First, since we use a continuum of agents, firing an individual employee would not affect the manager's utility; however, a mass layoff of a continuum of agents would.[8] Additionally, managers still undertake layoffs in the framework, and they trade off a personal reduction in utility from layoffs against the benefits of the layoffs for firm value. We test Prediction 1 empirically by examining the effect of undertaking layoffs on increased CEO mortality as a proxy for reduced utility.

Prediction 2. *New ($t = 1$) prosocial managers have a higher propensity to make layoffs than incumbent ($t = 2$) managers, given the same level of labor in the preceding period and cash on hand in the current period. Further, the new prosocial manager will always choose a layoff when that is the value-maximizing option, whereas the incumbent prosocial manager does not.*

While new managers having no incentive to avoid layoffs closely follows from our assumptions, it is not clear that incumbent managers would be less likely to undertake layoffs. For instance, an incumbent manager could be equally likely to undertake a layoff, but the layoff could be smaller in size. However, an incumbent,

[7] We model hiring over a continuum of employees to avoid edge cases.

[8] We use a continuum to avoid edge cases. If labor in our framework is interpreted as hours, then a small reduction in labor would correspond to a reduction in hours worked rather than the number of employees.

prosocial manager will choose to avoid small layoffs by choosing the same level of labor as the previous period because the mangager's marginal utility of labor is discontinuous at the threshold for layoffs. We test Prediction 2 by examining the propensity to make layoffs of (exogenously) new CEOs relative to incumbent CEOs in the same industry and the stock market reaction to layoffs made by the new CEOs.

Prediction 3. *As their tenure increases ($t = 1$ to $t = 2$), a prosocial manager*

(i) has a lower propensity to make layoffs (extensive margin);
(ii) lays off fewer employees conditional on a layoff (intensive margin),

assuming the same cash on hand in both periods.

In a nutshell, managerial prosociality induces a personal disutility cost of layoffs. After the initial period, this leads to an inaction region of no layoffs, lowering the manager's layoff propensity (extensive margin) as already discussed in Prediction 2. Since the disutility cost of layoffs is not fixed, but depends on the number of employees laid off, the manager will also choose to lay off fewer employees conditional on a layoff (intensive margin) as tenure increases.

We will test Prediction 3(i) by studying managers' layoff propensity over their tenure and as they form more connections inside the firm. In additional tests, we will also distinguish internally and externally hired CEOs.[9] Similarly, we test Prediction 3(ii) by examining the fraction of the firm laid off each year over CEOs' tenure.

Prediction 4. *After their initial period at the firm (i.e.,in $t = 2$), a prosocial manager reduces layoff propensity and layoff size more strongly*

1. *when layoffs affect employee utility more adversely and*
2. *for employees whose utility the manager weighs more heavily,*

than a manager with standard preferences, assuming the same cash on hand in both periods.

[9] 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 et al. (2005) find that social preferences among co-workers are stronger when friendship networks are stronger.

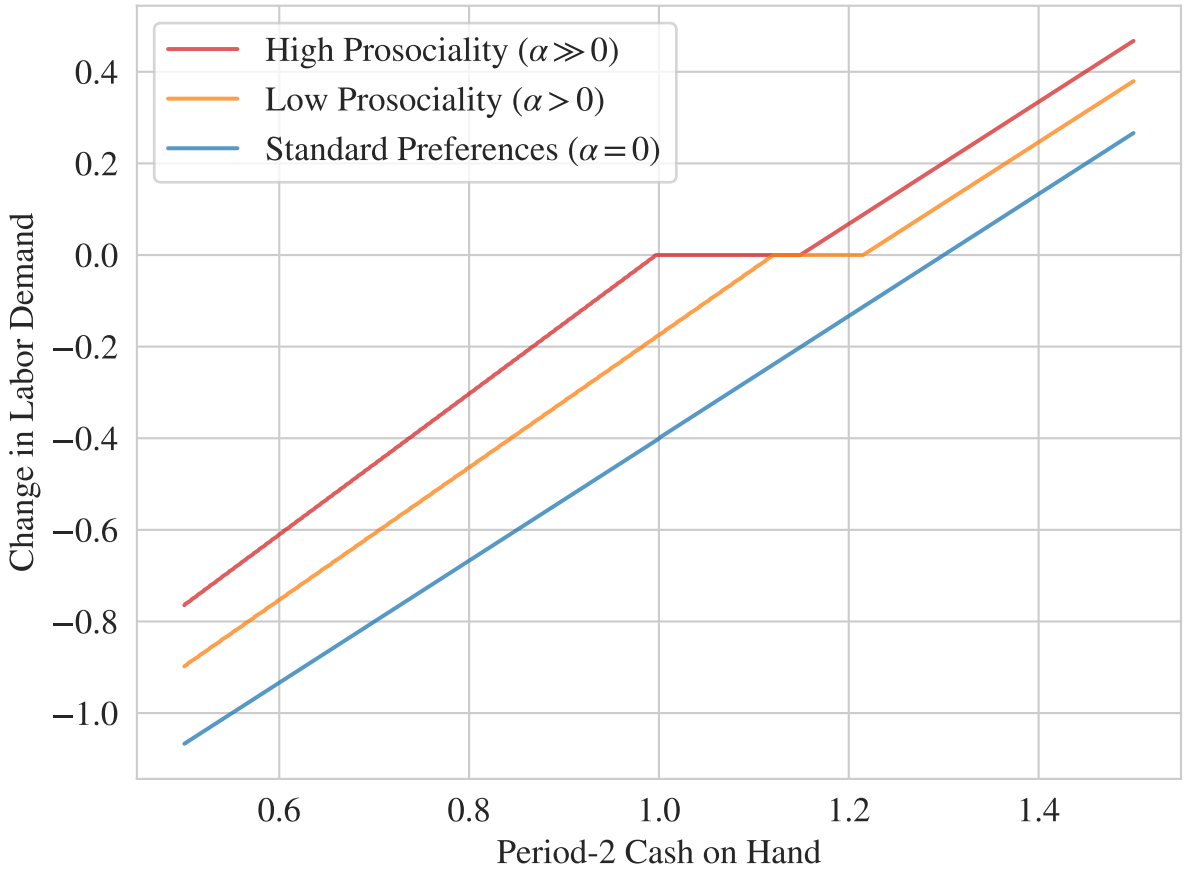
We use the standard manager as a benchmark since she always makes the optimal choice for firm value. Prediction 4 essentially states that the stronger the prosocial motives are, the more pronounced the extensive- and intensive-margin effects are. For our empirical test of Prediction 4(i), we will proxy for variation in the adverse effects on employees with their timing during recessions, when displaced employees experience long-term loss of earnings (Jacobson et al. 1993), and their timing during the holiday season. For our empirical test of Prediction 4(ii), we hypothesize that managers place more weight on employees who are "closer." We examine geographical closeness (i.e., propensity to lay off employees near versus far from the headquarters) as well as social closeness (i.e., the propensity to lay off white versus blue collar employees).

Prediction 5. *After their initial period at the firm (i.e., in $t = 2$), a prosocial manager reduces capital spending to offset higher labor spending than a manager with standard preferences, assuming the same cash on hand in both periods.*

Prediction 5 lays out the implication of managerial prosociality for capital spending. Since the manager's utility is lower when laying off employees, the manager will reduce the number of layoffs, which in turn increases labor spending. To offset the higher labor spending, the manager will reduce capital spending. We test Prediction 5, in conjunction with 3(i), by examining the relation between layoffs and R&D spending periods of industry distress. During industry distress, financing constraints are more likely to bind; however, as our empirical test of 3(i) shows, the difference in the propensity to undertake a layoff between shorter- and longer-tenured prosocial managers grows during industry distress. We focus on R&D spending as it is a key component of investment that can be more responsive to financing constraints than long-term physical infrastructure investments.

Graphical Illustration. Figure 1 illustrates the relation between prosociality and labor choices graphically. It displays the change in labor demand in period 2 relative to period 1, i. e., the hiring and firing decisions in period 2, as a function of cash on hand available in period 2. We plot the choices of managers with standard preferences in blue, of managers with some prosociality ($\alpha > 0$) in orange, and of managers with high prosociality ($\alpha >> 0$) in red. (Appendix-Section A.4 contains further details and figures from the numerical solution of the framework generating the plot.)

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



Notes: The figure plots the change in labor demand in period 2 relative to period 1 for different realizations of period-2 cash on hand, c_2, conditional on the choice of n_1 for a period-1 cash-on-hand level of $c_1 = 1.3$. The distribution of cash on hand is given by $c_t \overset{iid}{\sim} \mathcal{U}[.5, 1.5]$. Production is Cobb-Douglas with capital share $\gamma = \frac{1}{3}$ and labor share $\nu = \frac{2}{3}$. The rental cost of capital is $r = 0.2$ and the per period wage is $w = 0.5$. For all workers, the difference in utility between states is $u_{2,i}^{emp} - u_{2,i}^{unemp} = 1$. For all workers, the prosocial weight for the high and low managers are $\alpha_{2,i}^{high} = 0.4$ and $\alpha^{low} = 0.2$, respectively. See Internet Appendix Section A.3 for details on the setup of the model.

The figure shows that, when cash on hand is high and the firms spending is therefore less constrained, all types of managers hire additional employees.[10] With medium levels of cash on hand, however, prosocial managers remain at their period-1 labor choice to avoid the layoff disutility cost, whereas standard managers continuously adjust labor downward. When cash on hand is even lower, all managerial types make a layoff, though the size of the workforce reduction is smaller among more prosocial managers.

2.2 Underpinnings of Managerial Prosociality

This section discusses various potential underpinnings of the behavior attributed to managerial prosociality towards employees, i. e., the $\alpha_{2,i}$ weights in equation (1). We include both alternative interpretations within the realm of prosocial preferences and alternative neoclassical interpretations, and discuss to what extent each possible microfoundation is consistent with the empirical results that we will present below.

Norms and Implicit Contracts. One possibility is that managerial social considerations arise from norms or implicit contracts between management and employees. Gorton and Zentefis (2020) argue that social norms, formed inside the firm and directed by management, ensure a well-functioning organization. A mechanism based on implicit contracts and social norms is consistent with some but not all of our evidence. For example, establishing implicit contracts, e. g., by avoiding layoffs, might become more important later in a CEO's tenure, and potentially in particular for white-collar employees, which would be in line with the empirical results. However, it does not easily predict a personal disutility cost to CEOs from implementing layoffs. The social-contract mechanism predicts that the manager takes employee interests into account in the maximization, but *if* layoffs are warranted in that process, the "act of firing" does not lead to disutility costs. By contrast, as alluded to above, Section 4 will document that making layoffs predicts long-run CEO mortality holding fixed the firm's and industry's overall condition.

Career Concerns. Another possibility is that CEOs avoid layoffs, or layoffs of a certain kind or during certain times, because of career concerns. Career-concern

[10] The prosocial managers increase labor slightly more since, in the first period, they "shade" hiring in anticipation of possible future layoffs of people they have started to care about.

motives imply, however, that the manager maximizes self-interested utility in their layoff decisions, which is again hard to reconcile with increased mortality. Further, one might argue that layoffs in good times should hurt reputation more than those in recessions (e.g., Grenadier et al. 2014), whereas our heterogeneity tests find evidence consistent with stronger prosocial considerations during downturns. Additionally, career concerns would predict that you should be more likely to make layoffs as you get closer to retirement when your career is near its end, which is the opposite of what we find.[11]

Social Pressure. A related possibility is that CEOs display prosocial behavior as a result of social pressure from other stakeholders and agents, such as unions, (local) governments, or the media. Depending on the nature of such external demands, this could be consistent with some of our results, for example the geographic layoff heterogeneity, if pressures from local agents loom larger. At the same time, a social-pressure underpinning is again not easily reconcilable with our finding of personal costs of firing for CEOs. Under such a mechanism, the CEO will implement layoff decisions as "guided" or called for by others, effectively leaving little room for incurring personal disutility costs from such decisions.

Social Image. A further possibility is that managers have social image concerns, which may increase with tenure, and which can generate time-varying and heterogeneous prosociality weights. To what extent a social-image mechanism is consistent with all our findings depends on the precise nature of social image formation. On the one hand, it is plausible that social-image concerns might intensify during recessions. On the other hand, it is plausible that a manager's social image might suffer more when laying off blue-collar workers as opposed to white-collar workers, which would predict amplified effects for blue-collar workers, whereas empirically we find stronger effects for socially-close white-collar employees.

Empathy. Another possibility is that managers' prosociality arises from managerial empathy, which has been described as "the affective experience of the other person's actual or inferred emotional state ... feeling what another person is feeling, knowing what another person is feeling, and having the intention to respond compassionately to another person's distress" (Decety and Jackson 2004). This characterization of empathy corresponds closely to the disutility cost formulation

[11] Additionally, concerns about hiring in the future and risk aversion would point towards more layoffs closer to retirement.

in our conceptual framework (equation (1)).

Various additional facets of empathy align with our empirical approach and findings. For one, psychologists emphasize a distinction between negative empathy (i.e., empathetic concern) and positive empathy (Morelli et al. 2015), implying in our setting that layoffs and new hires are unlikely to serve as "substitutes" for prosocial managers. Additionally, prior work in neuropsychology documents stronger empathetic responses when the degree of self-other overlap is larger. Meyer et al. (2013) use neuroimaging-based techniques to show that when subjects observe friends suffering socially, pain-processing brain areas are activated that are associated with feeling pain and firsthand experiences of exclusion. When subjects observe strangers, activated brain areas instead are those associated with merely understanding others' states and intentions.[12] These findings by Meyer et al. (2013) predict our evidence of amplified managerial concerns for socially-close white-collar employees. Overall, a psychological underpinning of prosociality arising from managers' empathetic concern for employees is consistent with all of our empirical evidence.

3. Data

This section discusses data and descriptive statistics, with an emphasis on our newly assembled layoff dataset. Appendix-Section B contains further information on data sources and data processing, including more detail on the text-processing algorithms to identify layoffs, as well as variable definitions.

3.1 2002-2020 Layoff Data

The starting point for the construction of our new dataset on layoff announcements is the Standard and Poor's (S&P) Capital IQ Key Developments database. The dataset has reliable coverage starting in 2002 (Edmans et al. 2018; Cohn et al. 2020), and we restrict the sample period to 1/2002–2/2020, i. e., omit the COVID-19 period.

[12] The study concludes that their findings "support the idea that self-other overlap with a target may allow us to recruit brain mechanisms that indicate that we ourselves are experiencing the target's situation."

The database covers more than 250,000 companies worldwide. Since we rely on Execucomp for details about CEOs (see Section 3.2), we collect key developments for firms in Execucomp. We extract information for all observations where the type of announcement is categorized as "Discontinued Operations/Downsizings," amounting to 18,019 key developments as of the download date (January 28, 2022).

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, regulatory websites, and company websites.

We leverage NLP techniques, augmented by hand-coding, to (1) classify each article as a layoff, closure, or neither; (2) extract the number or percentage of workers laid off; (3) identify the layoff location at the international, state, and city level; and (4) classify layoffs as blue-, pink-, or white-collar.

For (1), we first lemmatize the headline and situation summary, i. e., standardize verbs and nouns. For example, "cutting" becomes "cut" and "jobs" is reduced to "job." We then create several word lists to aid in identifying layoffs and closures (of, e.g., a factory or branch): (i) layoff verbs, such as "cut" and "slash," (ii) closure verbs such as "mothball" or "shut down," and (iii) worker-related nouns, including words for synonyms of jobs like "position" or "role," words for occupations such as "accountant" or "banker," and collective job words, such as "headcount" or "workforce." A key development is classified as a layoff if the headline or sentence in the summary includes a layoff-related verb as well as a noun from one of the three worker-related lists specified above. If it contains only a layoff-related verb or worker-related noun, it is classified as a layoff with low confidence and flagged for additional attention when manually reviewed. It is classified as a closure if it includes a closure-related verb and is not classified as a layoff. And else it is classified as neither.

All key developments are manually reviewed for accuracy, with special attention given to low-confidence observations. We consider the key developments for a given firm in the order they were announced, allowing us to identify and drop any duplicate layoff announcements. The manual review also allowed for using criteria that NLP could not easily capture. Since closures frequently result in layoffs, especially when entire plants or branches are closed, we treat them as layoffs *unless* the key development specifically mentions that a closure comes with no layoffs,

e. g., due to employee reassignments. We also separate layoff announcements from business sales without effects on employees. Moreover, we distinguish involuntary layoffs from employee reassignments and voluntary departures such as early retirement.

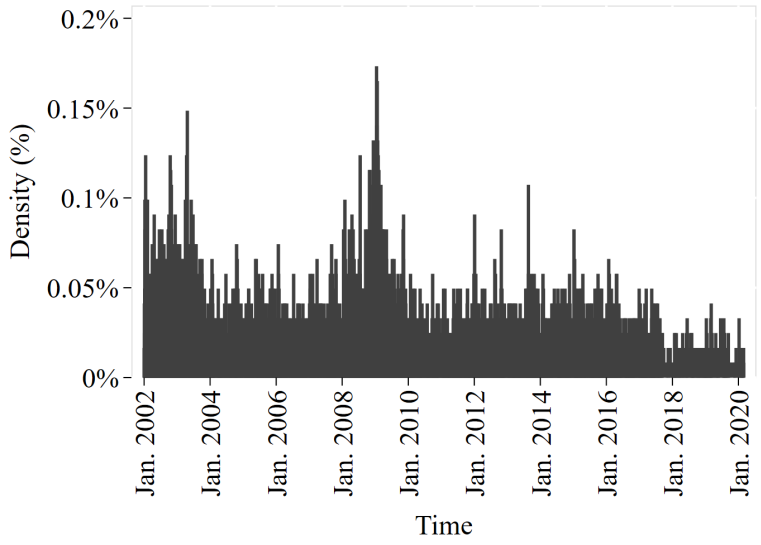
Figure 2a plots the resulting distribution of all identified layoffs across time. The number of layoffs peaks during the Great Recession and is lower than average in the pre-COVID-19 years, when unemployment was very low (Petrosky-Nadeau et al. 2019).

For (2), we extract the numbers and percentages of workers laid off. We use restricted text searches, commonly referred to as regular expressions, to capture all of the common ways to describe the count or proportion of jobs cut. For example, one pattern for percentages is *verb, other words, job words, other words, percent words*. The statement "reduce its workforce by 5%" would fall into this category. Corresponding patterns are used for "count" statements. These numbers were manually reviewed.

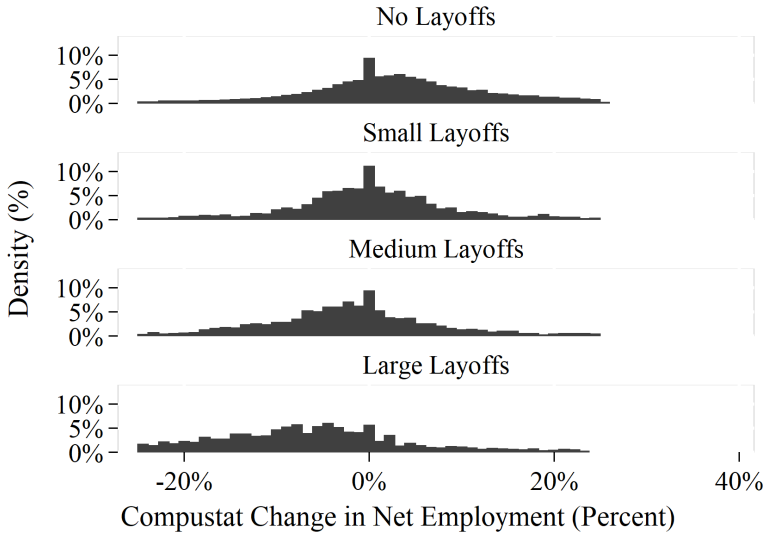
The detailed count of layoffs provides for a significant improvement over previous measures of layoffs, which have relied on net employment changes. Figure 2b compares layoffs identified in our sample directly to firms' net employment changes from Compustat. The figure plots the distribution of year-over-year net employment changes (in percent) for CEO-firm-years with no, small, medium, and large layoff activity, where the size of the layoff activity is determined by the proportion of the firm laid off.[13] With increasing layoff size, the distribution of net employment changes shifts to the left, implying that both variables are related. Yet, there remains a large dispersion in distribution of employment changes within each layoff group, including a significant fraction of firm years with a shrinking workforce despite no layoffs, and another sizable portion growing despite high layoff activity. Employment changes that are not driven by involuntary layoffs can include, for example, voluntary departures as well as early retirement. Overall, changes in the net employment count appear to be a highly imprecise proxy of layoffs. Another

[13] Our sample contains 2,258 firm-years with more than one CEO. This can be due to co-CEOs or a CEO turnover for which we include observations for both for the departing and the new CEO. Including both CEOs in the turnover year ensures that the layoff is correctly attributed to the CEO who made the decision. We calculate the proportion laid off as the sum of the proportions laid off in all layoffs in a given CEO-firm-year. Small, medium, and large activities are defined by terciles of the resulting distribution.

Figure 2. Layoff Events



(a) Layoffs by Month



(b) Layoffs Versus Net Employment Change

Notes: Panel (a) plots the number of all identified layoffs extracted from the S&P Capital IQ Key Developments database by month. Panel (b) plots the distribution of year-over-year net employment change from Compustat (in percent) for CEO-firm-years with no layoffs in the 2002-2020 S&P Capital IQ Key Developments data (top figure), as well as CEO-firm-years with layoff size data separated into small, medium, and large (bottom figure) layoff years, as defined by terciles of the proportion of the firm laid off.

source for layoffs is Worker Adjustment and Retraining Notification (WARN) Act filings. We examined the situation summaries for the key developments and found multiple direct references to WARN filings which suggests that our dataset likely captures relevant WARN filings.

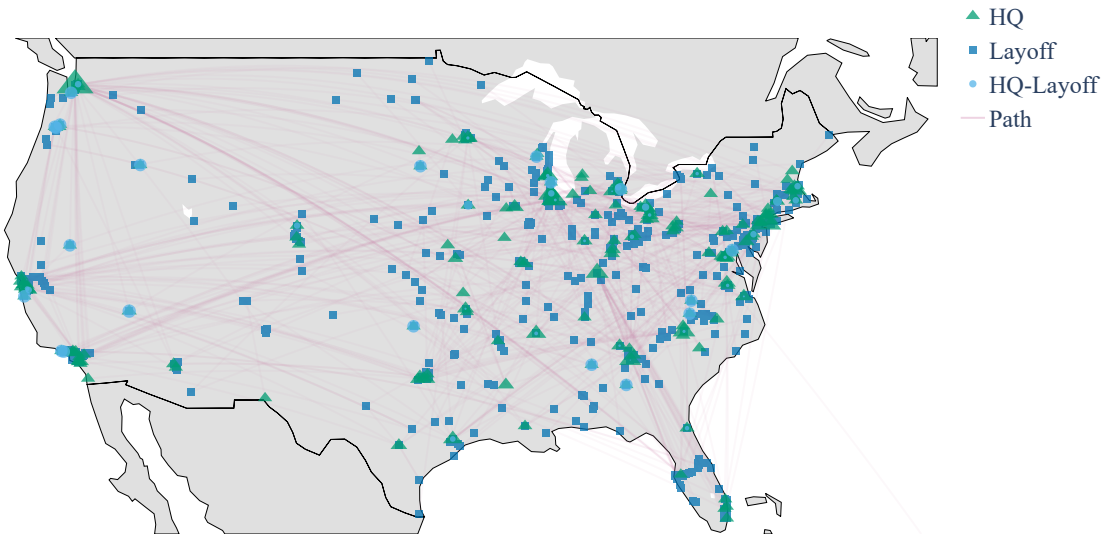
For (3), the geographic location of the layoff, we collect the location up to the city level for US layoffs and up to the country level for foreign layoffs. We also record layoffs that are specified as global, international, or similarly described, and we review all geographic classifications manually.

Figure 3 shows the geography of layoffs for two years in our sample: 2009 and 2015, allowing us to compare layoff patterns in the Great Financial Crisis versus a later point in time. The geographic separation between firms' headquarters (HQs) and layoff sites is frequently substantial, indicated by the lines connecting HQs (green triangles) and layoff locations (dark blue squares). Light blue dots identify HQ-city layoffs, which are rare compared to more distant layoffs. Comparing the two maps, we can see that layoff activity is substantially higher in 2009 than 2015.

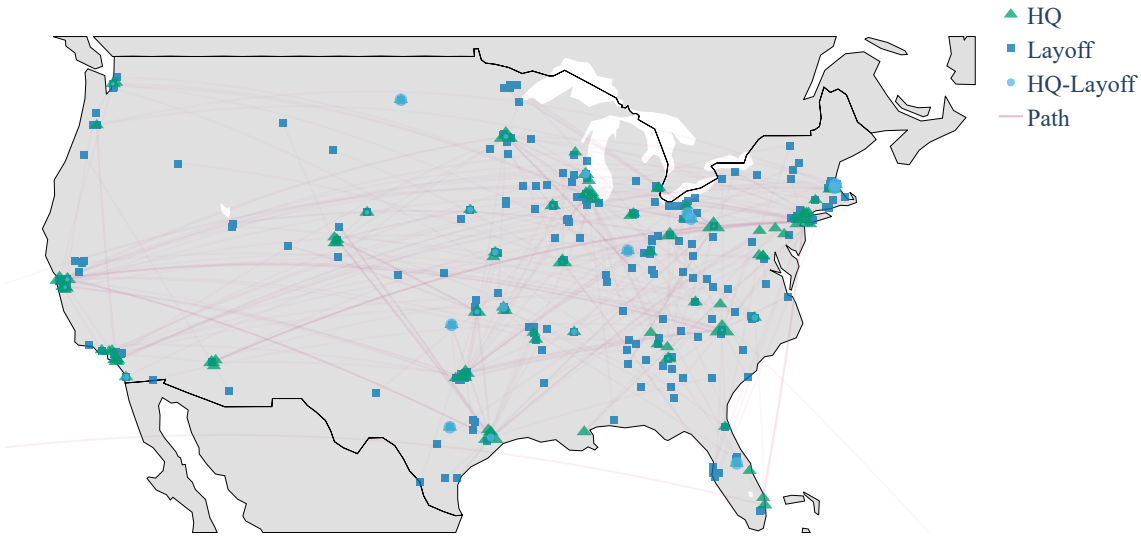
For step (4), we identify blue-, pink-, and white-collar layoffs based on a compilation of the 500 most common words in the sample overall. Among those words, we classify keywords that indicate blue-collar (e.g., factory, plant), pink-collar (service-oriented jobs; e.g., retail, store), and white-collar (e.g., corporate, headquarters) layoffs and categorize our layoff events correspondingly. We verify that the resulting classifications are sensible using city-level data on occupation frequencies from the 2000 U.S. Census (see again Appendix-Section B for additional details).

In our main empirical analyses, we focus on significant layoff events, namely, CEO-firm-years when a firm laid off at least 1% of the workforce or had three separate layoff events. For CEO-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 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. Our results are robust to using either the resulting indicator for significant layoff events or a layoff indicator based on *any* layoff activity in a given year. We use the indicator for *any* layoff activity when we study location-specific,

Figure 3. Layoffs Across Space



(a) Layoffs in 2009



(b) Layoffs in 2015

Notes: Panel (a) plots layoffs in 2009, and Panel (b) layoffs in 2015, both from the 2002-2020 Layoffs dataset whenever location data is available. Lines connect firms' headquarters and layoff locations. Green triangles identify headquarters. Dark blue squares identify layoff locations. Light blue dots identify headquarter-city layoffs.

month-specific, or employee-type-specific layoff activity in Tables 9 through 11.

3.2 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 CEOs, CFOs, and their tenure comes from Execucomp. We identify exogenous CEO changes by merging in the open-source database of CEO turnovers and dismissals by Gentry et al. (2021), which contains classifications for CEO turnovers. Data on firm characteristics, such as assets, employees, and profitability (operating income before depreciation divided by assets) 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 come from CRSP, and we calculate cumulative abnormal returns for our event study analysis based on the market-adjusted model.[14] Similar to prior work (Opler and Titman 1994; Acharya et al. 2007; Babina 2020), we define an industry-year as in distress if the two-year stock return of the median firm in a given SIC3 industry is -30% or less, where we consider both the prior two years and the prior and current year for the two-year horizon.[15] We also use governance data from the Institutional Shareholder Services (ISS, formerly RiskMetrics), to calculate measures of co-opted directors, described further in Section 5.2. The exact definitions for the full set of variables are in Appendix-Section B.2. The resulting CEO-firm-year panel dataset covers 2,779 unique firms.

3.3 1970–1999 Layoff Data and CEO 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 listed in the *Fortune 500* between 1970 and 1999 and provides a comprehensive list of layoff announcements collected from the *Wall Street Journal*.

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

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

We merge this layoff dataset with the mortality dataset from Borgschulte et al. (2023), which is an extension of the data in Gibbons and Murphy (1992) and covers all CEOs included in the *Forbes* Executive Compensation Surveys from 1975 to 1991. These surveys are based on corporate proxy statements and include the executives of the largest U.S. firms. The exact dates of CEOs' birth and death are sourced from ancestry.com, newspapers, and obituaries. CEOs who did not pass away by the cutoff date of October 1st, 2017 are censored.

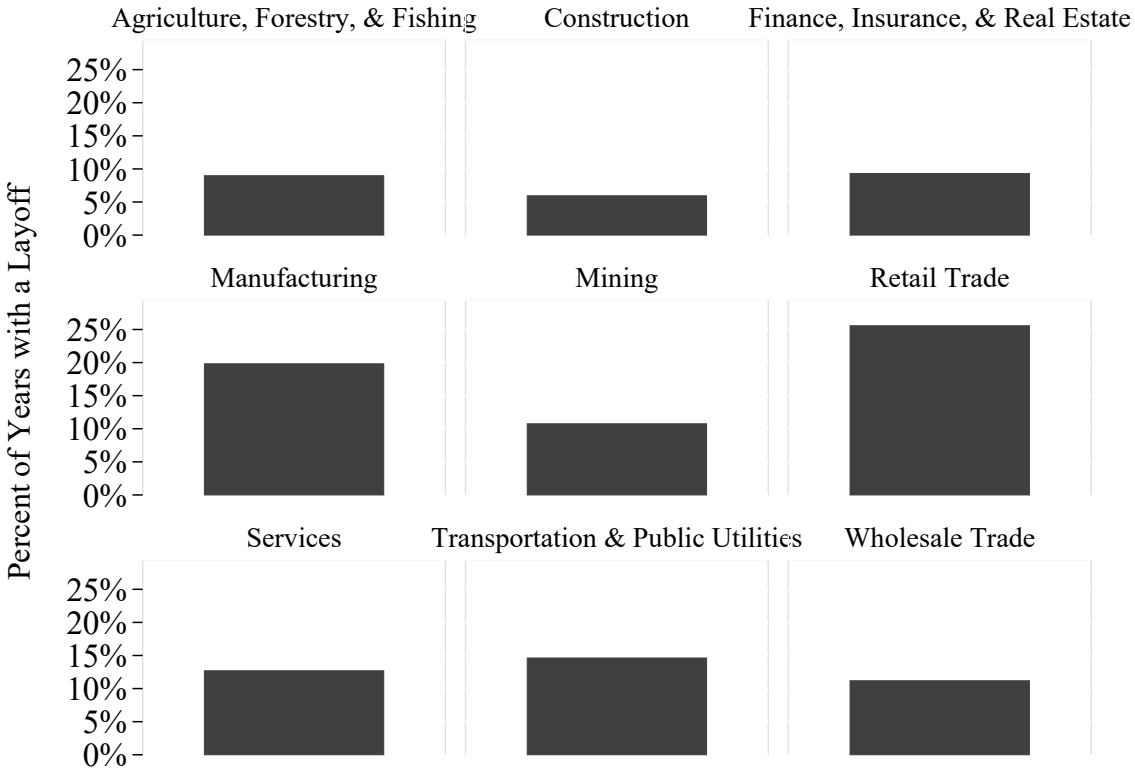
After further merging with Compustat and CRSP data, the final *CEO Mortality Data*, contains 31,917 CEO-year observations from 1,131 CEOs across 658 firms.

3.4 Descriptive Statistics

Table 1, Panel (a), presents the summary statistics for the *2002–2020 Firm–Layoffs Dataset*. One observation corresponds to a CEO-firm-year. The average CEO tenure is 8 years, and the average CFO tenure is 5 years. 19% of observations are CEO-firm-years in industry distress, and 13% are classified as layoff-years.

Figure 4 decomposes layoffs by industry. It shows that layoffs are particularly likely in the retail trade industry, which features seasonal labor demand (Anderson 1993), and the manufacturing sector, which has been affected by offshoring and automation (Slaper 2019). We note 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.

Figure 4. Layoffs by Industry



Notes: The figure plots the distribution of layoffs from our sample by industry classification based on SIC code. Data on layoffs assembled using NLP text processing and classification as well as hand-coding of S&P Key Developments data as detailed in Appendix-Section B. SIC codes are provided by Compustat.

Table 1, Panel (b), presents summary statistics for the *CEO Mortality Data* at the CEO level. The median CEO was born in 1928 and, conditional on having passed, died at age 82. 11% of CEOs experienced layoffs during times of distress and 38% experienced layoffs during nondistressed times. 43% of CEOs experienced industry distress. 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

We first examine personal long-term health consequences for CEOs associated with implementing layoffs as a direct way to detect firing-induced "disutility costs." We specifically examine accelerated mortality. This analysis builds on Borgschulte et al. (2023), who document adverse aging and mortality outcomes for CEOs arising from more stressful work environments, including industry crises.

We estimate survival models to detect predictors of CEO mortality in the *CEO Mortality Data*. Our key variable of interest is whether the CEO implemented a layoff during their tenure. We allow for heterogeneous mortality effects depending on whether layoffs are implemented during industry distress or non-distressed times. Layoffs during economy-wide or industry downturns are particularly painful and damaging for affected workers (Anderson 1993, Martin 2005, Hallock 2005). Downturns may also frequently force firms to lay off employees for reasons unrelated to their performance. Both aspects suggest particularly high and detectable CEO disutility costs associated with layoffs in times of crisis. Our main specification is of the form:

$$\begin{aligned}\text{Prob}(CEODeath_{i,t}) = \alpha + \beta_1\, DistressLayoff_{i,t} + \beta_2\, NonDistressLayoff_{i,t} \\ + \gamma_1 IndustryDistress + \boldsymbol{X}'_{i,t}\gamma_2\end{aligned} \tag{2}$$

where $CEODeath_{i,t}$ is one if CEO i passes away in year t and zero otherwise. *DistressLayoff* and *NonDistressLayoff* are indicator variables for a CEO's cumulative experience of a distress and non-distress layoff, respectively. *IndustryDistress* controls for the direct mortality effect of experiencing industry distress, and $\boldsymbol{X}$ is a vector of control variables, including CEO age, proxies for firm size (assets and employment), firm profitability, and year (or, alternatively, year fixed effects). In

addition, we include state and industry fixed effects as discussed below.

We estimate equation (2) both as a logit model and as a hazard model. In the logit estimation, shown in Table 2, we include an explicit event time control, i. e., control for the time that has passed since an observation first became "at risk" (which corresponds here to a person assuming the CEO position).[16] As in Borgschulte et al. (2023), 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, controlling for the direct effect of industry distress, CEO age, firm controls (assets, employees, profitability), and time. We also include HQ state fixed effects and industry fixed effects, as in Borgschulte et al. (2023). We cluster standard errors at the industry level as this is the level at which distress experience is defined (Abadie et al. 2017).

We find that distress layoff experience significantly accelerates mortality, consistent with these layoff experiences leaving long-run marks on CEOs. The logit 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, and of the same magnitude as the mortality effects associated with more stressful job environments documented in Borgschulte et al. (2023). By contrast, we find no evidence for mortality effects associated with layoffs during non-distressed times. We also note that the indicator for Industry Distress does not enter significantly. These results remain unchanged when replacing the linear time control with year fixed effects in column (2).

One potential concern regarding the estimates in columns (1) and (2) is heterogeneity in distress driving the results. That is, one might be worried about an omitted variable reflecting the severity of distress experienced by a given firm that could drive 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. This variable captures the severity of (possibly endogenous) firm distress over the course of a CEO's tenure and introduces variation in

[16] The time variable is created when the dataset is specified as a time-to-event dataset. See Efron (1988), Jenter and Kanaan (2015), and Guenzel (2023) for more details and finance applications of this approach.

"CEO experience," holding fixed whether a CEO has experienced industry distress. The coefficient on Distress Layoff barely changes. This suggests that our results are not driven simply by "bad distress" but specifically by the experience of and responsibility for distress-induced layoffs.

Robustness. We include several robustness tests in the Appendix. First, we re-estimate equation (2) using Cox (1972) hazard models instead of the logit estimations from Table 2. As expected, given the close link between logit models (with an explicit time control) and hazard models, we find very similar results (Appendix-Table A.1). Second, in Appendix-Tables A.2 and A.3, we repeat the logit and the hazard model estimations adding a control for CEOs' cumulative tenure, in light of our results below that longer-tenured CEOs are less likely to initiate layoffs. (We omit the CEO tenure control in our preferred specification, in line with Borgschulte et al. (2023), 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 a CEO for longer. Regardless, we continue to estimate large adverse effects of distress layoff experience on CEO mortality.

5. Variation in Layoffs by CEO Tenure

Having established a direct and personal cost of firing for CEOs, this section presents a series of empirical facts showing that CEOs with longer attachment to the firm are significantly less likely to lay off employees. We will consider plausibly-exogenous CEO turnover events, variation over the course of a CEO's tenure, and comparisons between externally and internally hired CEOs.

5.1 Layoff Propensity Around Plausibly-Exogenous CEO Turnovers

As a first step in identifying frictions in layoffs among CEOs who might be more attached to their employees, we examine how firms' layoff propensity varies around plausibly-exogenous CEO changes. Following prior work (e.g., Fee et al. 2013), we use in-office death or illness of the incumbent CEO to identify plausibly-exogenous CEO changes. Note that the differential mortality patterns by CEO layoff experience

documented in Section 4 are not inconsistent with this approach to identification as the former results only materialize in the long run, *after* CEOs have stepped down and retired. In fact, while the median CEO in the full *CEO Mortality Sample* passes away at age 82, the median CEO who is exogenously replaced due to a health shock is 60 years old at the time of replacement. We will also show that the identified exogenous CEO departures are not associated with any pre-trends in terms of key variables of interest (i. e., layoff propensity).

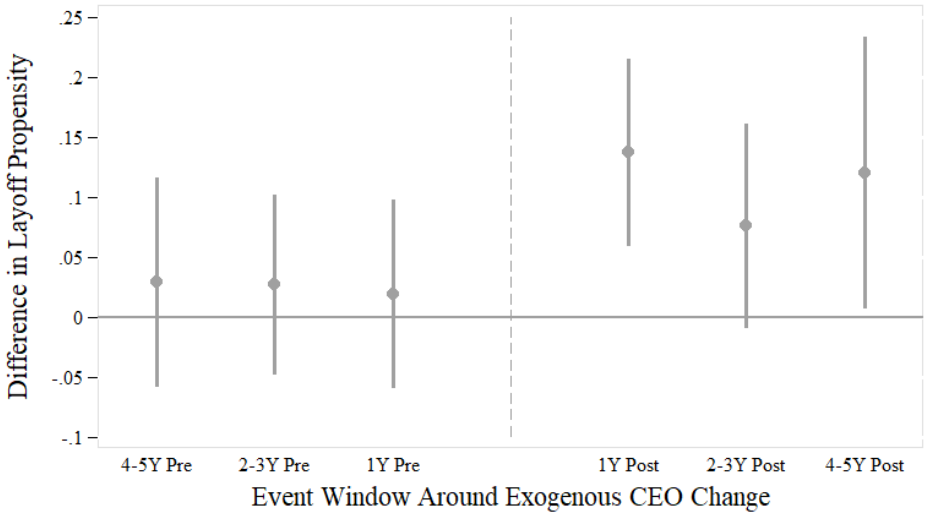
Stacked Difference-in-Differences Analysis. There are 115 CEOs in the *2002–2020 Layoffs Sample* who depart due to death or illness as per the Gentry et al. (2021) data. Since these events happen at different points in time, we implement a *stacked difference-in-differences* (DiD) analysis similar to Gormley and Matsa (2011) (cf. Goodman-Bacon (2021)). For each year with an exogenous CEO change in firm j, we construct a cohort c of treated and untreated firms in the same three-digit SIC industry k. We follow these cohorts from five years before to five years after the year of the CEO's exogenous departure, limiting the post-period to the tenure of the CEO who follows the turnover if less than five years. 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:

$$\begin{aligned} Layoff_{j,k,c,t} = \alpha + \alpha_{k,c} + \alpha_{c,t} + \beta_1 \, ExogCEOChange_{j,k,c} \\ + \beta_2 \, ExogCEOChange_{j,k,c} \times Post_t + \varepsilon_{j,k,c,t} \end{aligned} \tag{3}$$

where $Layoff_{j,k,c,t}$ is an indicator for layoff-years, 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). In addition, we include cohort-SIC3-industry fixed effects $\alpha_{k,c}$, which account for time-invariant differences between industries (within cohorts), and cohort-year fixed effects $\alpha_{c,t}$, which control for time trends (within cohorts) and also absorb the non-interacted $Post_{c,t}$ control. We now cluster at the firm level at which "treatment" is assigned (Abadie et al. 2017).

Figure 5 presents the stacked DiD results graphically, where equation (3) is

Figure 5. Layoff Propensity Around Exogenous CEO Changes



Notes: The figure plots the difference in layoff propensity around exogenous CEO departures relative to non-treated firms in the same industry cohort. Exogenous CEO changes are those occurring due to CEO death or illness of the incumbent CEO as identified in Gentry et al. (2021). The 95% confidence intervals are based on standard errors clustered at the firm level.

slightly modified to allow for time-varying coefficients on the interaction term of interest (β_2) within the pre- and post-periods.

The figure shows that, consistent with the assumptions of no pre-trends and parallel trends in the counterfactual state, treated and control firms evolve similarly with respect to their layoff propensity in years prior to the CEO change. In the year after the CEO transition, the difference in layoff propensity between firms with exogenously replaced CEOs and control firms jumps to +13.7 pp, becomes statistically significant at the 1% level, and remains elevated afterward. When we estimate equation (3) (Appendix-Table A.4), we find an average effect of 8.7 pp over the five-year period following the turnover, statistically significant at the 1% level. Hence, newly appointed exhibit significantly higher layoff propensities than their longer-tenured predecessors.

These results are consistent with layoffs increasing after a disruption in the social connections between CEO and employees and hence a role for prosocial attitudes of incumbent CEOs, who on average served for seven years prior to being

exogenously replaced.

Checks for Potential Confounds. While health- and death-related turnover events have been established as the most stringent approximation of plausibly exogenous CEO changes, we consider a number of potential confounds. These concern (1) the potential predictability of such departures, (2) a lower match quality of the successor, and (3) a potential shift in strategy by the successor, all of which might predict differences in layoffs. As for concerns about (1) the possible predictability of CEO departures, we conduct several tests using the data from the pre-period. We find that none of the firm characteristics (assets, employees, or profitability) predict CEO death- and health-related departures.

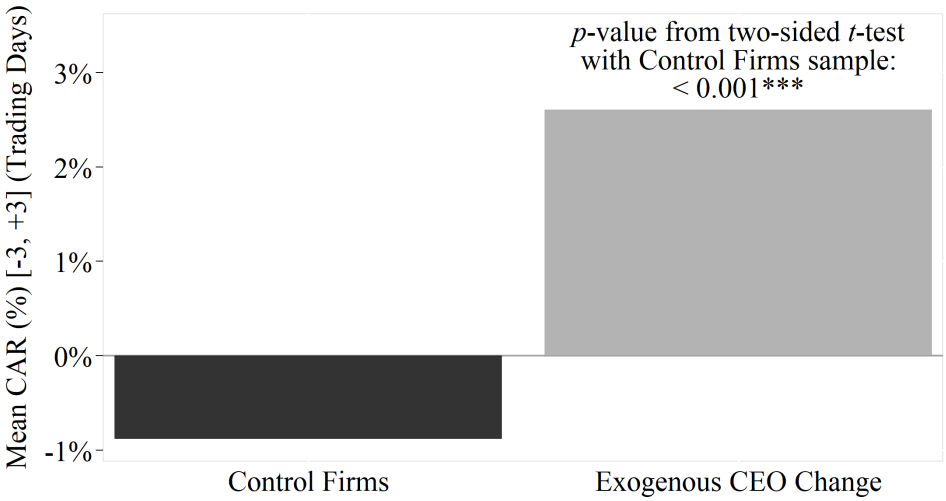
Turning to the concern that (2) the exogenously replaced CEOs were a superior match for their firm, we estimate the market reaction to the announcement of the exogenous CEO departures. The average +/-3-day announcement return is insignificantly positive in our sample (average CAR $= 0.08\%$, $p = 0.87$), leaving little room for the proposed confound.

Regarding (3) a shift in corporate strategy, we implement a Romer and Romer (2010)–style narrative approach of the layoff announcement descriptions after exogenous CEO turnovers. That is, we return to the key developments data and re-read the description of the key development for all layoffs implemented by the new CEO in our 2002-2020 Layoffs Data. We find that not a single text mentions a shift in strategy due to the new CEO as a layoff reason. As a second test regarding a potential shift in corporate strategy, we analyzed potential changes in other corporate outcome variables. Specifically, we implement a placebo test with firm leverage as the dependent variable and find neither pre- nor post-trends with respect to the financial side of the firm, as shown in Appendix-Figure A.1. This finding is consistent with Fee et al. (2013), who similarly do not find significant changes in leverage (nor in book asset growth or ROA) around exogenous CEO turnovers.

Market Reaction to Layoffs After Exogenous CEO Turnovers. We next study how investors react to layoffs made by newly appointed CEOs after exogenously determined turnovers. If the sharp increase in layoff propensity post-turnover reflects frictions prior to the CEO replacement, then we would predict a significantly positive reaction.

We calculate the +/-3-day announcement effects to layoff announcements by firms with exogenous CEO changes during the post-turnover period. We define

Figure 6. Layoff Announcement Returns After Exogenous CEO Changes



Notes: The bar plots present the average CAR (in %) to layoff announcements at control firms (left bar) and firms that had an exogenous CEO change (right bar) during the five-year post period as specified in the DiD analysis. Exogenous CEO changes are due to the death or illness as reported in Gentry et al. (2021).

the window in terms of trading days and require that return data is available for at least four of the seven days. The abnormal return is defined as the stock return minus the market return.[17] As indicated by the right bar in Figure 6, these layoff announcements trigger a pronounced positive reaction (average CAR $=$ $+2.61\%$). For comparison, layoff announcements in the matched control firms from the stacked difference-in-differences analysis (i. e., same-industry firms with no exogenous CEO change) trigger a slight negative market reaction of -0.9% during the post-period on average, similar to the average announcement effect in the full 2002-2020 sample (-0.3%). The difference in average layoff announcement returns between control and treated firms is highly statistically significant (two-sample t-test, p-value < 0.001). We can also reject that the announcement return samples have the same median (nonparametric equality-of-medians test, p-value < 0.001)

[17] Specifically, market returns are the value-weighted returns including dividends from the major US stock exchanges covered by WRDS: the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), National Association of Securities Dealers Automated Quotation System (NASDAQ), and Arca Exchange.

or are from the same distribution (two-sample Wilcoxon rank-sum test, p-value < 0.001).

Overall, the evidence in Figures 5 and 6 points to sizable layoff frictions under incumbent CEOs that are detrimental to shareholder value. One possible interpretation is that incumbent CEOs have developed more pronounced social concerns towards workers. Upon replacement, these social connections are eliminated, and the new CEO's concern for employees, as captured by the weight $\alpha_{t,i}$ in the conceptual framework (in Section 2) shrinks, leading to a higher propensity to make layoffs (cf. Prediction 2).

5.2 Layoffs Propensity over the Course of CEO Tenure

If CEOs' concerns for their employees ($\alpha_{t,i}$) increase over time, we would expect layoff activity to decrease over the course of CEOs' tenure (cf. Prediction 3 from Section 2).

We estimate the relationship between the layoff propensity of CEO i at the helm at firm j in year t and the CEO i's tenure using the following specification:

$$Layoff_{i,j,t} = \alpha_j + \alpha_t + \beta\, CEOTenure_{i,j,t} + \boldsymbol{X}'_{i,j,t}\gamma + \varepsilon_{i,j,t}\,, \tag{4}$$

where $Layoff_{i,j,t}$ is an indicator equal to 1 in layoff-years, $CEOTenure_{i,j,t}$ is accumulated tenure of the CEO measured in years, and α_j and α_t are firm and year fixed effects. (Below we also estimate models with more no, less, and more granular fixed effects.) We continue to cluster standard errors at the firm level.

Column (1) of Table 3 shows a strongly negative raw association between layoff propensity and CEO tenure. A one-year increase in tenure is associated with a reduction in the probability of a layoff in a given year by one half of a percent (0.427 pp). We expect this effect to be partially driven by "standard channels" such as a firm performance, i. e., better-performing firms seeing no need to either fire the CEO or lay off employees.

In line with this, we add a battery of firm- and industry-level controls to the empirical model, including lagged firm profitability and an indicator for industry-wide distress, as well as log assets, log employment, 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.) As shown in column (2),

the association between layoff propensity and CEO tenure remains strong, both economically and statistically, with these added controls and fixed effects. The size of the coefficient is reduced to 0.269 pp, though, while firm profitability emerges as another significantly negative predictor. Industry distress, instead, predicts a substantially higher layoff probability, as does firm size (number of employees or total assets).

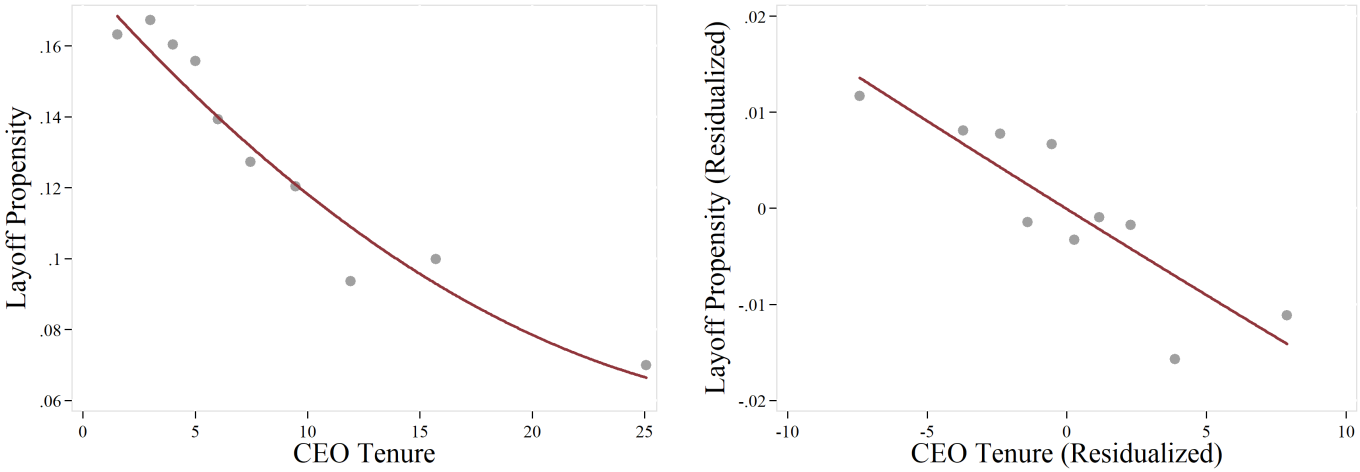
The layoff–CEO tenure relationship persists when we add firm fixed effects in column (3), albeit with a further reduction in magnitude to 0.187 pp. This robustness check accounts for any time-invariant firm characteristics and corresponding CEO matching that might affect the estimation results. For example, it rules out that we would pick up an effect where firms with long-serving CEOs have a preference (firm culture) for long-term relationships with employees across hierarchy levels.

The latter interpretation is further strengthened in column (4) when we additionally include the CFO's tenure at the firm. While CEO and CFO tenure are meaningfully correlated ($\rho = 0.20$, $p - \text{value} < 0.001$), the coefficient on CEO tenure remains almost unchanged after including CFO tenure as an additional explanatory variable, suggesting that there is a distinct CEO effect in this setting.

In terms of magnitudes, the column (4) estimates imply that an interquartile increase in CEO tenure (8 years) predicts a reduction in layoff propensity by 1.5 pp, 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 (from column (4)) on the right.

Robustness. The estimation results are robust to including various combinations of more granular fixed effects. In Appendix-Table A.5, we show the resulting coefficient estimates after including (1) state×year fixed effects to control for any state-specific economic fluctuations, (2) industry×year fixed effects to control for any industry-specific fluctuations, (3) both state×year and industry×year fixed effects, and (4) both state×year and industry×year fixed effects in addition to firm fixed effects. In all cases, the coefficient estimates on *CEO Tenure* remain very similar to the corresponding estimates from the baseline models estimated in Table 3, both without and with firms FE (columns 2 and 3, respectively).

Figure 7. Layoff Propensity and CEO Tenure



Notes: 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.

Alternative Explanations. While these results on the relation between *CEO Tenure* and layoff propensity are robust, they are correlational and not causal evidence of behavioral frictions. In the next subsection, we aim to strengthen the plausibility of the proposed interpretation by conducting several heterogeneity tests that are implied by a behavioral model of prosocial behavior, but inconsistent with other explanations.

Before we turn to those analyses, we evaluate several leading alternative explanations directly.

Firm (Under-)Performance. One alternative explanation for our estimation results might be unobserved determinants of firm performance. That is, CEOs' layoff choices might not be explained by their concern about workers but instead reflect fluctuations in firms' growth potential and investment opportunities. While such determinants are not necessarily increasing in CEO tenure, one might posit that they play an increasing role over the course of a CEO's tenure or that they are characteristic of CEOs who ultimately achieve long tenure.

To address such concerns, we extend our empirical model to include several additional measures of physical- and human-capital investment opportunities. Our

baseline analysis in Table 3 already includes several measures related to firm productivity or performance, including firm profitability. In Appendix-Table A.6, we add several additional controls for employment growth, investment opportunities, debt maturity, and default risk. (See Appendix B.2 for details of the variable construction.) 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 et al. (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 et al. (2021). As a measure of default risk, we use the naïve probability of default from Bharath and Shumway (2008), which they show outperforms the more computationally intensive application of Merton (1974) by Moody's KMV both in- and out-of-sample.[18]

As shown in Appendix-Table A.6, the tenure coefficient remains highly significant in all specifications, and moves very little relative to the corresponding baseline specifications (without or with firm fixed effects) from Table 3. As expected, firms with higher labor and capital productivity, higher debt maturity, and a lower probability of defaulting 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, which are closely related to investment opportunities or debt maturity, do not appear to affect or drive our results.

CEO Power and Co-Opted Directors. Another alternative explanation relates to prior evidence on CEOs accumulating power over the course of their tenure. Pan et al. (2016) document a positive association between CEO tenure and firm investment in *physical* assets, and argue that it is largely driven by increasing CEO power, in particular the fraction of the board appointed by the incumbent CEO.[19] While they do not argue that *human* capital investment is explained by CEO power, we test for its role, in combination with empire building, as an underlying mechanism

[18] KMV, acquired by Moody's in 2002, developed a model based on Merton (1974) to calculate the probability that a firm will default on its debt within the next year. For more details, see Bharath and Shumway (2008).

[19] The idea is that director appointments during a CEO's tenure are, at least to some extent, under the CEO's influence, which empire-desiring CEOs may be able to use to their advantage, and increasingly so over their tenure. This idea was first formalized in Hermalin and Weisbach (1998); see also Coles et al. 2014.

in our setting. To this end, we construct the percent of new directors appointed during a CEO's tenure using data from the Institutional Shareholder Services (ISS), as well as additional CEO power indicator variables for CEO–president and CEO–chairperson duality.

Table 4 performs "horse race" regressions as in Pan et al. (2016), with both CEO tenure and the CEO power measures as independent variables. 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 and layoff propensity. However, when we add CEO tenure in columns (2) and (4), the CEO tenure effect dominates, whereas the CEO power effect becomes insignificant or changes sign. We conclude that increasing CEO power of empire-desiring CEOs is unlikely to be a primary mechanism of our findings.

Going beyond the measures employed in Pan et al. (2016), we also consider the CEO entrenchment index of Bebchuk et al. (2009), which aggregates six governance provisions: staggered boards, limits to shareholder by-law amendments, poison pills, golden parachutes, and supermajority requirements for mergers and charter amendments. Since 2007, this data has been collected by ISS, but restricted to the first four measures listed above.[20] Using the ISS data, we construct a partial E-index, which ranges from 0 to 4, increasing by $+1$ for each provision. The resulting index is available for approximately two-thirds of our observations from our *2002–2020 Layoff Data*. Columns (1) and (3) of Appendix-Table A.7 regress layoffs on a dummy for each level of the E-index from one to four as well as the two duality controls. None of the E-index dummy variables have statistically significant coefficients. When we add back the CEO Tenure variable in columns (2) and (4), the estimated coefficients on *CEO Tenure* are similar to our baseline estimates, both in terms of magnitude and statistical significance.

Taken together, our results suggest that CEO entrenchment neither significantly drives layoff propensity nor serves as a primary mechanism for our findings.

First-Year Effects. We also consider the possibility of endogenous "first-year effects," such as new CEOs being hired with the explicit purpose of "taking a big bath" and implementing layoffs. While those types of effects cannot explain the

[20] The primary source of data in Bebchuk et al. (2009) is the Investor Responsibility Research Center (IRRC). However, the IRRC stopped producing this data after 2006.

post-turnover jump in layoff propensity from Figure 5, given the quasi-exogenous nature of the turnovers considered there, they might explain the behavior of other CEOs in their first year. More generally, CEOs may face less judgment for layoffs in the initial window of their tenure.

To address such concerns about special first-year effects, we re-estimate our empirical model after dropping the first year of all CEOs' tenure. As shown in Appendix-Table A.8, the tenure coefficient estimates remain highly statistically significant in spite of the reduced sample size, and their magnitudes are, if anything, slightly larger and more stable than in our baseline regressions. In particular, they are even less affected by the introduction of firm fixed effects than the estimates on the full sample.

Other CEO Differences. A more general concern is that the estimated CEO tenure–layoff link might reflect other CEO traits that are correlated with tenure. To check for systematic differences in the propensity to lay off workers across CEOs who attain shorter versus longer tenure, we take a two-pronged approach.

First, we group our sample of CEOs into bins in terms of their total tenure: short (up to five years), medium (above five and up to 10 years), and long (above 10 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). We then calculate the average layoff propensity tenure-year by tenure-year across CEOs within each subsample. As shown in Appendix-Figure A.2, the year-by-year layoff probabilities closely match each other across groups (i. e., up to 5 years for all groups, and up to 10 years for the groups with medium and long total tenure). That is, the graph suggests that the year-by-year propensities to lay off workers does *not* systematically differ across groups of CEOs who ultimately achieve shorter or longer tenure. Moreover, the graph confirms the strong association between cumulative tenure up to the layoff year and layoff probability, regardless of whether a CEO attains shorter or longer overall tenure.

Going one step further in addressing concerns about CEO differences that might be correlated with tenure, we implement the approach of Graham et al. (2020) and Altonji and Shakotko (1987) of using the fraction of a CEO's total tenure completed so far as an instrument for tenure (measured in years).[21] The authors argue that the fraction measure provides a plausible instrument since the fraction of

[21] Specifically, the instrument is $\textit{CEO Tenure Prop} \equiv (\textit{Tenure}_{i,j,t} - \overline{\textit{Tenure}_{i,j}}) / \max_t \textit{Tenure}_{i,j,t}$.

tenure completed is (a) correlated with actual tenure (in years), but (b) orthogonal to the CEO-firm match quality and other CEO characteristics that might affect tenure length. As they point out, all CEOs start at zero percent and complete one hundred percent of their tenure, which explains why the variation in the proportion of tenure completed cannot be correlated with CEO-firm pair specific traits or other characteristics, such as match quality. Intuitively, this instrument purges the estimation of differences in average tenure across CEO-firm pairs.

Implementing this approach in Appendix-Table A.9, we estimate a strong first stage, both in the specification without firm fixed effects (column 1) and in the specification with firm fixed effects (column 3), with the *F*-statistic well above 10. In addition, we continue to estimate a significantly negative effect of (instrumented) CEO tenure on the probability of a layoff after instrumenting. The coefficients remain very similar in magnitude to the coefficients found in Table 3, and are, in fact, larger after including firm fixed effects. These results lend additional support to the idea that the documented layoff–CEO tenure relation is not simply driven by cross-CEO differences.

In summary, firm performance, CEO power, first-year effects, or time-invariant CEO traits (that are correlated with total tenure) are unlikely to explain our results.

In the next Section, we will perform additional tests that evaluate more specifically the proposed mechanism of behavioral frictions.

Layoff Size and CEO Tenure. Our detailed layoff data allow us to also take into account the number of employees laid off. Prediction 3(ii) states that prosocial considerations will not solely reduce the layoff propensity but also reduce the layoff size.[22] Table 5 replaces the layoff indicator with the *fraction of employees laid off* in a given year, defined as zero for non-layoff years. CEO tenure also strongly predicts layoff size. As in Table 3, the CEO tenure coefficient is significant at 1% 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. This also holds for the instrumented tenure variable, see Appendix-Table A.10 which replicates columns (2) and (3) of Table 5 using the IV approach.

[22] The results in Table 3 could, in principle, arise from new CEOs, who are presumably less familiar with many parts of the firm, making more frequent layoffs involving fewer employees per layoff, without the *layoff size* actually changing over the CEO's tenure.

5.3 Layoff Propensity of Internally Versus Externally Hired CEOs

Finally, we also compare the layoff propensities of internally versus externally hired CEOs to capture an additional source of variation in the attachment the CEO may have developed towards the firm and its employees. Internal CEOs have been employees of the firm before, have pre-existing ties within the firm, and may thus be more reluctant than externally hired CEOs to implement layoffs. In fact, 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, analyzing a broader set of firms and layoff decisions. Needless to say that the selection of internal CEOs can reflect a wide range of determinants, and it is not possible to find sources of quasi-random variation as we did for CEO turnover in Section 5.1. Nevertheless, the correlational analysis merely complements the prior and subsequent analyses.

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 et al. 2013). Hence, our classification of CEOs as external versus internal hires results in a more than two-thirds reduction in sample size. Nonetheless, in columns (1) and (2) of Table 6, we use the reduced sample and reestimate columns (2) and (3) from Table 3, including an indicator for internally hired CEOs, *Internal CEO*. In column (1) with year, state, and industry fixed effect, we find that internal CEOs are 2.9 percentage points less likely to have a layoff in a given CEO-firm-year, a 22% reduction from the baseline. In column (2) with year and firm fixed effects, we find that internal CEOs are 4.8 percentage points less likely to conduct a layoff, a 37% reduction relative to the baseline. While we cannot fully remedy endogeneity concerns in these estimations, we can rule out that the type of firms that appoint internal CEOs are also firms with lower layoff frequencies. Further, in both columns, the estimated effect of CEO tenure on layoff propensity is significant and substantially more negative than in Table 3. This strongly suggests the CEO tenure effect we document is not driven by the selection of internal CEOs. In columns (3) and (4) of Table 6, we reestimate the same regressions restricting the sample to non-manufacturing firms, i.e., sectors not studied in Bai and Mkrtchyan (2023). This further reduced sample is less than 20% the size of our baseline sample used in Table 3. In column (1) with year, state, and industry fixed effect, we estimate, albeit

marginally insignificantly ($p = .11$), that internal CEOs are 2 percentage points less likely to have a layoff in a given CEO-firm-year, a 15% reduction from the baseline. In column (2) with year and firm fixed effects, we find that internal CEOs are 5.3 percentage points less likely to conduct a layoff. This estimate is statistically significant at the 5% level, in spite of the small sample size, and constitutes a 40% reduction relative to the baseline. Overall, Table 6 shows that internally hired CEOs display significantly lower layoff propensity, robust to including firm fixed effects, and extends Bai and Mkrtchyan (2023) findings to non-manufacturing firms.

6. Variation in Layoffs by Layoff Type

This section turns to heterogeneity in the effect of CEOs on layoff decisions, guided by the predictions of the conceptual framework in Section 2 as to when managerial prosocial concerns for workers should be particularly pronounced.

6.1 Heterogeneity in the 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 more pronounced for "pain–inducing" layoffs during recessions, the long-term adverse effects of job loss are especially severe for workers displaced during downturns (Jacobson et al. 1993). Considering this evidence, Table 7 tests whether CEOs' tenure-induced prosocial concerns for workers are particularly impactful in recession times (cf. Prediction 4). We find that 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 prosocial-concerns interpretation of the CEO tenure effect from Table 3. Consistent with theory, it indicates heterogeneity in the degree of prosocial concerns based on how bleak the job loss implications for workers are. These findings are also generally robust when we use the instrumented tenure variable, particularly when firm fixed effects are

included, see Appendix-Table A.11 which replicates Table 7 using the IV approach.

Layoffs During Recessions: R&D Expenditures. As an auxilary analysis, we turn our attention to how other firm activities are affected during times of distress, potentially leading the CEO to be facing both a tighter budget and more disutility from laying off workers. We specifically focus on R&D expenditures, testing Predictions 4 and 5. Given that in subsection 6.1, we document that CEO tenure is associated with a reduction in the propensity to lay off employees, particularly during recessions, it is possible that the reduction in layoffs comes at the expense of other firm activities, such as investment in R&D. These tradeoffs might be exacerbated during periods of economic distress, when financing is more difficult.[23] (We note that given the fact that our framework has a binding financing constraint, it is particularly applicable to distress.)

While one might initially expect a tradeoff between human capital investment and physical capital investment, the literature suggests that the latter does not respond strongly or negatively to recessions (Campello et al. 2010, Opler and Titman 1994).[24] Instead, Brown and Petersen (2009) find that while investment-cash flow sensitivity of physical capital largely disappeared between 1970 and 2006, it remained comparatively strong for R&D. Further, Brown et al. (2009) find that R&D investment for young firms is strongly driven by access to internal and external equity finance. Therefore, we might expect that firms with longer-tenured CEOs, who are less likely to lay off employees during recessions, may in fact cut R&D expenditures.[25] While our framework only incorporates capital and labor, capital broadly captures all short term expenditures other than labor and given its greater cash flow sensitivity, R&D expenditures may more closely parallel the capital investment in the framework than capital expenditures.

We next formally test how tenure, and in particular tenure during distress, affects R&D expenditures. To normalize R&D expenditures across firms, we follow

[23] For example, Campello et al. (2010) find that CFOs report financing constraints were more likely to affect investment during the credit crisis of 2008 than during normal times.

[24] Campello et al. (2010) finds that, during the 2008 credit crisis, CFOs of publicly traded US firms expected cuts in all categories surveyed, except for capital expenditures. Further evidence that capital expenditures remain stable or growing during distress is found by Opler and Titman (1994), who find that capital expenditure growth increases during industry distress.

[25] Pan et al. (2016) find that CEO tenure is positively associated with capital expenditures, but note no such correlation for R&D expenditures. Given that longer-tenured CEOs are not associated with higher R&D expenditures, this is consistent with R&D being a form of investment a long-tenured CEO may be most willing to cut.

Pan et al. (2016) by focusing on the R&D rate, defined as the ratio of R&D expenditures in the current year to total assets at the beginning of the year. Further, we limit our sample for R&D analysis to firms with positive R&D expenditures in at least one year in our sample period. To examine how CEO tenure during recessions affects R&D expenditures, Table 8 reestimates the same regressions as in Table 7 but with the R&D rate as the dependent variable. Consistent with Pan et al. (2016), we do not find a consistently statistically significant relationship between CEO tenure and R&D expenditures, although we estimate positive point estimates throughout. Additionally, we find that the interaction between CEO tenure and industry distress is significantly negative, indicating that longer-tenured CEOs reduce R&D expenditures during recessions and consistent with the idea that longer-tenured CEOs cut R&D expenditures in order to avoid layoffs during recessions. Based on the estimate of column (4) of Table 8, an interquartile increase in CEO tenure is associated with a 0.16 percentage point decrease in the R&D rate during recessions. This is a 2% reduction relative to the average R&D rate of 7.3% and a 4% reduction relative to the median R&D rate of 4.2%. These results are generally robust when using the instrumented tenure variable, especially with firm fixed effects, see Appendix-Table A.16 which replicates Table 8 using the IV approach.

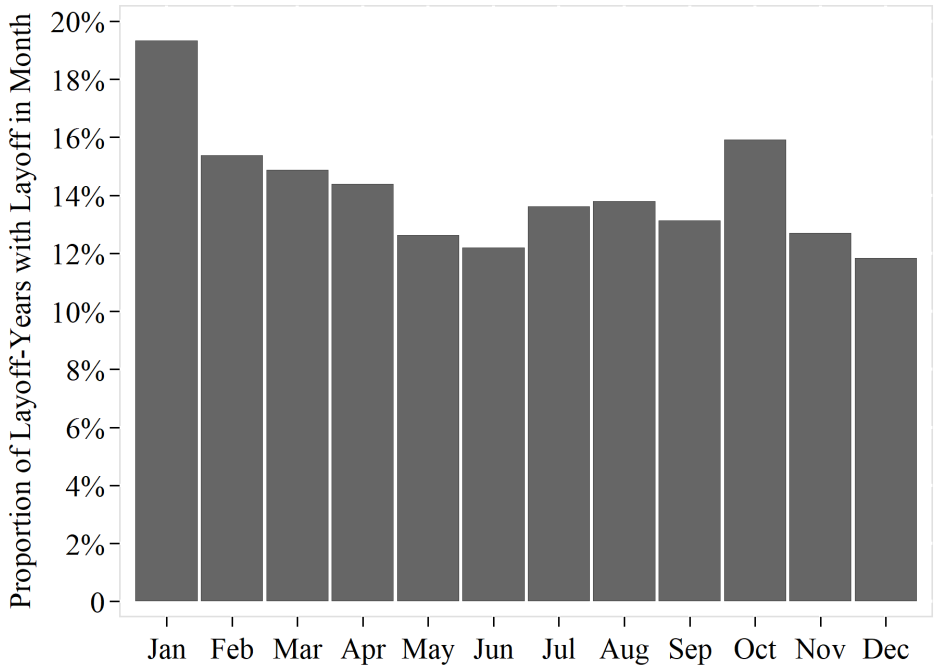
In sum, these findings suggest that CEOs offset the reduced cost savings from a reduction in layoffs during recessions by cutting other investment expenditures, particularly in R&D.

Layoffs Around the Holiday Season. A second differentiator in how pain-inducing layoffs are is the timing of layoffs during the year rather than their timing in the business cycle. The interviews with top managers in Hallock (2005) contain many responses that convey reluctance to implement layoffs around the holidays.[26] Figure 8 presents, for each calendar month, the percent of layoff-years in which a layoff occurs. Consistent with managers' responses, we observe that December has lowest percent of layoff-years with a layoff. January has the highest percent of layoff-years with a layoff, followed by October. This pattern could result from managers shifting the layoffs to January or undertaking them in October before the holiday season begins. Table 9 tests whether CEOs' tenure-driven prosocial considerations

[26] For example, one senior manager noted that they "didn't want to have layoffs in December for emotional reasons...[not] at Christmas" while another executive commented "Is that appropriate to be laying people off around the holidays?."

for workers are intensified around the holiday season (cf. again Prediction 4). In columns (1) and (2), we examine how the unconditional probability of a December layoff depends on the CEO's accumulated tenure. An interquartile shift in tenure is associated with a strong reduction in the probability of a December layoff by 0.5 percentage points, which is 25% of the baseline unconditional probability.

Figure 8. Layoffs By Month of the Year



Notes: This figure plots the percent of layoff-years with a layoff in each calendar month. See Appendix-Section B for details on data construction.

In columns (3) and (4), we examine how the occurrence of holiday layoffs varies with CEO tenure *conditional* on the firm announcing a layoff in a given year. Here, an interquartile tenure increase is estimated to lower the inclination of a holiday layoff by about 2.9 percentage points, or 25% relative to the baseline conditional probability. These conditional results are particularly indicative of intensifying prosocial considerations over a CEO's tenure, as they are derived from *when*—rather than whether—CEOs implement layoffs. That is, endogeneity concerns related to "whether" a CEO implements a layoff does not apply in this case.

The results are robust to including the first quarter or the first and the second quarter of the subsequent calendar year into the window of layoffs conditioned

upon (cf. Appendix-Table A.12). These results also hold when using the instrumented tenure variable, see Appendix-Table A.13) which replicates Table 9 using the IV approach.

Overall, these results imply a within-year layoff timing, i.e., a *choice* to avoid holiday layoffs that become more important to CEOs as they form more connections inside the firm throughout their tenure.

We note that the decreasing December-layoff propensity with CEO tenure is *not* predicted by CEOs learning over time to "strategically" release bad news. On the contrary, investors appear *more* distracted during the December holiday season (Chava and Paradkar (2016)), and December layoff announcements do *not* come significantly different announcement returns ($p = .21$).

Finally, to further buttress the results in Table 9, Appendix-Table A.12 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.

6.2 Heterogeneity in Social or Geographic Proximity

We next focus on heterogeneity in "closeness," which might proxy for the intensity of social interactions between CEOs and employees (cf. Prediction 4 of the framework in Section 2). We consider both "social proximity" as captured by the distinction of white-, blue- and pink-collar employees, and geographic closeness, as captured by the geographic location of the layoff site relative to the headquarter.

Layoffs of White-Collar Employees. As a first way to measure heterogeneity in the intensity of social connections, we examine managers' and employees' social proximity. 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). Further, as discussed in Section 2.2, neuroimaging-assessed empathetic responses are found to be stronger toward individuals within one's close social circle compared to strangers and when there is a greater degree of self-other overlap (Meyer et al. 2013).

We leverage our classifications of layoffs as blue-collar, pink-collar, and white-collar layoffs (see Section 3.1) and test whether, in particular with increasing tenure,

managers become more prosocial towards white-collar employees ($\alpha_{i,white,t} > \alpha_{j,blue,t}$).[27]

Table 10 shows the results for the relation 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. In column (2), an interquartile increase in tenure is associated with a 0.79 pp reduction in the probability of a white-collar layoff. This is a 25% 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 10 estimate the effect of tenure on white-collar layoffs, conditional on a CEO-firm-year being a year in which layoffs occurred. Also, conditionally, white-collar layoffs become substantially 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 3.2 pp decrease in the probability of a white-collar layoff in a year with layoffs. This constitutes a 16% reduction relative to the baseline probability of 19.4% that a CEO-firm-year with layoff activity involves white-collar layoffs. The baseline results hold when using the instrumented tenure variable, see Appendix-Table A.14 which replicates Table 10 using the IV approach. The conditional results are directionally consistent but much smaller.

Layoffs Close to Firm's Headquarters. As a second way to capture heterogeneity in social interactions, we examine the geographic, rather than social, proximity of laid off employees ($\alpha_{i,close,t} > \alpha_{j,distant,t}$), leveraging the geographic detail of our layoff dataset. Column (1) of Table 11 shows that layoff activity in the state of the firm's HQ declines in CEO tenure. An interquartile increase in tenure reduces the propensity of HQ-state layoffs by 0.6 percentage points, or 15% relative to the baseline probability of HQ-state layoffs of 4%. 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%.

[27] The anecdotal evidence from the practitioners-oriented book by Martin (2005) is consistent with this hypothesis, with one respondent saying, "[a]lways, the most difficult decisions are those that affect families of people that have become friends." Relatedly, using data from one firm, Elvira and Zatzick (2002) find evidence that white employees are at lesser risk of being laid off, in general, compared to non-white employees holding occupation and job level fixed.

Similar to above, columns (3) and (4) condition on years with layoff activity. In column (3), conditional on a year involving layoffs, an interquartile tenure increase is associated with a 1.4 percentage point reduction in the propensity of HQ-city layoffs, or 13% relative to the baseline conditional probability of 11%. In column (4), conditional on a year involving layoffs in the HQ-state, an interquartile tenure increase is associated with a 3.7 percentage point reduction in the layoff propensity of HQ-city layoffs, or 8% relative to the baseline conditional probability of 45%. However, standard errors increase substantially in this most narrowly defined subsample, and the point estimate is statistically insignificant ($p = 0.118$).[28] Thee baseline results also hold when using the instrumented tenure variable, see Appendix-Table A.15 which replicates columns (1), (2), and (3) Table 9 using the IV approach. The coefficient for the regression conditional on layoff-years is consistent in sign and magnitude, but not statistically significant.

Overall, the results in Tables 10 and 11 are consistent with a prosociality-based explanation of layoff decision-making and increasing social considerations of longer-tenured CEOs, especially in relation to socially and geographically close employees.

6.3 CEO Heterogeneity in Prosociality

In addition to heterogeneity by the timing of layoffs or type of workers affected, we ask to what extent it is possible to detect heterogeneity in prosocial concerns across CEOs, and examine the resulting differential effects on labor decision-making. In other words, it is plausible that managerial prosociality weights on employees' utility in our framework from Section 2 are not only heterogeneous by employee type i versus j ($\alpha_{i,close} > \alpha_{j,distant}$), but also heterogeneous across CEOs, i.e., that $\alpha_i^m > \alpha_i^{m'}$ comparing a manager m with high prosocial concerns and a manager m' with, relatively speaking, low prosocial concerns.

Testing for differences in prosociality across managers is challenging as it requires direct proxies that capture variation in the level of prosociality across high-profile individuals. Many initial proxies that one might consider exhibit inherent shortcomings, for two key reasons. A first challenge is that, for many proxies, it is unclear to what extent they capture the precise variation of interest in our setting,

[28] All columns in Table 11 include industry and location fixed effects. We estimate similar economic magnitudes when we include firm fixed effects instead, though we lose power in the conditional specifications in columns (3) and (4).

i.e., variation in empathetic concern for others and "being human," and variation in the extent to which one takes on the feelings and emotions of others (cf. the discussion of psychological underpinnings in Section 2.2).[29] A related, second challenge is that the shortcomings of many proxies are particularly significant in the case for wealthy individuals, i.e., our population of interest.

For example, consider donation behavior. While empathy and prosociality may serve as potential motivators for individuals to donate, including for wealthy individuals, a large literature in (behavioral) economics and finance has at the same time identified a variety of other determinants of giving behavior that are less easily associated with *other-regarding* prosocial motives. For example, Kumru and Vesterlund (2010) provide evidence that individuals donate for selfish reasons to gain social status. Similarly, and directly relevant for our context, Yermack (2009) finds that high-profile CEOs frequently nominally contribute to charities but do so because of incentives to reduce their personal tax liability.

Given these challenges, we instead strive to isolate variation in the level of managerial prosociality by leveraging prior work that has directly assessed personality characteristics among U.S. CEOs, and established a link between variation in empathy-related managerial attributes and well-known measures of CEO behavior that can be constructed for a larger sample.

Specifically, Kaplan et al. (2012) use detailed personality assessments of U.S. CEO candidates to identify primary dimensions along which managers differ. Particularly informative for our purposes, they find that managerial overconfidence (resoluteness) on the one hand and empathy on the other hand are primary distinguishing factors of CEOs (Kaplan et al. 2012, p. 975). Corroborating the distinction between overconfident and empathetic CEO types, Kaplan et al. (2022) find that the *Longholder* measure, the most widely used measure of managerial overconfidence, predicts significantly lower managerial scores on empathy-related attributes.[30] For example, non-overconfident managers score significantly higher on *Listening Skills* (= lets others speak and seeks to understand their viewpoints) as well as

[29] See, e.g., this Forbes article for a non-academic summary of the concept of empathy, emphasizing that empathy refers to "experiencing a fraction of [others'] emotions and feelings because you see things from their perspective" (forbes.com/sites/forbescoachescouncil/2018/08/13/the-critical-difference-between-sympathy-and-empathy/?sh=1262df5016a3).

[30] The *Longholder* measure was first introduced by Malmendier and Tate (2005) and identifies managers as overconfident if they fail to diversify and exercise own-firm stock options until the last year of their duration.

Commitments (= lives up to verbal and written agreements, regardless of personal cost).[31]

Motivated by this evidence, we use the *Longholder* measure to empirically distinguish between less empathetic (*Longholder* = 1) and more empathetic (*Longholder* = 0) CEOs. Our prediction is then that the declining layoff propensity of CEOs with tenure and as they form more connections inside the firm should be driven by non-overconfident, more empathetic CEOs. Of course, one concern is that the *Longholder*-based overconfidence-vs-empathy distinction may contain other differences across managers that are not related to empathy and prosociality, such as actual overconfidence and general ability. After presenting our results, we discuss how our specific empirical setup may help alleviate such concerns.

Table 12 repeats Table 3, separating the effect of CEO tenure on layoff propensity by whether we classify the CEO as overconfident or empathetic (non-overconfident). Column (1) is the same as Column (3) of Table 3. Column (2) re-estimates Column (1) on the subsample for which the *Longholder* measure is available, finding a similar baseline economic effect of CEO tenure on layoff propensity, albeit standard errors increase substantially as a result of the reduced sample size.[32] Column (3) separates the effect of CEO tenure by CEO type. The decline in layoff propensity over CEOs' tenure is fully driven by empathetic CEOs. An interquartile increase in tenure is estimated to reduce the propensity to implement layoffs by 21% relative to the baseline for empathetic CEOs of 12% ($p = 0.010$), whereas the relation between layoff propensity and tenure is close to flat for remaining CEOs.[33] In sum, the evidence in Table 12 is consistent with our overall hypothesis of managerial prosociality affecting labor decisions, and more empathetic CEO types driving the reduction in layoff propensity as CEOs' connections inside the firm deepen over the course of their tenure.

As a further corroborating analysis, we also test whether CEOs' increasing tendency to avoid layoffs during the holiday season—i.e., their decision as to when, as opposed to whether, to implement layoffs—is driven by empathetic CEOs as per

[31] Interestingly, the description of *Commitments* as "regardless of personal cost" maps quite closely to our framework and formulation of disutility costs to managers when "terminating commitments to workers" and making layoffs.

[32] The *Longholder* measure reduces the sample size by approximately one third.

[33] The p-value for the difference between the coefficients on the interaction terms in Column (3) is 0.033.

the *Longholder* measure. As Appendix-Table A.17 shows, this is indeed the case. As before, Columns (1) and (2) re-estimate the baseline relation between holiday layoffs and CEO tenure, conditional on the firm making layoffs at some point during the year, in the full sample and the *Longholder*-subsample. Column (3) shows that the tenure-induced reduction in holiday layoffs is once again driven by empathetic CEOs, with the estimated economic magnitude being twice as large compared to remaining CEOs.

As alluded to above, one concern with using the *Longholder* measure to distinguish overconfident and empathetic CEOs is other differences across these managerial types that are not related to empathy and prosociality, such as actual overconfidence and general ability. Two empirical aspects help to at least partially ameliorate such concerns. First, in both Tables 12 and A.17 above, our prediction is about the Longholder/empathy *interaction* effect with CEO tenure. This alleviates alternative interpretations that instead operate through a level effect, such as a lower general need for layoffs in higher-ability managers. Second, since in Table A.17 we examine layoff *timing* during the year by conditioning on firm-years with layoff activity, we can mitigate additional alternative explanations, such as increasing levels of CEO overconfidence with tenure reducing the propensity to make layoffs over time.

Altogether, despite the possible limitations of our proxies for variation in managerial empathy, the combined evidence corroborates the conclusion that managerial prosocial concerns for employees significantly predict layoff decisions within firms as well as the variation in these decisions over time and across firms.

6.4 Layoffs and CEO Pay

In a final analysis, our setting allows us to also study to what extent managers may be compensated for implementing difficult and personally costly decisions such as layoffs. The literature on compensating differentials predicts that more demanding working conditions induced by the stress and resulting adverse health effects of laying off employees should be associated with higher CEO pay. Conversely, when non-executive employees face layoffs, CEOs' capacity to negotiate for higher pay may be constrained by heightened public scrutiny of top-level benefits, or due to the underlying adverse economic circumstances.

We examine the empirical association between layoffs and CEO pay in Table

13. Columns (1) and (2) regress CEOs' total compensation (in logs) on an indicator for layoffs occurring in the same CEO-firm-year, and include the same controls and fixed effects as columns (2) and (3) of Table 3. Reflecting some stickiness in pay schemes, CEO pay is not significantly correlated with contemporaneous layoff activity. By contrast, columns (3) and (4) uncover a significant lead-lag relationship between CEO pay and layoffs. In the year after CEOs implement layoffs, CEO pay *decreases* by 3–4% on average, controlling for (twice-lagged) firm characteristics such as profitability. The negative layoff–pay relation is robust to additionally controlling for firm profitability in the year in which the layoff occurs, as opposed to only the prior year.

These findings indicate sizable limitations for CEOs in negotiating pay in ways that reflect the underlying demands and costs associated with CEOs' jobs. This, in turn, raises further questions, such as which CEO "types" select out of the top job and which choose to stay after high-demand periods, such as when implementing layoffs and in the absence of a compensating wage differential. More broadly, our results highlight the interplay between CEO (prosocial) preferences, job demands, labor market outcomes, and long-term personal consequences.

7. Conclusion

This paper offers a new interpretation of firms' human capital choices and examines the impact of CEO prosocial considerations on layoff decision-making. We establish a number of results to argue that top-level managers exhibit prosocial concerns for workers, with this constituting an economically important factor in managers' 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 mortality. Second, consistent with in-office labor decisions of incumbent CEOs being influenced by prosocial considerations, exogenous CEO changes trigger more layoffs that come with large, positive stock market announcement returns. Third, consistent with a channel whereby CEO prosocial concerns deepen through social interactions, layoff propensity is declining in CEO tenure. Finally, this effect is amplified when we expect prosocial motives to have a larger influence, as gauged by heterogeneity in the consequences of job loss and the intensity of social interactions

between the CEO and employees.

Our findings suggest several avenues for further investigation. Our findings have new corporate governance implications. Along similar lines as Cheng et al. (2023), 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' prosocial considerations.

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 prosociality towards employees opens up a series of new research opportunities.

Finally, considering the long-term personal costs associated with the top job and layoff decision-making, and the absence of a compensating wage differential, certain "types" may be particularly likely to select into, or out of, the CEO position. Our findings highlight the importance of accounting for the interplay between CEO (prosocial) preferences, job demands, and labor market as well as personal outcomes.

References

Abadie, A., S. Athey, G. W. Imbens, and J. Wooldridge (2017). When should you adjust standard errors for clustering? Working Paper, National Bureau of Economic Research.

Acemoglu, D., A. He, and D. le Maire (2022). Eclipse of Rent-Sharing: The Effects of Managers' Business Education on Wages and the Labor Share in the US and Denmark. Working Paper, National Bureau of Economic Research.

Acharya, V. V., S. T. Bharath, and A. Srinivasan (2007). Does industry-wide distress affect defaulted firms? Evidence from creditor recoveries. *Journal of Financial Economics 85*(3), 787–821.

Agrawal, A. K. and D. A. Matsa (2013). Labor unemployment risk and corporate financing decisions. *Journal of Financial Economics 108*(2), 449–470.

Altonji, J. G. and R. A. Shakotko (1987). Do wages rise with job seniority? *The Review of Economic Studies 54*(3), 437–459.

Anderson, P. M. (1993). Linear adjustment costs and seasonal labor demand: evidence from retail trade firms. *The Quarterly Journal of Economics 108*(4), 1015–1042.

Angrist, J. D. and J.-S. Pischke (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Babina, T. (2020). Destructive creation at work: How financial distress spurs entrepreneurship. *The Review of Financial Studies 33*(9), 4061–4101.

Bai, J. J. and A. Mkrtchyan (2023). What do outside CEOs really do? Evidence from plant-level data. *Journal of Financial Economics 147*(1), 27–48.

Bandiera, O., I. Barankay, and I. Rasul (2005). Social preferences and the response to incentives: Evidence from personnel data. *The Quarterly Journal of Economics 120*(3), 917–962.

Bandiera, O., R. Lemos, A. Prat, and R. Sadun (2018). Managing the family firm: Evidence from CEOs at work. *The Review of Financial Studies 31*(5), 1605–1653.

Bandiera, O., A. Prat, S. Hansen, and R. Sadun (2020). CEO behavior and firm performance. *Journal of Political Economy 128*(4), 1325–1369.

Bebchuk, L., A. Cohen, and A. Ferrell (2009). What matters in corporate governance? *The Review of Financial Studies 22*(2), 783–827.

Becker, G. S. (1981). Altruism in the Family and Selfishness in the Market Place. *Economica 48*(189), 1–15.

Bertheau, A., M. Kudlyak, B. Larsen, and M. Bennedsen (2022). Why firms lay off workers instead of cutting wages: Evidence from matched survey-administrative data. *Available at SSRN 4267332*.

Bertrand, M. and S. Mullainathan (2003). Enjoying the quiet life? Corporate governance and managerial preferences. *Journal of Political Economy 111*(5), 1043–1075.

Bharath, S. T. and T. Shumway (2004). Forecasting default with the KMV-Merton model. In *AFA 2006 Boston Meetings Paper*.

Bharath, S. T. and T. Shumway (2008). Forecasting default with the Merton distance to default model. *The Review of Financial Studies 21*(3), 1339–1369.

Bilal, A., N. Engbom, S. Mongey, and G. L. Violante (2022). Firm and worker dynamics in a frictional labor market. *Econometrica 90*(4), 1425–1462.

Billger, S. M. and K. F. Hallock (2005). Mass layoffs and CEO turnover. *Industrial Relations: A Journal of Economy and Society 44*(3), 463–489.

Borgschulte, M., M. Guenzel, C. Liu, and U. Malmendier (2023). CEO Stress, Aging, and Death. *The Journal of Finance, forthcoming*.

Brown, J. R., S. M. Fazzari, and B. C. Petersen (2009). Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. *The Journal of Finance 64*(1), 151–185.

Brown, J. R. and B. C. Petersen (2009). Why has the investment-cash flow sensitivity declined so sharply? Rising R&D and equity market developments. *Journal of Banking & Finance 33*(5), 971–984.

Campello, M., J. R. Graham, and C. R. Harvey (2010). The real effects of financial constraints: Evidence from a financial crisis. *Journal of financial Economics 97*(3), 470–487.

Chava, S. and N. Paradkar (2016). December Doldrums, Investor Distraction, and the Stock Market Reaction to Unscheduled News Events. *Georgia Tech Scheller College of Business Research Paper* (17-25).

Chen, H., Y. Xu, and J. Yang (2021). Systematic risk, debt maturity, and the term structure of credit spreads. *Journal of Financial Economics 139*(3), 770–799.

Chen, Y. and S. X. Li (2009). Group identity and social preferences. *American Economic Review 99*(1), 431–57.

Cheng, I.-H., H. Hong, and K. Shue (2023). Do managers do good with other people's money? *The Review of Corporate Finance Studies 12*(3), 443–487.

Cohn, J. B., U. G. Gurun, and R. Moussawi (2020). A project-level analysis of value creation in firms. *Financial Management 49*(2), 423–446.

Coles, J. L., N. D. Daniel, and L. Naveen (2014). Co-opted boards. *The Review of Financial Studies 27*(6), 1751–1796.

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society: Series B (Methodological) 34*(2), 187–202.

Cronqvist, H., F. Heyman, M. Nilsson, H. Svaleryd, and J. Vlachos (2009). Do entrenched managers pay their workers more? *The Journal of Finance 64*(1), 309–339.

Cronqvist, H. and F. Yu (2017). Shaped by their daughters: Executives, female socialization, and corporate social responsibility. *Journal of Financial Economics 126*(3), 543–562.

Deb, P., W. T. Gallo, P. Ayyagari, J. M. Fletcher, and J. L. Sindelar (2011). The effect of job loss on overweight and drinking. *Journal of health economics 30*(2), 317–327.

Décaire, P. and D. Sosyura (2022). CEO pet projects. *Working Paper*.

Decety, J. and P. L. Jackson (2004). The functional architecture of human empathy. *Behavioral and Cognitive Neuroscience Reviews 3*(2), 71–100.

Doms, M. and T. Dunne (1998). Capital adjustment patterns in manufacturing plants. *Review of Economic Dynamics 1*(2), 409–429.

Edmans, A., L. Goncalves-Pinto, M. Groen-Xu, and Y. Wang (2018). Strategic news releases in equity vesting months. *The Review of Financial Studies 31*(11), 4099–4141.

Efron, B. (1988). Logistic regression, survival analysis, and the Kaplan-Meier curve. *Journal of the American Statistical Association 83*(402), 414–425.

Elvira, M. M. and C. D. Zatzick (2002). Who's displaced first? The role of race in layoff decisions. *Industrial Relations: A Journal of Economy and Society 41*(2), 329–361.

Fama, E. F. and K. R. French (1997). Industry costs of equity. *Journal of Financial Economics 43*(2), 153–193.

Farber, H. S. and K. F. Hallock (2009). The changing relationship between job loss announcements and stock prices: 1970–1999. *Labour Economics 16*(1), 1–11.

Fee, C. E., C. J. Hadlock, and J. R. Pierce (2013). Managers with and without style: Evidence using exogenous variation. *The Review of Financial Studies 26*(3), 567–601.

Fehr, E. and J. A. List (2004). The hidden costs and returns of incentives—trust and trustworthiness among CEOs. *Journal of the European Economic Association 2*(5), 743–771.

Gentry, R. J., J. S. Harrison, T. J. Quigley, and S. Boivie (2021). A database of CEO turnover and dismissal in S&P 1500 firms, 2000–2018. *Strategic Management Journal 42*(5), 968–991.

Gibbons, R. and K. J. Murphy (1992). Optimal incentive contracts in the presence of career concerns: Theory and evidence. *Journal of Political Economy 100*(3), 468–505.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics 225*(2), 254–277.

Gormley, T. A. and D. A. Matsa (2011). Growing out of trouble? Corporate responses to liability risk. *The Review of Financial Studies 24*(8), 2781–2821.

Gorton, G. B. and A. K. Zentefis (2020). Corporate Culture as a Theory of the Firm. Working Paper, National Bureau of Economic Research.

Graham, J. R., H. Kim, and M. Leary (2020). CEO-board dynamics. *Journal of Financial Economics 137*(3), 612–636.

Grenadier, S. R., A. Malenko, and I. A. Strebulaev (2014). Investment Busts, Reputation, and the Temptation to Blend in with the Crowd. *Journal of Financial Economics 111*(1), 137–157.

Guenzel, M. (2023). In Too Deep: The Effect of Sunk Costs on Corporate Investment. *The Journal of Finance, forthcoming*.

Guenzel, M. and U. Malmendier (2020). Behavioral Corporate Finance: The Life Cycle of a CEO Career. *Oxford Research Encyclopedia of Economics and Finance, September 2020*.

Hallock, K. F. (1998). Layoffs, top executive pay, and firm performance. *American Economic Review*, 711–723.

Hallock, K. F. (2005). A descriptive analysis of layoffs in large US firms using archival data over three decades and interviews with senior managers.

Hamermesh, D. S. (1989). Labor demand and the structure of adjustment costs. *American Economic Review 79*(4), 674–689.

Hermalin, B. E. and M. S. Weisbach (1998). Endogenously chosen boards of directors and their monitoring of the CEO. *American Economic Review*, 96–118.

Hirshleifer, D. (2020). Presidential address: Social transmission bias in economics and finance. *The Journal of Finance 75*(4), 1779–1831.

Hjort, J. (2014). Ethnic divisions and production in firms. *The Quarterly Journal of Economics 129*(4), 1899–1946.

Hoffman, M. and S. Tadelis (2021). People management skills, employee attrition, and manager rewards: An empirical analysis. *Journal of Political Economy 129*(1), 243–285.

Jacobson, L. S., R. J. LaLonde, and D. G. Sullivan (1993). Earnings losses of displaced workers. *The American Economic Review*, 685–709.

Jenter, D. and F. Kanaan (2015). CEO turnover and relative performance evaluation. *The Journal of Finance 70*(5), 2155–2184.

Jenter, D. and K. Lewellen (2015). CEO preferences and acquisitions. *The Journal of Finance 70*(6), 2813–2852.

Jiang, J. X., K. R. Petroni, and I. Y. Wang (2010). CFOs and CEOs: Who have the most influence on earnings management? *Journal of Financial Economics 96*(3), 513–526.

Jovanovic, B. and P. L. Rousseau (2002). The Q-theory of mergers. *American Economic Review 92*(2), 198–204.

Kaplan, S. N., M. M. Klebanov, and M. Sørensen (2012). Which CEO characteristics and abilities matter? *The Journal of Finance 67*(3), 973–1007.

Kaplan, S. N., M. Sørensen, and A. A. Zakolyukina (2022). What is CEO overconfidence? Evidence from executive assessments. *Journal of Financial Economics 145*(2), 409–425.

Kárpáti, D. and L. Renneboog (2023). Corporate financial frictions and employee mental health. *Journal of Financial and Quantitative Analysis*, 1–67.

Keum, D. and S. Meier (2023). License to Fire? Unemployment Insurance and the Moral Cost of Layoffs. *Organizational Science, conditionally accepted*.

Kuhn, A., R. Lalive, and J. Zweimüller (2009). The public health costs of job loss. *Journal of health economics 28*(6), 1099–1115.

Kumru, C. S. and L. Vesterlund (2010). The effect of status on charitable giving. *Journal of Public Economic Theory 12*(4), 709–735.

Landier, A., V. B. Nair, and J. Wulf (2009). Trade-offs in staying close: Corporate decision making and geographic dispersion. *The Review of Financial Studies 22*(3), 1119–1148.

Landier, A., J. Sauvagnat, D. Sraer, and D. Thesmar (2013). Bottom-up corporate governance. *Review of Finance 17*(1), 161–201.

Levitt, S. D. and J. A. List (2007). What do laboratory experiments measuring social preferences reveal about the real world? *Journal of Economic Perspectives 21*(2), 153–174.

Livdan, D. and A. Nezlobin (2021). Investment, capital stock, and replacement cost of assets when economic depreciation is non-geometric. *Journal of Financial Economics 142*(3), 1444–1469.

Malmendier, U. (2018). Behavioral Corporate Finance. In *Handbook of Behavioral Economics: Applications and Foundations 1*, Volume 1, pp. 277–379. Elsevier.

Malmendier, U., V. Pezone, and H. Zheng (2023). Managerial duties and managerial biases. *Management Science 69*(6), 3174–3201.

Malmendier, U. and G. Tate (2005). CEO overconfidence and corporate investment. *The Journal of Finance 60*(6), 2661–2700.

Martin, C. (2005). *Tough Management: The 7 Ways To Make Tough Decisions Easier, Deliver The Numbers, And Grow Business In Good Times And Bad*. McGraw-Hill.

Matsa, D. A. and A. R. Miller (2013). A female style in corporate leadership? Evidence from quotas. *American Economic Journal: Applied Economics 5*(3), 136–169.

Matsa, D. A. and A. R. Miller (2014). Workforce reductions at women-owned businesses in the United States. *Industrial and Labor Relations Review 67*(2), 422–452.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of finance 29*(2), 449–470.

Meyer, M. L., C. L. Masten, Y. Ma, C. Wang, Z. Shi, N. I. Eisenberger, and S. Han (2013). Empathy for the social suffering of friends and strangers recruits distinct patterns of brain activation. *Social Cognitive and Affective Neuroscience 8*(4), 446–454.

Morelli, S. A., M. D. Lieberman, and J. Zaki (2015). The emerging study of positive empathy. *Social and Personality Psychology Compass 9*(2), 57–68.

Opler, T. C. and S. Titman (1994). Financial distress and corporate performance. *The Journal of Finance 49*(3), 1015–1040.

Pan, Y., T. Y. Wang, and M. S. Weisbach (2016). CEO investment cycles. *The Review of Financial Studies 29*(11), 2955–2999.

Petrosky-Nadeau, N., R. G. Valletta, et al. (2019). Unemployment: lower for longer? *FRBSF Economic Letter 21*.

Roelfs, D. J., E. Shor, K. W. Davidson, and J. E. Schwartz (2011). Losing life and livelihood: a systematic review and meta-analysis of unemployment and all-cause mortality. *Social science & medicine 72*(6), 840–854.

Romer, C. D. and D. H. Romer (2010). The macroeconomic effects of tax changes: estimates based on a new measure of fiscal shocks. *American Economic Review 100*(3), 763–801.

Rothschild, M. (1971). On the cost of adjustment. *The Quarterly Journal of Economics*, 605–622.

Schmieder, J. F., T. M. von Wachter, and J. Heining (2022). The costs of job displacement over the business cycle and its sources: Evidence from Germany. Working Paper, National Bureau of Economic Research.

Slaper, T. F. (2019). Automation and offshoring in durable goods manufacturing: An Indiana case study. *Economic Development Quarterly 33*(1), 19–38.

Sullivan, D. and T. Von Wachter (2009). Job displacement and mortality: An analysis using administrative data. *The Quarterly Journal of Economics 124*(3), 1265–1306.

Taylor, L. A. (2010). Why are CEOs rarely fired? Evidence from structural estimation. *The Journal of Finance 65*(6), 2051–2087.

Teisberg, E. O. (1993). Capital investment strategies under uncertain regulation. *The RAND Journal of Economics*, 591–604.

Yermack, D. (2006). Flights of fancy: Corporate jets, CEO perquisites, and inferior shareholder returns. *Journal of Financial Economics 80*(1), 211–242.

Yermack, D. (2009). Deductio' ad absurdum: CEOs donating their own stock to their own family foundations. *Journal of Financial Economics 94*(1), 107–123.

Yonker, S. E. (2017). Do managers give hometown labor an edge? *The Review of Financial Studies 30*(10), 3581–3604.

Table 1. Summary Statistics

(a) 2002–2020 Firm-Layoffs Sample (Sections 3.1 and 3.2)

	N	Mean	SD	P25	Median	P75
Layoff	34,683	0.13	0.34	0.00	0.00	0.00
Layoff (Unrestricted)	34,683	0.17	0.37	0.00	0.00	0.00
December Layoff	34,683	0.02	0.14	0.00	0.00	0.00
White Collar Layoff	34,683	0.03	0.18	0.00	0.00	0.00
HQ-State Layoff	34,683	0.04	0.20	0.00	0.00	0.00
HQ-City Layoff	34,683	0.02	0.13	0.00	0.00	0.00
Frac. Laid Off	33,251	0.01	0.03	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
Ln Assets	34,683	7.68	1.85	6.39	7.57	8.86
Ln Employment	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
Exogenous CEO Turnovers:						
CEO Age at Turnover	115	60.75	9.13	54.00	61.00	65.00

(b) CEO Mortality Sample (Section 3.3)

	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
CEO Age at Death	680	80.80	9.72	75.00	82.00	88.00
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
Ln Assets	1,131	7.35	1.66	6.33	7.38	8.42
Ln Employment	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

Notes: Panel (a) shows summary statistics for the *2002–2020 Layoff Data*. One observation is a CEO-firm-year observation. Panel (b) shows summary statistics for the *CEO Mortality Data*. One observation is a CEO. More details about the data are in Section 3 and Appendix-Section B.

Table 2. Layoffs and CEO Mortality

	(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)
Ln Assets	−0.137*	−0.134*	−0.130*
	(0.078)	(0.079)	(0.078)
Ln Employment	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

Notes: This table reports estimated coefficients from logit regression where the dependent variable is an indicator that equals one if the CEO dies in a given year. Distress Layoff is an indicator equal to one in year t if, prior to or in year t, a CEO has undertaken a layoff during industry-wide distress. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. CEO Age is the CEO's age at time t. Minimum stock performance is defined as the worst stock performance in any six-month period during the CEO's tenure. Ln assets and Ln employees from the first year that the CEO assumed the top office are included in all specifications. Firm profitability is included for all years that the CEO is in office and then profitability from the CEO's final year in office thereafter. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by industry, are in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3. Layoffs and CEO Tenure

	(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)
Ln Assets		0.029^{***}	0.028^{***}	0.029^{***}
		(0.003)	(0.007)	(0.007)
Ln Employment		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

Notes: Table reports coefficients from linear regression where the dependent variable is equal to one for significant layoff events, defined as CEO-firm-years with at least three layoff events or where 1% of the firm laid off and 0 otherwise. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. Ln assets is the log of total assets. Ln employment is the log of total employment. Firm profitability is operating income before depreciation divided by total assets. CEO and CFO tenure are the number of years the CEO and CFO have been in their respective positions, respectively. We normalize tenure by dividing by 100. Firm characteristics are from the beginning of the year. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4. Layoff Propensity and CEO Tenure—CEO Power

	(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 Chair	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)
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	23,621	23,621	23,425	23,425

Notes: Table reports coefficients from linear regression where the dependent variable is equal to one for significant layoff events, defined as CEO-firm-years with at least three layoff events or where 1% of the firm laid off and 0 otherwise. Controls are industry distress, log assets, log employment and firm profitability. % of new directors is between 0 and 1 and is calculated as the percent of directors appointed in the years following the CEO's appointment. CEO and Chair is a dummy equal to one if the CEO is also the chair of the board. CEO and President is a dummy equal to one if the CEO is also the president of the firm. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. Ln assets is the log of total assets. Ln employment is the log of total employment. Firm profitability is operating income before depreciation divided by total assets. CEO tenure is the number of years the CEO has been in that position. We normalize tenure by dividing by 100. Firm characteristics are from the beginning of the year. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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

	(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)
Ln Assets		0.002^{***}	0.002^{***}	0.003^{***}
		(0.000)	(0.001)	(0.001)
Ln Emp.		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

Notes: Table reports coefficients from linear regression where the dependent variable is the proportion of the firm laid off in that CEO-firm-year. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. Ln assets is the log of total assets. Ln employment is the log of total employment. Firm profitability is operating income before depreciation divided by total assets. CEO and CFO tenure are the number of years the CEO and CFO have been in their respective positions, respectively. We normalize tenure by dividing by 100. Firm characteristics are from the beginning of the year. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6. Layoff Propensity and Internally Versus Externally Hired CEO

	Full Sample		Non-Manufacturing	
	(1)	(2)	(3)	(4)
Internal CEO	−0.029***	−0.048**	−0.020	−0.053**
	(0.010)	(0.019)	(0.012)	(0.026)
CEO Tenure / 100	−0.369***	−0.247***	−0.368***	−0.228*
	(0.056)	(0.095)	(0.073)	(0.119)
Industry Distress	0.060***	0.046***	0.078***	0.064***
	(0.013)	(0.013)	(0.016)	(0.016)
Ln Assets	0.027***	0.033**	0.020***	0.010
	(0.005)	(0.014)	(0.006)	(0.015)
Ln Emp.	0.039***	0.060***	0.038***	0.052***
	(0.005)	(0.017)	(0.005)	(0.017)
Firm Profitability	−0.327***	−0.270***	−0.251***	−0.247***
	(0.044)	(0.063)	(0.063)	(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	10,952	10,872	6,280	6,224

Notes: Table reports coefficients from linear regression where the dependent variable is equal to one for significant layoff events, defined as CEO-firm-years with at least three layoff events or where 1% of the firm laid off and 0 otherwise. Internally hired CEOs are CEOs who have been with the firm for at least one year before assuming the CEO position. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. Ln assets is the log of total assets. Ln employment is the log of total employment. Firm profitability is operating income before depreciation divided by total assets. CEO tenure is the number of years the CEO has been in that position. We normalize tenure by dividing by 100. Firm characteristics are from the beginning of the year. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 7. Layoff Propensity and CEO Tenure—Recession Periods

	(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 / 100 × 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

Notes: Table reports coefficients from linear regression where the dependent variable is equal to one for significant layoff events, defined as CEO-firm-years with at least three layoff events or where 1% of the firm laid off and 0 otherwise. Control variables are begininning of year firm profitability, log assents, and log employees. Control interactions are interactions between each of the control variables and industry distress. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. Ln assets is the log of total assets. Ln employment is the log of total employment. Firm profitability is operating income before depreciation divided by total assets. CEO tenure is the number of years the CEO has been in that position. We normalize tenure by dividing by 100. Firm characteristics are from the beginning of the year. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8. Research and Development Expenditures and Tenure

	(1)	(2)	(3)	(4)
CEO Tenure / 100	0.066***	0.018	0.066***	0.018
	(0.026)	(0.012)	(0.026)	(0.012)
Industry Distress	0.004	0.005***	0.013	0.005
	(0.003)	(0.002)	(0.015)	(0.010)
CEO Tenure × Industry Distress	−0.065***	−0.035**	−0.066***	−0.038**
	(0.024)	(0.015)	(0.024)	(0.015)
Controls	Yes	Yes	Yes	Yes
Control Interactions	No	No	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	15,052	14,994	15,052	14,994

Notes: Table reports coefficients from linear regression where the dependent variable is research and development expenditures divided by assets at the beginning of the year. Control variables are begininning of year firm profitability, log assents, and log employees. Control interactions are interactions between each of the control variables and industry distress. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. Ln assets is the log of total assets. Ln employment is the log of total employment. Firm profitability is operating income before depreciation divided by total assets. CEO tenure is the number of years the CEO has been in that position. We normalize tenure by dividing by 100. Firm characteristics are from the beginning of the year. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 9. Layoff Propensity and CEO Tenure—Layoffs Around Holiday Season (December)

	Full Sample		Layoff-Years	
	(1)	(2)	(3)	(4)
CEO Tenure / 100	-0.067^{***}	-0.065^{***}	-0.331^{***}	-0.392^{***}
	(0.010)	(0.016)	(0.077)	(0.135)
Industry Distress	0.008^{***}	0.005	0.026^{**}	0.042^{**}
	(0.003)	(0.003)	(0.013)	(0.018)
Ln Assets	0.006^{***}	0.003	0.006	0.005
	(0.001)	(0.003)	(0.006)	(0.023)
Ln Emp.	0.006^{***}	0.011^{***}	0.010	0.016
	(0.001)	(0.003)	(0.006)	(0.022)
Firm Profitability	-0.046^{***}	-0.026^{**}	-0.075	0.015
	(0.008)	(0.010)	(0.052)	(0.089)
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	32,301	32,301	5,325	4,806

Notes: Table reports coefficients from linear regression where the dependent variable is equal to one for years with at least one layoff in December and zero otherwise. Layoff-years are CEO-firm-years with at least one layoff. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. Ln assets is the log of total assets. Ln employment is the log of total employment. Firm profitability is operating income before depreciation divided by total assets. CEO tenure is the number of years the CEO has been in that position. We normalize tenure by dividing by 100. Firm characteristics are from the beginning of the year. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 10. Layoff Propensity and CEO Tenure—Layoffs of White-Collar Employees

	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)
Ln Assets	0.013***	0.009***	0.021***	−0.009
	(0.001)	(0.003)	(0.008)	(0.026)
Ln Emp.	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

Notes: Table reports coefficients from linear regression where the dependent variable is equal to one for years with at least one white-collar layoff and zero otherwise. Layoff-years are CEO-firm-years with at least one layoff. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. Ln assets is the log of total assets. Ln employment is the log of total employment. Firm profitability is operating income before depreciation divided by total assets. CEO tenure is the number of years the CEO has been in that position. We normalize tenure by dividing by 100. Firm characteristics are from the beginning of the year. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 11. Layoff Propensity and CEO Tenure—Geographic Proximity of Layoffs

	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)
Ln Assets	0.014^{***}	0.007^{***}	0.018^{***}	0.012
	(0.002)	(0.001)	(0.007)	(0.021)
Ln Emp.	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

Notes: The dependent variables are indicator variables that equal one if a firm makes at least one layoff at the respective geographic level in a given year and zero otherwise. Layoff-years are CEO-firm-years with at least one layoff. HQ-state layoff-years are CEO-firm-years with any layoff in the state of the firm's headquarters. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. Ln assets is the log of total assets. Ln employment is the log of total employment. Firm profitability is operating income before depreciation divided by total assets. CEO tenure is the number of years the CEO has been in that position. We normalize tenure by dividing by 100. Firm characteristics are from the beginning of the year. More details about the data are in Section 3 and Appendix-Section B Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 12. Layoff Propensity and CEO Tenure–Heterogeneity in Prosociality

	Full Sample	CEO Empathy / OC Sample	
	(1)	(2)	(3)
CEO Tenure / 100	-0.187^{***}	-0.102	
	(0.039)	(0.066)	
CEO Tenure × Empathy			-0.317^{**}
			(0.124)
CEO Tenure × Overconfidence			-0.016
			(0.075)
CEO Overconfidence		-0.012	-0.026^{*}
		(0.012)	(0.014)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	34,565	21,357	21,357

Notes: Table reports coefficients from linear regression where the dependent variable is equal to one for significant layoff events, defined as CEO-firm-years with at least three layoff events or where 1% of the firm laid off and 0 otherwise. *CEO Overconfidence* is an indicator variable defined based on the *Longholder* measure of managerial overconfidence (Malmendier and Tate 2005, Malmendier et al. 2023). *CEO Empathy* is an indicator variable equal to one if the CEO is not classified as overconfident, motivated by Kaplan et al. (2012) and Kaplan et al. (2022) that overconfidence and empathy are primary distinguishing characteristics of managers. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. Ln assets is the log of total assets. Ln employment is the log of total employment. Firm profitability is operating income before depreciation divided by total assets. CEO and CFO tenure are the number of years the CEO and CFO have been in their respective positions, respectively. We normalize tenure by dividing by 100. Firm characteristics are from the beginning of the year. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 13. Layoffs and CEO Pay (Total Compensation)

	(1) Log TC, t	(2) Log TC, t	(3) Log TC, $t+1$	(4) Log TC, $t+1$
Layoff	-0.003	-0.011	-0.044^{***}	-0.036^{***}
	(0.015)	(0.012)	(0.016)	(0.012)
CEO Tenure / 100	-0.256^{*}	0.114	-0.324^{**}	0.060
	(0.152)	(0.143)	(0.163)	(0.166)
Industry Distress	-0.054^{***}	-0.047^{***}	-0.068^{***}	-0.048^{***}
	(0.018)	(0.014)	(0.019)	(0.015)
Ln Assets	0.356^{***}	0.216^{***}	0.350^{***}	0.138^{***}
	(0.012)	(0.019)	(0.013)	(0.021)
Ln Emp.	0.051^{***}	0.062^{***}	0.051^{***}	0.084^{***}
	(0.011)	(0.020)	(0.012)	(0.021)
Firm Profitability	1.003^{***}	0.751^{***}	0.916^{***}	0.485^{***}
	(0.099)	(0.086)	(0.100)	(0.087)
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	32,686	32,568	27,639	27,490

Notes: Table reports coefficients from linear regression where the dependent variable is log total compensation of the CEO. Layoff is a variable equal to one if there are at least three layoff events or 1% of the firm laid off in that CEO-firm-year and zero otherwise. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. Ln assets is the log of total assets. Ln employment is the log of total employment. Firm profitability is operating income before depreciation divided by total assets. CEO tenure is the number of years the CEO has been in that position. We normalize tenure by dividing by 100. Firm characteristics are from the beginning of the year. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Online Appendix
Prosociality and Layoffs

Not For Publication

Marius Guenzel Clint Hamilton Ulrike Malmendier

A. Conceptual Framework: Proofs and Numerical Solution

A.1 Additional Framework Details

We assume that managers maximize the sum of current and future utility, without discounting for simplicity. Utility is the sum of firm profits and the disutility cost of firing,

$$u(n_t, k_t) = \pi(n_t, k_t) + \int_0^{n_{t-1}} f_{t,i}\left(s_{t,i}\right) \, \mathrm{d}i,$$

subject to the spending constraint, $wn_t + rk_t \leq c_t$, where c_t is the firm's cash on hand in period t, w is the wage, and r is the rental cost of capital. c_t is drawn from an independent and identically distributed (i.i.d.) atomless distribution with a strictly positive density over support $[c_l, c_h]$ with the probability density function (PDF) denoted as $q(\cdot)$. Firm production is Cobb-Douglas with constant returns to scale, so the firm's profit is given by

$$\pi(n_t, k_t) = n_t^{\nu} k_t^{\gamma} - wn_t - rk_t,$$

where ν and γ are both positive and sum to one. There is an exogenously assigned employment level $n_0 \in (\nu c_l, \nu c_h)$. To ensure the manager chooses to operate the firm, we assume that the $\alpha_{t,i}$ is sufficiently small that the manager's utility is always positive. We also assume that the marginal products of labor and capital are sufficiently high relative to costs that cash on hand is always fully utilized.

For all proofs for predictions, we use a three-period framework. We assume $\alpha_{2,i}$, $u_{2,i}^{\text{emp}}$, $u_{2,i}^{\text{unemp}}$ are the same for all i and thus we can drop the subscript i. This allows us to simplify the notation as in this case $\int_0^{n_{t-1}} f_{t,i}\left(s_{t,i}\right) \, \mathrm{d}i = \alpha_2(u_2^{\text{emp}} - u_2^{\text{unemp}}) \min\{n_2 - n_1, 0\}$. We define a standard manager as a manager with $\alpha_t = 0$ for all t. We define a prosocial manager as a manager with $\alpha_1 = 0$ and $\alpha_2 > 0$. Define $\tilde{\alpha}_t \equiv \alpha_t(u_t^{\text{emp}} - u_t^{\text{unemp}})$ and $\Psi_t = -\frac{\partial}{\partial n_t} \mathrm{E}_t\left[u(n_{t+1}^*, k_{t+1}^*)|n_t\right]$ where $\mathrm{E}_t\left[u(n_{t+1}^*, k_{t+1}^*)|n_t\right]$ is the expected utility in period 2 assuming the optimal employment and capital levels n_2^* and k_2^* are chosen for c_2 given the choice n_1. Note that $\Psi_2 = 0$ by construction.

A.2 Lemmas

In this subsection, we provide the proofs for the lemmas that are used in the proofs of the predictions.

Lemma 1. *The general solution for the optimal choice of labor is given by*

$$n_t = \begin{cases} H\left(\Psi_t \mid c_t\right) & \text{if} \quad n_{t-1} \leq H\left(\Psi_t \mid c_t\right) \\ n_{t-1} & \text{if} \quad H\left(\Psi_t \mid c_t\right) < n_{t-1} \leq H\left(\Psi_t - \tilde{\alpha}_t \mid c_t\right) \\ H\left(\Psi_t - \tilde{\alpha}_t \mid c_t\right) & \text{if} \quad n_{t-1} > H\left(\Psi_t - \tilde{\alpha}_t \mid c_t\right) \end{cases}$$

where $H\left(\cdot \mid c_t\right) \equiv h^{-1}\left(\cdot \mid c_t\right)$ *and*

$$h\left(x \mid c_t\right) \equiv \frac{x^{\nu-1}\left(\frac{c_t - wx}{r}\right)^{\gamma-1}\left(\nu c_t - wx\right)}{r}.$$

Proof of Lemma 1. The Lagrangian for the prosocial manager in period 1 is

$$\begin{aligned} \mathcal{L} =& n_t^{\nu} k_t^{\gamma} - w n_t - r k_t + \lambda_t (w n_t + r k_t - c_t) \\ &+ \tilde{\alpha}_t \min\{n_t - n_{t-1}, 0\} + \mathrm{E}_t\left[u(n_{t+1}^*, k_{t+1}^*) | n_t\right], \end{aligned}$$

where λ_t is the Lagrange multiplier for the spending constraint in period 1. The three first-order conditions can be combined, by substituting out λ_t and k_t, to give the following expression for the optimal employment level in the second period:

$$\frac{n_t^{\nu-1}\left(\frac{c_t - w n_t}{r}\right)^{\gamma-1}\left(\nu c_t - w n_t\right)}{r} = \tilde{\alpha}_t \mathbb{1}_{n_t < n_t - 1} + \Psi_t. \tag{A.1}$$

Using the above definition for h, we can rewrite the above equation as $h\left(n_t \mid c_t\right) = \Psi_t + \tilde{\alpha}_t$. Note that

$$h\left(x \mid c_t\right) = \frac{c_t^2(\nu-1)\nu p x^{\nu-2}\left(\frac{c_t - wx}{r}\right)^{\gamma}}{\left(c_t - wx\right)^2} < 0$$

for $x \in (0, \frac{c_t}{w})$ as $(\nu - 1) < 0$. Monotonicity of h implies a single-valued inverse function $H \equiv h^{-1}$ exists. Further, by the inverse function theorem, $H\left(x \mid c_t\right)$ is strictly decreasing in x and thus $H\left(\Psi_t \mid c_t\right) < H\left(\Psi_t - \tilde{\alpha}_t \mid c_t\right)$. Thus, there is no case where both interior solutions are valid. If $n^*_{2,\text{standard}} < n_1 < n^*_{2,\text{layoff}}$, then an interior solution does not exist, and the boundary solution n_1 is the optimal choice for n_2. This follows from the concavity of the optimization problem, which implies that the marginal utility is increasing from both sides of the boundary solution towards it. Thus, $H(\Psi_t \mid c_t)$ or $H(\Psi_t - \tilde{\alpha}_t \mid c_t)$ is the optimal solution if it is greater or less than n_{t-1}, respectively. If neither of these conditions are satisfied, then n_{t-1} is the optimal solution.

□

Lemma 2. Ψ_1 *is weakly positive.*

Proof of Lemma 2. Define $\hat{\hat{c}}$ as the value of c that satisfies the equation $H(0 \mid \hat{\hat{c}}) = n_1$. Define $\hat{c}$ as the value of c that satisfies the equation $H(-\tilde{\alpha}_2 \mid \hat{c}) = n_1$. The expected

value for period 2 in period 1, given n_1, can thus be written as

$$E_1\left[u(n_2^*,k_2^*)|n_1\right] = \int_{c_l}^{\hat{c}} q(c)\left(\pi(H(-\tilde{\alpha}_2 \mid c),(1/r)(c-H(\tilde{\alpha}_2 \mid c))) + -\tilde{\alpha}_2(H(-\tilde{\alpha}_2 \mid c)-n_1)\right)dc$$
$$+ \int_{\hat{c}}^{\hat{\hat{c}}} q(c)\left(\pi\left(n_1, \frac{c-n_1 w}{r}\right)\right)dc$$
$$+ \int_{\hat{\hat{c}}}^{c_h} q(c)\left(\pi(H(0 \mid c),(1/r)(c-wH(0 \mid c)))\right)dc.$$

Taking the derivate with respect to n_1, yields

$$\frac{\partial}{\partial n_1}E_1\left[u(n_2^*,k_2^*)|n_1\right] = -\int_{c_l}^{\hat{c}} q(c)\tilde{\alpha}_2 dc$$
$$+ \int_{\hat{c}}^{\hat{\hat{c}}} q(c)\left(\frac{n_1^{\nu-1}\left(\frac{c-n_1 w}{r}\right)^{\gamma}(n_1 w - c\nu)}{n_1 w - c}\right)dc \leq 0.$$

Note that while $\hat{c}$ and $\hat{\hat{c}}$ both depend on n_1, the terms that arise from applying the Leibniz rule cancel out exactly in this derivative. The first term is clearly negative as long as $\hat{c}$ is in the support of q and 0 otherwise. The second term is negative as long as $\hat{\hat{c}}$ is in the support of q and 0 otherwise because the denominator is clearly negative and by the definition of $\hat{\hat{c}}$, $\forall_{c<\hat{\hat{c}}} n_1 w - c\nu > 0$. Thus, we have shown that

$$\frac{\partial}{\partial n_1}E_1\left[u(n_2^*,k_2^*)|n_1\right] \leq 0.$$

This implies that $\Psi_1 = -\frac{\partial}{\partial n_1}E_1\left[u(n_2^*,k_2^*)|n_1\right] \geq 0$. □

A.3 Proofs

Proof of Prediction 1. For the prosocial manager, the utility in period 2 is given by $\pi(n_2,k_2) + \tilde{\alpha}_2 \min\{n_2 - n_1, 0\}$. It is clear that $\tilde{\alpha}_2 \min\{n_2 - n_1, 0\}$ is a manager-specific disutility cost of layoffs that does not affect firm value or managers who are not prosocial. If $n_2 < n_1$ a layoff occurs and the manager suffers a direct disutility cost $\tilde{\alpha}_2(n_2 - n_1) < 0$. □

Proof of Prediction 2. Suppose that both the new and incumbent managers have the initial level of labor from the previous period $\bar{n}$ and the same cash on hand $\bar{c}$. By Lemma 1, a new manager will choose $n_1 = H(\Psi_1 \mid \bar{c})$ by and not consider n_0 as $\alpha_1 = \tilde{\alpha}_1 = 0$. An incumbent manager will choose $n_2 \geq H(0 \mid \bar{c})$. By Lemma 2 and the monotonically decreasing property of H noted in the proof of Lemma 1, $H(0 \mid \bar{c}) \geq H(\Psi_1 \mid \bar{c})$. Thus for any values of $\bar{n}$, such that $H(0 \mid \bar{c}) \geq \bar{n} \geq H(\Psi_1 \mid \bar{c})$, the new manager will choose a layoff and the incumbent manager will not. Further note that since $H(0 \mid \bar{c})$ is the choice of a value-maximizing manager not subject to prosocial considerations, the new manager will always choose a layoff when that is

the value-maximizing option since $\bar{n} > H(0 \mid \bar{c})$ implies that $\bar{n} > H(\Psi_1 \mid \bar{c})$. □

Proof of Prediction 3. Part (i) is equivalent to the statement in Prediction 2 that a new, alternatively shorter-tenured, prosocial manager has a higher propensity to make layoffs than an incumbent, alternatively longer-tenured, prosocial manager given the manager only makes decisions for two-periods.

We thus only need to prove part (ii). Let the level of cash-on-hand be given by $\bar{c}$. By Lemma 1, conditional on a layoff by a shorter-tenured manager and longer-tenured prosocial manager, the shorter-tenured manager will choose $n_1 = H(\Psi_1 \mid \bar{c})$ and the longer-tenured manager will choose $n_2 = H(-\tilde{\alpha}_2 \mid c_2)$. By the strictly decreasing property of h noted in the proof of Lemma 1, $H(-\tilde{\alpha}_2 \mid c_2) > H(\Psi_1 \mid c_1)$. Thus, the reduction in labor from the initial/previous period level will be smaller for the longer-tenured ($t = 2$) prosocial manager since $\bar{n} - n_2 \leq \bar{n} n_1$ which is part (ii) of Prediction 3.

□

Proof of Prediction 4. Note that both parts of the prediction lead to an increase in $\tilde{\alpha}_2$. Thus, we need to show that the increase in $\tilde{\alpha}_2$ for a prosocial manager to $\tilde{\alpha}_2'$ for a more prosocial manager leads to a larger reduction in layoff propensity and layoff size for a prosocial manager than a standard manager.

First, we consider layoff size. Conditional on a layoff for both managers, the prosocial manager will choose $n_2 = H(-\tilde{\alpha}_2 \mid c_2)$ and the more prosocial manager will choose $n_2 = H(-\tilde{\alpha}_2' \mid c_2)$. By the strictly decreasing property of H noted in the proof of Lemma 1, $H(-\tilde{\alpha}_2' \mid c_2) > H(-\tilde{\alpha}_2 \mid c_2)$. Thus, the reduction in labor from the initial/previous period level will be smaller for the more prosocial manager.

Next, we consider layoff propensity. The lowest realization of c_2, denoted $\hat{c}$, before a prosocial manager will undertake layoffs is characterized by $H(-\tilde{\alpha}_2|\hat{c}) = n_1$. This is

$$n_1^{\nu-1} \left(c_2 - n_1 w\right)^{\gamma-1} \left(c_2 \nu - n_1 w\right) = -r^{\gamma} \tilde{\alpha}_2.$$

We then apply the implicit differentiation technique to find the derivative of c_2 with respect to $\tilde{\alpha}_2$ to get

$$\frac{dc_2}{d\tilde{\alpha}_2} = \frac{-r^{\gamma}}{\frac{\partial}{\partial c_2}\left(n_1^{\nu-1} \left(c_2 - n_1 w\right)^{\gamma-1} \left(c_2 \nu - n_1 w\right)\right)}.$$

Since $\frac{\partial}{\partial c_2}\left(n_1^{\nu-1} \left(c_2 - n_1 w\right)^{\gamma-1} \left(c_2 \nu - n_1 w\right)\right) > 0$, we can conclude that $\frac{dc_2}{d\tilde{\alpha}_2} < 0$. This implies that the lowest value of c before layoffs are undertaken is decreasing in $\tilde{\alpha}_2$, meaning that a manager with a greater $\tilde{\alpha}_2$ parameter is weakly more likely to conduct layoffs. The difference is only weak as there may be no c_2 realizations low enough to necessitate a layoff for the considered $\tilde{\alpha}_2$ values.

□

Proof of Prediction 5. Recall that the budget constraint holds with equality and thus given n_t and c_t, $k_t = \frac{c_t - w n_t}{r}$. Thus, the proof for Prediction 3, which finds higher n_2

for a higher-tenured prosocial manager than a lower-tenured prosocial manager, implies that k_2 is lower for the higher-tenured prosocial manager given the same value of cash-on-hand, thus proving the prediction.

□

A.4 Numerical Results

This subsection provides additional details about how the numerical results are generated. The distribution of cash on hand is given by $c_t \overset{iid}{\sim} \mathcal{U}[.5, 1.5]$. Production is Cobb-Douglas with capital share $\gamma = \frac{1}{3}$ and labor share $\nu = \frac{2}{3}$. The rental cost of capital is $r = 0.2$ and the per period wage is $w = 0.5$. For all workers, the difference in utility between states is $u_{2,i}^{emp} - u_{2,i}^{unemp} = 1$. For all workers, the prosocial weight for the high and low managers are $\alpha_{2,i}^{high} = 0.4$ and $\alpha^{low} = 0.2$, respectively. See Internet Appendix Section A.3 for details on the setup of the model. 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 a unit of labor.

We discretize the cash-on-hand distribution and the labor choice variable using 1,001 gridpoints for each. The framework is solved using backward induction where the second period is solved first by finding the optimal choice of n_2 for all potential choices for n_1 and all potential realizations of c_2. We then calculate the expected value for the second period for each choice of n_1 and solve for the optimal choice of n_1 in the first period.

B. Data Appendix

B.1 2002–2020 Layoff Data: Construction

This section provides more details about the Standard and Poor's (S&P) Capital IQ Key Developments database, our data processing using NLP, and manual review. The goal is to identify all significant layoff events in each of our sample firms as well as detailed information about those events (size, location, type of employees laid off). The default definition of significant layoff events (and the main dependent variable in our empirical analysis) includes all cases where a firm has either a layoff affecting 1% or more of the firm's employees or has at least three layoff events in a given year. (Our results are robust to removing these restrictions.)

Each key development in the Capital IQ Key Developments data 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 use the announcement dates, headlines, and situation summaries. The headlines are typically a phrase and the summaries are generally between one sentence and a small paragraph. According to S&P, the content is based on a variety of sources including "news aggregators, stock exchanges and regulatory websites as well as company websites." For our analyses, we use and classify all key developments given the "Discontinued Operations/Downsizings" type which includes layoff announcements and closure announcements.

As discussed in the main text, we leverage NLP techniques to extract key data points from the text. Specifically, we automate four functions: (1) classifying each article as a layoff, closure, or neither, (2) extracting the number of workers laid off and/or the percentage of workers laid off, (3) identifying relevant geographies at the international, state, and city levels, and (4) classifying layoffs as blue-, pink-, or white-collar.

For (1), we first lemmatize the headline and situation summary and construct three lists of words to aid in identifying layoffs and closures: (i) layoff verbs, such as "cut" and "slashed," (ii) closure verbs such as "mothball" or "shut down," and (iii) worker-related nouns, including (iii.α) job words for synonyms of jobs like "position" or "role," (iii.β) occupations words for industry-specific jobs such as "accountant" or "banker," and (iii.γ) collective job words referring to jobs generally, such as "headcount" or "workforce." A key development is classified as a layoff if the headline or sentence in the summary includes a layoff-related verb as well as a noun from one of the three worker-related lists specified above. Key developments were identified as low confidence layoffs if only either a layoff-related verb or worker-related noun is present. If the key development does not contain a layoff-related verb or worker-related noun, but contains a closure-related verb, then it is classified as a closure. Additionally, we eliminate any layoff or closure that is a speculation or consideration. We create a list of words that indicate uncertainty,

such as "pondering" or "considering." If the sentence contains the relevant layoff-related verb, worker-related noun, and/or closure-related verb also includes a word indicating uncertainty, then the key development is not classified as a layoff or closure.

Next, for (2) we extract the number and/or the percentage of workers laid off when available.[IA.1] In addition to the restricted text searches (regular expressions) for percentages and numbers discussed in the main text, we also use these patterns to extract the percentages or numeric values that are not expressed as numbers. We use a list of common number and proportion words for fractions like "one half" or "two-thirds" and numbers like "thirty", and convert them to their numerical integer values. For general quantities like "hundreds" or "thousands," we encode them as the largest possible value, i.e. 999 or 9999, respectively. If none of the patterns patterns were present, proportions or counts from sentences with a layoff-related verb or a worker-related noun were still extracted, but denoted as low confidence for the manual review.

For (3), the geographic location of the layoff, we collect the location up to the city level for US layoffs and up to the country level for foreign layoffs. At the international level, we identify foreign locations in the text of each key development based on lists of country names, demonyms for people from the respective countries, and names of large global cities, such as Tokyo. If no specific country can be identified, we record words that would imply layoffs outside the US (e.g., foreign, international, etc.). We also note if the US or a US state is mentioned since this might imply that at least some employees were laid off domestically. At the domestic level, we identify states by their names or variants (e.g., Alaska, Alas., AK). We identify cities from constructions of the form "city, state" (e.g., "Buffalo, NY") and from a list of the 1,000 largest cities in the US based on 2013 Census data.[IA.2] If only a city name was identified, then the NLP would include a list of all states with a city of the same name in parentheses ordered by population.

After NLP-based steps (1) to (3), we conduct a manual review of the prepopulated data for all key developments, regardless of how they are classified by NLP, with the goal of ensuring accuracy, checking low-confidence cases, adding missing information, applying more complex screening criteria and calculations, and eliminating duplicates. Reviewers were given comprehensive instructions about how to classify each case in both text and video form consistent with the description here. The key development data was put into Microsoft Excel along with the classifications, layoff sizes, and locations from NLP. Low-confidence classifications were highlighted and it was made clear to reviewers that they should pay close attention to these cases. Reviewers examined all of the output from NLP and updated the

[IA.1] If only the percent of a subset of workers being laid off is referenced, this number is not collected since we only have the number of total employees at the firm in Compustat.

[IA.2] We exclude York and Knoxville to avoid confusion with places/names that may contain these names.

relevant data columns to make them accurate. Reviewers were instructed to classify a key development as a layoff if it described a layoff where "it is clear people lost their jobs." Thus, business sales, including exits via sales where no jobs were lost, and temporary furloughs were not coded as layoffs. If workers were having their job terminated, but being reassigned to other positions within the company or taking early retirement, this was not considered a layoff. If some portion of the workers laid off were reassigned or retired early, they were subtracted from the total layoff size. A key development was classified as a closure if it described a closure (and not also a layoff) and neither if it did not describe either. Additionally, precise instructions were given to not consider any layoffs and closures that were only speculative or under consideration, as neither a closure nor a layoff.

In the case, that only a US city name was listed without a specific state, the reviewer would make their best guess for the state the layoff occurred in. If the city name was identified in the top 1,000, the NLP algorithm would list the state with the highest population first making this a straightforward best guess if no additional information was available. In some situations, it may be clear or likely that the layoff occurred in a specific state based on the context from other key developments. Reviewers did not use outside information generally; however, reviewers were told to use additional research to determine the state if it was otherwise unclear and could quickly be determined (e.g., through a Google search with the city name and company name). Additionally, if there was a place listed with a clear location (e.g., a very specific mall) where the city could be easily identified, but was not included in the text, the reviewer may also have used outside information to determine the city if straightforward (e.g., a Google search of a specific mall's name).

As part of the manual review, duplicate layoffs/closures are noted when possible, e. g., when the summary notes that the announced layoff was part of an earlier announcement or the execution of an alternative announcement, or when it is obvious from context, e. g., if the text specifies a certain factory being shut down in two announcements. In some cases, the announcement of a closure may take place separately from, and potentially earlier than, the announcement of a related layoff that is part of the closure. All duplicates are removed from the dataset to prevent double counting of layoff events and the number of people laid off. If two duplicates contain the same information, then the earlier announcement is chosen. If one of the duplicates contains more information (e.g., number of people laid off, location), then that one is chosen. In such cases, the closure announcement is followed by a separate announcement, which specifies an associated layoff. In this case, the closure announcement is classified as a duplicate. We classify the closure announcement as a duplicated since, by definition, it does not contain details about the workers being affected.

Lastly, in case of an error during manual review. We also double-checked certain cases noted as atypical or with formatting errors. We checked all key developments where the percent of the firm laid off was entered as less than 1%. Further, if we

identified more than two-thirds of the firm was laid off across all layoffs in a given firm-year, we checked all layoff entries for that firm. We also checked cases where we identified the percent laid off column had an entry recorded as a date in Excel or there were parentheses in a city or state entry for one of the key developments.

After constructing an initial data set with NLP and manual review, we conducted an additional search for data on all key developments in our baseline regression sample with missing information on layoff size in layoff-years that did not (yet) qualify as significant layoff events, i. e., that had fewer than three layoffs and less than 1% of firm employment laid off included so far. For this subset of layoff, we conducted manual searches for layoff size using the web and LexisNexis in an effort. When the original news source is included in the data, that was the preferred source for the layoff size when found. If it could not be found or was missing, another source would be used if available. The additional searches generated the missing information on layoff size for about 10.67% of the key developments, suggesting that this information is usually included in the key development text when it is publicized.

We also conducted manual reviews (e.g., by using a search engine) for identifying locations. Examples include searches for states when only the city was specified, and searches for cities when only non-city locations such as business complexes were specified.

Duplicates were specified as "when an observation is believed to be a duplicate of a previous observation."

With these refinements and additions, we turned to NLP step (4) in order to classify layoff events into blue-, pink-, and white-collar layoffs. Here, we utilize the count of words from each category 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. 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. The reason for employing a higher hurdle towards white-collar classification is that, when a blue- or pink-collar word appears in the description, we found it to be almost certainly not a white-collar layoff as the latter would typically not discuss factories or retail stores.

As mentioned in the main text, to verify our classification of layoff type leveraging the data on the locations of layoffs from the 2000 US Census downloaded from Social Explorer, a third-party data tool. Using the "Occupation For Employed Civilian Population 16 Years And Over" data at the geographic level of "Places," which includes cities and townships, linked to our layoff location data, we construct a proxy for the percent of predominantly blue-collar occupations, white-collar occupations, and pink-collar occupations in a given city (layoff location). There are 13 broad occupation 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. We calculate the proportion of the employed population in the city in each of these categories. If the layoff or closure takes place in more than one city, we take the average of the proportions across the cities for all cities where data is available. We are able to construct this proxy for 80.4% of the layoff and closure events in our sample where we identify at least one city. We find that the proportion of the city, or average proportion of the cities, employed in white-collar jobs is 37.2% for the key developments text-based NLP classifies as white-collar compared to only 33.5% for the other key developments. While this difference may not seem large it is statistically significant with p-value of less than 0.0001 for a two-sample t-test. We also conduct analogous two-sample t-tests for layoffs/closures classified as blue-collar and pink-collar and find p-values of less than 0.0001 in both cases as well.

B.2 2002–2020 Layoff Data: Variable Definitions

Layoff. We classify a CEO-firm year as a layoff if there are three separate layoff events or at least 1% of the workforce is laid off. 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 the value "CEO". CEO tenure is calculated using the "BECAMECEO" variable as the starting year when it is available. Otherwise, we calculate it using the Execucomp panel, which starts in 1992.

CFO Tenure. We identify CFOs using ExecuComp's classification, where the CFOANN variable has the value "CFO" or a close variation such as "Chief Financial Officer." Otherwise, we identify CFOs from the text of their title. Following Jiang et al. (2010), we employ the following order of titles: 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.

CEO Power (% of New Directors). We construct 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 and includes the directors in each year for each firm and the year they became a director. 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. To match the ISS data between the current and legacy samples, we also rely on the director link between the current and legacy samples published as a part of, and described in, Coles et al. (2014). The link is necessary as it fills in missing director IDs from surrounding years, corrects

errors in the ISS data, and resolves inconsistencies between the current and legacy director identifiers.

Industry Distress. As in prior literature, we define an industry-year as in distress if the median firm's stock price declined by at least 30% over a two-year horizon. For the context of layoffs, we consider both the prior two years and, alternatively, the prior and current year, and set the Industry Distress indicator equal to 1 if the firm is in distress over either horizon. Following 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.

Ln Assets. Natural log of total assets (AT) from Compustat.

Ln Employment. Natural log of total employment (EMP) from Compustat.

Firm Profitability. Measured as $\frac{OIDBP}{AT}$, where $OIDBP$ is operating income before depreciation and AT is total assets, both from Compustat. This variable is winsorized at the 1st and 99th percentiles.

Market-to-Book Ratio. Defined as $\frac{PRCC_F \cdot CSHO}{AT}$, where $PRCC_F$ is the annual closing stock price from CRSP, $CSHO$ the number of common shares outstanding from CRSP, and AT total assets from Compustat. This variable is winsorized at the 1st and 99th percentiles.

Tobin's Q. Defined as $\frac{DLC+DLTT+PRCC_F \cdot CSHO}{PPEGT}$, where DLC is debt in current liabilities from Compustat, $DLTT$ long-term debt from Compustat, and $PPEGT$ gross property, plant and equipment from Compustat. We use the variable winsorized at the 5th and 95th percentiles and 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. Defined as $\frac{EMP_t - EMP_{t-1}}{EMP_{t-1}}$, where EMP is total employment from Compustat. This variable is winsorized at the 1st and 99th percentiles.

Debt Maturity. 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 two years. This variable is winsorized at the 1st and 99th percentiles.

P(Default). Defined as $\mathcal{N}(-\text{naïve}\, DD))$ from Bharath and Shumway (2008), where naïve DD is the naïve distance-to-default and $\mathcal{N}$ is the cummulative distribution function for the normal distribution. naïve $DD)$ is defined as $\frac{\ln[(E+F)/F] + \left(r_{it-1} - 0.5 \text{ naïve } \sigma_V^2\right)}{\text{naïve } \sigma_V}$, where E is the equity value of the firm, F is the face value of the debt, r_{it-1} is the stock return over the previous year, and σ_V is the volatility of firm value. E is defined as the fiscal year end share price times the number of shares outstanding from Compustat, $PRCC_F \cdot CSHO$. F is defined as

the face value of short term debt plus one half the face value of long term debt from Compustat, $DLC + \frac{1}{2}DLTT$. r_{it-1} is defined as the proportion by which equity has increased (e.g., the ex-dividend return), approximated by the log difference in equity value from one year to the next following the SAS code corresponding to the Bharath and Shumway (2004), a pre-publication version of Bharath and Shumway (2008). Intuitively, this is consistent with a simple model of firms which do not issue dividends. A firm which issues dividends suddenly reduces its value and thus moves closer to default. σ_V is defined as $\frac{E}{E+F}\sigma_E + \frac{F}{E+F}(0.05 + 0.25 * \sigma_E)$, where σ_E is the standard deviation of r_i, the log difference in equity value from one year to the next.

B.3 CEO Mortality Data: Variable Definitions

Death. Based on hand-collected mortality data from Borgschulte et al. (2023). 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 et al. (2023).

Industry Distress. The variable used in our analysis is equal to one if the CEO has experienced industry distress, as defined in Section B.2.

Ln Assets. We define log assets as the natural log of total assets from Compustat, variable code AT. We use assets as of the first year that the CEO has assumed the top position. When values are missing, we interpolate the missing values or, at the beginning and end of the sample, use the closest available year.

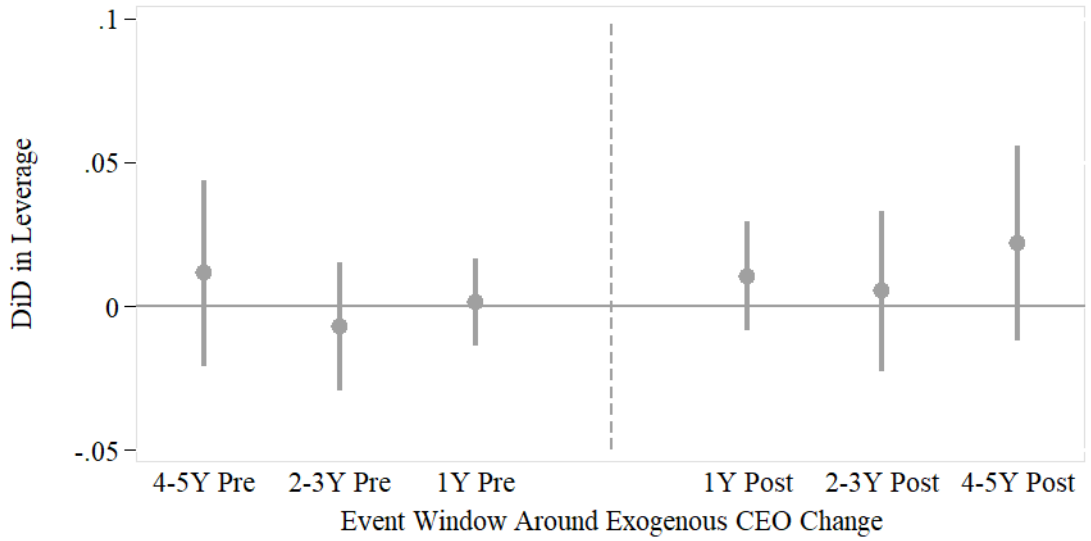
Ln Employment. We define log employment as the natural log total employment from Compustat, variable code EMP. We use employees as of the first year that the CEO has assumed the top position. When values are missing, we interpolate the missing values or, at the beginning and end of the sample, use the closest available year.

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. This variable is winsorized at the 1st and 99th percentiles. When values are missing, we interpolate the missing values or, at the beginning and end of the sample, use the closest available year.

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

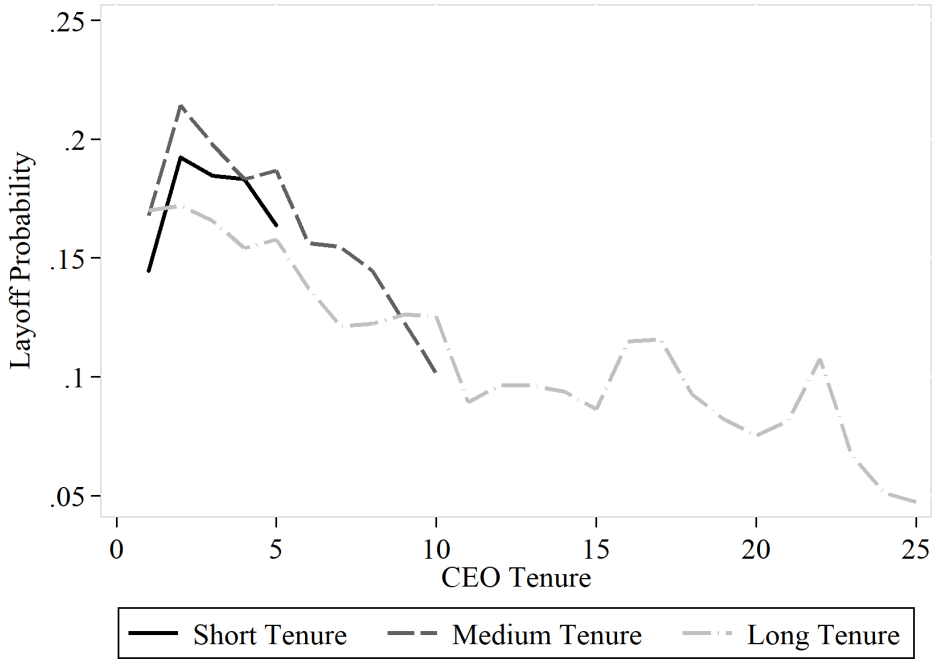
C. Additional Figures and Tables

Appendix-Figure A.1. Placebo Test



Notes: 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 (3)). Exogenous CEO changes are defined as those occurring due to CEO death or illness of the incumbent CEO and come from Gentry et al. (2021). See Section 5.1 for additional details. The figure also plots 95% confidence intervals based on standard errors clustered at the firm level.

Appendix-Figure A.2. Layoff Propensity and Tenure—Fixed CEO Differences?



Notes: 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 assembled using NLP text processing and classification as well as hand-coding of S&P Key Developments data as detailed in Appendix-Section B. CEO tenure based on Execucomp data.

Appendix-Table A.1. Layoffs and CEO Mortality—Stratified Cox Hazard Model

	(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)
Ln Assets	0.004	0.005	0.006
	(0.073)	(0.071)	(0.071)
Ln Employment	−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

Notes: Table reports hazard ratios estimated from a Cox (1972) proportional hazards model. The dependent variable is an indicator that equals one if the CEO dies in a given year. Distress Layoff is an indicator equal to one in year t if, prior to or in year t, a CEO has undertaken a layoff during industry-wide distress. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. CEO Age is the CEO's age at time t. Minimum stock performance is defined as the worst stock performance in any six-month period during the CEO's tenure. Log assets and log employees from the first year that the CEO assumed the top office are included in all specifications. Firm profitability is included for all years that the CEO is in office and then profitability from the CEO's final year in office thereafter. More details about the data are in Section 3 and Appendix-Section B. Survival models are stratified by firms' industry affiliation. Standard errors, clustered by industry, are in parentheses. Significance levels are indicated by *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Appendix-Table A.2. Layoffs and CEO Mortality—CEO Tenure Control

	(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)
Ln Assets	−0.158**	−0.154**	−0.152**
	(0.076)	(0.077)	(0.076)
Ln Employment	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

Notes: This table reports estimated coefficients from logit regression where the dependent variable is an indicator that equals one if the CEO dies in a given year. The dependent variable is an indicator that equals one if the CEO dies in a given year. Distress Layoff is an indicator equal to one in year t if, prior to or in year t, a CEO has undertaken a layoff during industry-wide distress. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. Cumulative CEO tenure is CEO tenure while CEO and total tenure thereafter. CEO Age is the CEO's age at time t. Minimum stock performance is defined as the worst stock performance in any six-month period during the CEO's tenure. Log assets and log employees from the first year that the CEO assumed the top office are included in all specifications. Firm profitability is included for all years that the CEO is in office and then profitability from the CEO's final year in office thereafter. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by industry, are shown in parentheses. Standard errors, clustered by industry, are in parentheses. Significance levels are indicated by *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Appendix-Table A.3. Layoffs and CEO Mortality—Stratified Cox Hazard Model With Tenure Control

	(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)
Ln Assets	−0.023	−0.023	−0.021
	(0.071)	(0.069)	(0.069)
Ln Employment	−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

Notes: Table reports hazard ratios estimated from a Cox (1972) proportional hazards model. The dependent variable is an indicator that equals one if the CEO dies in a given year. Distress Layoff is an indicator equal to one in year t if, prior to or in year t, a CEO has undertaken a layoff during industry-wide distress. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. Cumulative CEO tenure is CEO tenure while CEO and total tenure thereafter. CEO Age is the CEO's age at time t. Minimum stock performance is defined as the worst stock performance in any six-month period during the CEO's tenure. Log assets and log employees from the first year that the CEO assumed the top office are included in all specifications. Firm profitability is included for all years that the CEO is in office and then profitability from the CEO's final year in office thereafter. More details about the data are in Section 3 and Appendix-Section B. Survival models are stratified by firms' industry affiliation. Standard errors, clustered by industry, are in parentheses. Significance levels are indicated by *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Appendix-Table A.4. Layoff Propensity Around Exogenous CEO Changes

	(1)	(2)
Treat	−0.022	−0.002
	(0.029)	(0.019)
T minus 5	−0.012	
	(0.049)	
T minus 4	0.062	
	(0.055)	
T minus 3	0.012	
	(0.047)	
T minus 2	0.040	
	(0.044)	
T minus 1	0.019	
	(0.040)	
T plus 1	0.137***	
	(0.040)	
T plus 2	0.103*	
	(0.058)	
T plus 3	0.047	
	(0.050)	
T plus 4	0.120*	
	(0.067)	
T plus 5	0.120	
	(0.073)	
Treat × Post		0.087***
		(0.031)
Controls	Yes	Yes
Cohort-Year FE	Yes	Yes
Cohort-Industry FE	Yes	Yes
Observations	39,864	39,864

Notes: Stacked difference-in-differences analysis estimating the change in layoff propensity around exogenous CEO changes relative to non-treated firms. Exogenous CEO changes are those due to the death or illness of the incumbent CEO as identified in Gentry et al. (2021). The pre-period is the five years before the exogenous CEO change, and the post-period is the five years after the exogenous CEO change or the tenure of the CEO immediately following the exogenous turnover, whichever is shorter. Column 1 estimates equation (3) modified by using indicators for each pre- and post-year (instead of one indicator for Post) interacted with the treatment indicator. Column (2) estimates equation (3). Controls are log assets, log employment, and profitability. Control variable coefficients are estimated separately for pre- and post-periods. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Appendix-Table A.5. Layoff Propensity and CEO Tenure—Time-Varying Fixed Effects

	(1)	(2)	(3)	(4)
CEO Tenure / 100	−0.267***	−0.266***	−0.265***	−0.173***
	(0.030)	(0.029)	(0.030)	(0.041)
Ln Assets	0.030***	0.029***	0.029***	0.024***
	(0.003)	(0.003)	(0.003)	(0.007)
Ln Emp.	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

Notes: Table reports coefficients from linear regression where the dependent variable is equal to one for significant layoff events, defined as CEO-firm-years with at least three layoff events or where 1% of the firm laid off and 0 otherwise. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. Ln assets is the log of total assets. Ln employment is the log of total employment. Firm profitability is operating income before depreciation divided by total assets. CEO tenure is the number of years the CEO has been in that position. We normalize tenure by dividing by 100. Firm characteristics are from the beginning of the year. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Appendix-Table A.6. Layoff Propensity and CEO Tenure—Additional Controls

	(1)	(2)	(3)	(4)
CEO Tenure / 100	−0.265***	−0.252***	−0.172***	−0.163***
	(0.036)	(0.036)	(0.049)	(0.050)
Industry Distress	0.057***	0.058***	0.050***	0.050***
	(0.009)	(0.009)	(0.009)	(0.009)
Ln Assets	0.033***	0.038***	0.026***	0.035***
	(0.003)	(0.004)	(0.009)	(0.009)
Ln Emp.	0.022***	0.017***	0.053***	0.048***
	(0.003)	(0.003)	(0.009)	(0.010)
Firm Profitability	−0.244***	−0.266***	−0.183***	−0.225***
	(0.031)	(0.030)	(0.045)	(0.044)
Debt Maturity	−0.028***	−0.028***	−0.011	−0.010
	(0.009)	(0.009)	(0.009)	(0.009)
P(Default)	0.077***	0.081***	0.065***	0.070***
	(0.019)	(0.020)	(0.020)	(0.020)
Employment Growth	−0.071***	−0.063***	−0.041***	−0.040***
	(0.012)	(0.012)	(0.012)	(0.012)
Market-to-Book	−0.007***		−0.013***	
	(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	24,242	23,767	24,045	23,573

Notes: Table reports coefficients from linear regression where the dependent variable is equal to one for significant layoff events, defined as CEO-firm-years with at least three layoff events or where 1% of the firm laid off and 0 otherwise. Independent variables are defined in B.2. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Appendix-Table A.7. Layoff Propensity and CEO Tenure—CEO Entrenchment

	(1)	(2)	(3)	(4)
CEO Tenure / 100		-0.260^{***}		-0.166^{***}
		(0.036)		(0.051)
E-Index = 1	0.018	0.021	0.038	0.036
	(0.040)	(0.039)	(0.040)	(0.041)
E-Index = 2	0.020	0.021	0.024	0.021
	(0.039)	(0.037)	(0.038)	(0.038)
E-Index = 3	0.019	0.019	0.035	0.033
	(0.038)	(0.037)	(0.038)	(0.038)
E-Index = 4	0.012	0.012	0.027	0.025
	(0.039)	(0.038)	(0.039)	(0.039)
CEO and Chair	-0.005	0.009	0.001	0.009
	(0.006)	(0.006)	(0.007)	(0.007)
CEO and President	0.005	0.002	0.022^{***}	0.018^{***}
	(0.005)	(0.005)	(0.006)	(0.006)
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	23,323	23,323	23,241	23,241

Notes: Table reports coefficients from linear regression where the dependent variable is equal to one for significant layoff events, defined as CEO-firm-years with at least three layoff events or where 1% of the firm laid off and 0 otherwise. Controls are industry distress, log assets, log employment and firm profitability. The E-index 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. CEO and Chair is a dummy equal to one if the CEO is also the chair of the board. CEO and President is a dummy equal to one if the CEO is also the president of the firm. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. Ln assets is the log of total assets. Ln employment is the log of total employment. Firm profitability is operating income before depreciation divided by total assets. CEO tenure is the number of years the CEO has been in that position. We normalize tenure by dividing by 100. Firm characteristics are from the beginning of the year. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix-Table A.8. Layoffs and CEO Tenure—Drop First CEO-Year

	(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)
Ln Assets		0.030^{***}	0.029^{***}	0.029^{***}
		(0.003)	(0.007)	(0.007)
Ln Emp.		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

Notes: Table reports coefficients from linear regression where the dependent variable is equal to one if there are at least three layoff events or 1% of the firm laid off in that CEO-firm-year and 0 otherwise. The sample is restricted to CEO-firm-years where the CEO has been in office for at least one year. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. Ln assets is the log of total assets. Ln employment is the log of total employment. Firm profitability is operating income before depreciation divided by total assets. CEO and CFO tenure are the number of years the CEO and CFO have been in their respective positions, respectively. We normalize tenure by dividing by 100. Firm characteristics are from the beginning of the year. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix-Table A.9. Layoff Propensity and CEO Tenure—IV Approach

	1st Stage	2nd Stage	1st Stage	2nd Stage
	(1)	(2)	(3)	(4)
CEO Tenure Proportion	0.128***		0.138***	
	(0.002)		(0.002)	
CEO $\widehat{\text{Tenure}}$ / 100		−0.182***		−0.264***
		(0.069)		(0.066)
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	34,565	34,565

Notes: Table reports coefficients from two-stage linear regression. The dependent variable in the first stage is CEO tenure. The dependent variable in the second stage is equal to one if there are at least three layoff events or 1% of the firm laid off in that CEO-firm-year and 0 otherwise. CEO Tenure Proportion is defined as$(Tenure_{i,j,t} - \overline{Tenure_{i,j}})$ / $\max_t Tenure_{i,j,t}$ for CEO i at firm j in year t. The instrumented values of CEO tenure are used in the second stage. CEO tenure is the number of years the CEO has been in that position. We normalize tenure by dividing by 100. Controls are industry distress, log assets, log employment and firm profitability. Control variables are from the beginning of the year and defined in B.2. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix-Table A.10. Fraction Laid Off and CEO Tenure—IV Approach

	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		−0.014**		−0.027***
		(0.006)		(0.006)
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	33,251	33,251	33,130	33,130

Notes: Table reports coefficients from two-stage linear regression. The dependent variable in the first stage is CEO tenure. The dependent variable in the second stage is the proportion of the firm laid off in that CEO-firm-year. CEO Tenure Proportion is defined as$(Tenure_{i,j,t} - \overline{Tenure_{i,j}}) / \max_t Tenure_{i,j,t}$ for CEO i at firm j in year t. The instrumented values of CEO tenure are used in the second stage. CEO tenure is the number of years the CEO has been in that position. We normalize tenure by dividing by 100. Controls are industry distress, log assets, log employment and firm profitability. Control variables are from the beginning of the year and defined in B.2. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix-Table A.11. Layoffs and CEO Tenure—Recession Periods, IV Approach

	(1)	(2)	(3)	(4)
CEO $\widehat{\text{Tenure}}$ / 100	-0.137^{*}	-0.196^{***}	-0.116	-0.177^{**}
	(0.074)	(0.072)	(0.074)	(0.072)
CEO Tenure / $\widehat{100 \times \text{Industry Distress}}$	-0.260	-0.383^{*}	-0.406^{*}	-0.516^{**}
	(0.231)	(0.222)	(0.226)	(0.217)
Controls	Yes	Yes	Yes	Yes
Control Interactions	No	No	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	34,683	34,565	34,683	34,565

Notes: Table reports coefficients from the second stage of two-stage linear regression. The dependent variables in the first stage regressions are CEO tenure and CEO Tenure interacted with industry distress. The dependent variable in the second stage is the proportion of the firm laid off in that CEO-firm-year. CEO Tenure Proportion is defined as$(Tenure_{i,j,t} - \overline{Tenure_{i,j}}) / \max_t Tenure_{i,j,t}$ for CEO i at firm j in year t. The instrumented values of CEO tenure are used in the second stage. CEO tenure is the number of years the CEO has been in that position. We normalize tenure by dividing by 100. Controls are industry distress, log assets, log employment and firm profitability. Control variables are from the beginning of the year and defined in B.2. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix-Table A.12. Layoff Propensity and CEO Tenure—Layoffs Around Holiday Season With Extended Layoff-Year Window

	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

Notes: The table reports coefficients from linear regression where the dependent variable is equal to one for years with at least one layoff in December and zero otherwise. Layoff-Years + Q1 are CEO-firm-years with at least one layoff either in the CEO-firm-year or the three following months. Layoff-Years + Q1 + Q2 are CEO-firm-years with at least one layoff either in the CEO-firm-year or the six following months. Controls are industry distress, log assets, log employment and firm profitability. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. Ln assets is the log of total assets. Ln employment is the log of total employment. Firm profitability is operating income before depreciation divided by total assets. CEO tenure is the number of years the CEO has been in that position. We normalize tenure by dividing by 100. Firm characteristics are from the beginning of the year. More details about the data are in Section 3 and Appendix-Section B. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix-Table A.13. Layoff Propensity and CEO Tenure—Holiday Layoffs, IV Approach

	Full Sample		Layoff-Years	
	(1)	(2)	(3)	(4)
CEO $\widehat{\text{Tenure}}$ / 100	-0.177^{***}	-0.174^{***}	-0.925^{***}	-1.116^{***}
	(0.030)	(0.029)	(0.179)	(0.201)
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	34,683	34,565	5,722	5,174

Notes: Table reports coefficients from the second stage of two-stage linear regression. The dependent variable in the first stage is CEO tenure. The dependent variable in the second stage is equal to one for years with at least one layoff in December and zero otherwise. CEO Tenure Proportion is defined as$(Tenure_{i,j,t} - \overline{Tenure_{i,j}})$ / $\max_t Tenure_{i,j,t}$ for CEO i at firm j in year t. The instrumented values of CEO tenure are used in the second stage. CEO tenure is the number of years the CEO has been in that position. We normalize tenure by dividing by 100. Controls are industry distress, log assets, log employment and firm profitability. Control variables are from the beginning of the year and defined in B.2. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix-Table A.14. Layoff Propensity and CEO Tenure—White Collar, IV Approach

	Full Sample		Layoff-Years	
	(1)	(2)	(3)	(4)
CEO $\widehat{\text{Tenure}}$ / 100	−0.060*	−0.060*	−0.043	−0.057
	(0.034)	(0.033)	(0.195)	(0.219)
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	34,683	34,565	5,722	5,174

Notes: Table reports coefficients from the second stage of two-stage linear regression. The dependent variable in the first stage is CEO tenure. The dependent variable in the second stage is equal to one for years with at least one white-collar layoff and zero otherwise. CEO Tenure Proportion is defined as$(Tenure_{i,j,t} - \overline{Tenure_{i,j}})$ / $\max_t Tenure_{i,j,t}$ for CEO i at firm j in year t. The instrumented values of CEO tenure are used in the second stage. CEO tenure is the number of years the CEO has been in that position. We normalize tenure by dividing by 100. Controls are industry distress, log assets, log employment and firm profitability. Control variables are from the beginning of the year and defined in B.2. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Appendix-Table A.15. Layoff Propensity and CEO Tenure—Geography, IV Approach

	HQ-State Layoff	HQ-City Layoff	
	(1) HQ-State Layoff	(2) HQ-City Layoff	(3) HQ-City Layoff
CEO $\widehat{\text{Tenure}}$ / 100	-0.091^{**}	-0.066^{**}	-0.245
	(0.042)	(0.028)	(0.164)
Sample	Full	Full	Layoff-Years
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Firm FE	No	No	No
Observations	34,683	34,683	5,722

Notes: Table reports coefficients from the second stage of two-stage linear regression. The dependent variable in the first stage is CEO tenure. The dependent variables in the second stage are indicator variables that equal one if a firm makes at least one layoff at the respective geographic level in a given year and zero otherwise. Layoff-years are CEO-firm-years with at least one layoff. CEO Tenure Proportion is defined as$(Tenure_{i,j,t} - \overline{Tenure_{i,j}}) / \max_t Tenure_{i,j,t}$ for CEO i at firm j in year t. The instrumented values of CEO tenure are used in the second stage. CEO tenure is the number of years the CEO has been in that position. We normalize tenure by dividing by 100. Controls are industry distress, log assets, log employment and firm profitability. Control variables are from the beginning of the year and defined in B.2. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix-Table A.16. R&D and CEO Tenure—IV Approach

	(1)	(2)	(3)	(4)
CEO $\widehat{\text{Tenure}}$ / 100	0.008	0.037***	0.006	0.036***
	(0.019)	(0.013)	(0.019)	(0.013)
CEO Tenure / $\widehat{100 \times \text{Industry Distress}}$	−0.097*	−0.098***	−0.089*	−0.089***
	(0.052)	(0.030)	(0.051)	(0.029)
Controls	Yes	Yes	Yes	Yes
Control Interactions	No	No	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	15,052	14,994	15,052	14,994

Notes: Table reports coefficients from the second stage of two-stage linear regression. The dependent variables in the first stage regressions are CEO tenure and CEO Tenure interacted with industry distress. The dependent variable in the second stage is research and development expenditures divided by assets at the beginning of the year. CEO Tenure Proportion is defined as$(Tenure_{i,j,t} - \overline{Tenure_{i,j}}) / \max_t Tenure_{i,j,t}$ for CEO i at firm j in year t. The instrumented values of CEO tenure are used in the second stage. CEO tenure is the number of years the CEO has been in that position. We normalize tenure by dividing by 100. Controls are industry distress, log assets, log employment and firm profitability. Control variables are from the beginning of the year and defined in B.2. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Appendix-Table A.17. Layoff Propensity and CEO Tenure—Holiday Layoffs, Heterogeneity in Prosociality

	Full Sample	CEO Empathy / OC Sample	
	(1)	(2)	(3)
CEO Tenure / 100	−0.407***	−0.409**	
	(0.129)	(0.194)	
CEO Tenure × Empathy			−0.672**
			(0.297)
CEO Tenure × Overconfidence			−0.304
			(0.234)
CEO Overconfidence		−0.008	−0.024
		(0.025)	(0.033)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	5,174	3,131	3,131

Notes: Table reports coefficients from linear regression where the dependent variable is equal to one for years with at least one layoff in December and zero otherwise. *CEO Overconfidence* is an indicator variable defined based on the *Longholder* measure of managerial overconfidence (Malmendier and Tate 2005, Malmendier et al. 2023). *CEO Empathy* is an indicator variable equal to one if the CEO is not classified as overconfident, motivated by Kaplan et al. (2012) and Kaplan et al. (2022) that overconfidence and empathy are primary distinguishing characteristics of managers. Industry distress is an indicator equal to one if the median firm of the industry had a stock price decline of at least 30% in the two years prior or the prior and current year. Ln assets is the log of total assets. Ln employment is the log of total employment. Firm profitability is operating income before depreciation divided by total assets. CEO tenure is the number of years the CEO has been in that position. We normalize tenure by dividing by 100. Firm characteristics are from the beginning of the year. More details about the data are in Section 3 and Appendix-Section B. Standard errors, clustered by firm, are shown in parentheses. Significance levels are indicated by *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.