Check for updates

The Journal of FINANCE
The Journal of THE AMERICAN FINANCE ASSOCIATION

THE JOURNAL OF FINANCE • VOL. LXXX, NO. 6 • DECEMBER 2025

CEO Stress, Aging, and Death

MARK BORGSCHULTE, MARIUS GUENZEL, CANYAO LIU, and ULRIKE MALMENDIER*

ABSTRACT

We assess the long-term effects of managerial stress on aging and mortality. Using a difference-in-differences design, we apply neural network–based machine-learning techniques to CEOs' facial images and show that exposure to industry distress shocks during the Great Recession produces visible signs of aging. We estimate a one-year increase in "apparent" age. Moreover, using data on CEOs since the mid-1970s, we estimate a 1.1-year decrease in life expectancy after an industry distress shock, but a two-year increase when antitakeover laws insulate CEOs from market discipline. The estimated health costs are significant, both in absolute terms and relative to other health risks.

MUCH OF THE ACADEMIC AND policy discussion about high-profile jobs in business and other arenas revolves around pay, performance, and incentives.

*Mark Borgschulte is with the Department of Economics, University of Illinois and IZA. Marius Guenzel is at the Wharton School, University of Pennsylvania. Canyao Liu is with Hudson River Trading. Ulrike Malmendier is with the Department of Economics and Haas School of Business, University of California, Berkeley, NBER, CEPR, briq, and IZA.We thank Amit Seru (the Editor), an anonymous Associate Editor, and two anonymous referees for thoughtful comments. We thank Martijn Cremers, Allen Ferrell, Kevin J. Murphy, and Emmanuel Saez for sharing their data. We thank Grigory Antipov, Moez Baccouche, Sid-Ahmed Berrani, and Jean-Luc Dugelay for sharing their age estimation software. We also thank Tania Babina, Xavier Gabaix, Kevin J. Murphy, Owen O'Donnell, Joe Gladstone, Christopher Parsons, and Mike Wittry, as well as seminar and conference participants at the 2018 briq Workshop on Skills, Preferences, and Educational Inequality (University of Bonn), the 2018 Berkeley-Stanford Joint Behavioral Economics Mini-Conference, the 2019 NBER Organizational Economics Fall Conference, the 2019 Finance, Organizations and Markets (FOM) Conference, the 2020 American Finance Association Annual Meeting, the 2020 Behavioral Science & Health Symposium, the 2022 NBER Conference on Aging and Health, the 2022 Chicago Booth Behavioral Approaches to Financial Decision-Making Conference, ASU, Berkeley Economics, Berkeley Haas, the University of Connecticut, Columbia, Dartmouth, Harvard Business School, the University of Illinois at Chicago, the University of Illinois at Urbana-Champaign, the University of Leeds, LSE, the University of Maryland, the University of Minnesota, the University of Pennsylvania, Princeton, Stanford, Texas A&M, and Yale SOM for helpful comments and suggestions. We thank Nikki Azerang, Clint Hamilton, and Tim Zhang for outstanding research assistance. We have read *The Journal of Finance* disclosure policy and have no conflicts of interest to disclose.

Correspondence: Marius Guenzel, The Wharton School, University of Pennsylvania, Steinberg-Dietrich Hall, 3620 Locust Walk, Philadelphia, PA 19104, USA; e-mail: mguenzel@wharton.upenn.edu.

This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

DOI: 10.1111/jofi.13497

© 2025 The Author(s). *The Journal of Finance* published by Wiley Periodicals LLC on behalf of American Finance Association.

In the classical agency problem, a manager aims to extract private benefits such as higher pay, loans, or perks at the expense of the owner (shareholders). Less attention has been paid to another type of private benefit (or cost)—managers' personal health and well-being. The more effort managers exert and the more stressors they are exposed to on their job, the lower this benefit.

In this paper, we document that heightened managerial stress due to industry crises and corporate monitoring predicts significantly accelerated aging and mortality among managers. Job demands and work-related stressors are increasingly recognized as key determinants of population health and well-being across all levels of organizational hierarchies.[1] Yet there is little quasi-experimental evidence that links health outcomes to variation in job demands and stress. One reason for the lack of causal evidence is that, in the typical study sample of lower ranked workers, income loss and financial hardship tend to confound estimates of the causal effects of job stressors. That is, while work pressures and the consequences of underperformance are in many ways harsher in the context of lower ranked workers compared to managers, as they include (long-term) unemployment, financial hardship, and loss of health insurance, these consequences also make it harder to isolate the health effects of work-related stressors from the effects of low income and financial constraints.

We overcome these identification hurdles by focusing on chief executive officers (CEOs) of large, publicly traded U.S. companies. The CEO context allows us to isolate the effects of high job demands from financial and other confounds as these CEOs are wealthy and unlikely to be affected by financial hardship even if they lose their job. That said, the role of work-related stressors in the CEO context is of interest in its own right for several reasons. First, CEOs work long hours, make high-stakes decisions such as layoffs and plant closures, and face uncertainty in times of crisis (Bandiera et al. (2020), Porter and Nohria (2018)). They are closely monitored and criticized when their firm is underperforming, and the media frequently reports on "overworked [and] overstressed" CEOs.[2] Second, CEOs bear the ultimate responsibility for the firm and its employees. Given their overarching role in determining firm performance and job stability of workers, how incentives and performance affect CEOs personally is of first-order importance. Third, the health implications of CEOs' job demands affect their ability to stay on the job and, if anticipated, their willingness to select into a CEO position. When CEOs like Tesla's Elon Musk talk about sleeping only a few hours per night and working up to 120 hours a week,[3] how do such remarks affect selection?

[1] See, for example, Marmot (2005), Ganster and Rosen (2013), and Kaplan and Schulhofer-Wohl (2018).

[2] See CNN's "Route to the Top" segment (cnn.com/2010/business/03/12/ceo.health.warning/index). See also the *Harvard Business Review* article "How Top CEOs Cope with Constant Stress" (hbr.org/2011/04/how-top-ceos-cope-with-constan) and expert psychologists' statements in "Strategies for CEOs to reduce stress" (vistage.com/research-center/personal-development/20200402-ceo-stress).

[3] See cnbc.com/2021/02/12/elon-musk-ceo-of-tesla-spacex-on-getting-six-hours-of-sleep.html.

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

We exploit two sources of variation in work-related stress: periods of industry-wide crisis and variation in the intensity of CEO monitoring due to changing corporate governance regulation. With respect to the first, prior work shows that industry shocks and financial distress affect CEO pay and turnover (Bertrand and Mullainathan (2001), Garvey and Milbourn (2006), Jenter and Kanaan (2015)). We identify industry distress shocks based on a 30% decline in the median firm's stock price over a two-year period, similar to prior work (Opler and Titman (1994), Acharya, Bharath, and Srinivasan (2007), Babina (2020)). With respect to the second source of variation, we identify variation in CEO monitoring from the staggered passage of antitakeover laws across U.S. states in the mid-1980s. The laws shielded CEOs from market discipline by making hostile takeovers more difficult, reducing CEOs' job demands and allowing them to "enjoy the quiet life" (Bertrand and Mullainathan (2003)).[4] A large prior literature uses the passage of these laws as a proxy for less intense monitoring and demonstrates effects on CEO behavior.[5] Although some studies question whether the passage of antitakeover laws did in fact reduce hostile takeover activity (e.g., Cain, McKeon, and Solomon (2017)), it arguably constituted a significant shift in managers' *perception* of their job environment.[6] Thus, the two sources of variation constitute separate and oppositely signed changes in job demands. Importantly, both build on the notion of distress and protection from stress in the economic literature (and on the popular notion of stress), rather than a biomedical measurement of adrenaline or cortisol levels.[7]

To investigate the link between work-related stress and health, we employ two measures of health outcomes: visible signs of aging and life expectancy. Visible signs of aging, which correspond to how old a person looks rather than their actual chronological age, are widely used by clinicians to assess patient health. These assessments of so-called "apparent" age have been validated as biological markers predicting mortality and other health outcomes since at least the Baltimore Longitudinal Study of Aging (BLSA) beginning in 1958 (Borkan and Norris (1980)). Prior medical studies identify apparent

[4] The prevailing view in law and economics at the time the laws were passed was that the "continuous threat of takeover" is an important incentive that promotes managerial performance (Easterbrook and Fischel (1981)). Scharfstein (1988) develops a formal model in which the threat of a takeover disciplines management, and in his opinion in *Edgar v. MITE* then-U.S. Supreme Court Justice Byron White emphasizes "[t]he incentive the tender offer mechanism provides incumbent management to perform well."

[5] For example, when protected by antitakeover laws, CEOs become less tough in wage negotiations and their rate of plant closures and openings decreases (Bertrand and Mullainathan (2003)), they undertake value-destroying actions to reduce their firms' risk of distress (Gormley and Matsa (2016)), they reduce their stock ownership (Cheng, Nagar, and Rajan (2004)), and their patent count and quality decreases (Atanassov (2013)).

[6] Consistent with CEOs' perceptions of antitakeover laws changing job demands, we find suggestive evidence that takeover-protected CEOs remain on the job longer. We also show, however, that prolonged tenure is unlikely to explain the estimated longevity effects.

[7] Stress arises from experiencing demands without sufficient resources to cope (Lazarus and Folkman (1984)). Biomedically, changes in hormones and other bodily processes due to stress can cause long-term damage and accelerate aging (Brondolo et al. (2017), Franceschi et al. (2018), Kennedy et al. (2014)).

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

age from facial photographs (e.g., Christensen et al. (2004), Christensen et al. (2009)) and assess visible aging by comparing photographs of an individual's face over time. In this paper, we build on these studies, but integrate recent developments in visual machine learning (ML). Specifically, we employ the algorithms of Antipov et al. (2016) that are designed to estimate a person's apparent age. This software is trained on more than 250,000 images and won the 2016 ChaLearn Looking At People competition in the apparent-age estimation track. Visual ML techniques offer a promising avenue for the assessment of work-induced stress. To the best of our knowledge, we are the first to introduce them into the finance and economics literature.

Our analysis comprises three main parts. In the first part, we exploit industry-level distress shocks during the Great Recession and relate them to visible signs of accelerated aging, as identified by neural network–based ML estimations. In the second part, we exploit industry-level distress shocks from longer and earlier time periods and relate them to CEO mortality. In the third part, we continue to focus on CEO mortality and study the effect of variation in the intensity of CEO monitoring due to corporate governance legislation. Across both health outcome measures and both types of variation in managerial stress, we find consistent results of very similar magnitudes.

For the first part of the analysis, we collect a sample of 3,002 facial images of Fortune 1000 CEOs serving in 2006 (the "CEO Apparent Aging Data Set"). The images are from different points in time during a CEO's tenure, both before and after the 2007 to 2008 financial crisis. This crisis lends itself to analysis of the effects of managerial stress as the large disruptions associated with the Great Recession led firms to re-optimize many aspects of their operations, including plant closures and layoffs, two of the tasks that CEOs most avoid when corporate governance is weak (Bertrand and Mullainathan (2003)). At the same time, the financial crisis affected different sectors differently, providing a suitable source of variation. It is also recent enough to ensure image availability.

Using a difference-in-differences design, we estimate that CEOs in industries that experienced a distress shock look one year older post-crisis than CEOs in other industries. The estimated difference between distressed and nondistressed CEOs increases over time and amounts to 1 to 1.2 years for pictures taken five years or more after the onset of the crisis. We include a detailed description of the procedure and address issues that have been shown to impact the use of visual ML in other settings (Wang and Kosinski (2018), Dotsch, Hassin, and Todorov (2016), Agüera y Arcas, Todorov, and Mitchell (2018)). To the best of our knowledge, our analysis represents the first application of visual ML to a quasi-experimental research design. Our application illustrates the potential of visual ML for the study of health and aging to complement standard measures based on mortality, hospital admissions, or survey responses.

In the second and third parts of the analysis, we study mortality effects associated with industry distress and corporate governance legislation. For these analyses, we extend Gibbons and Murphy's (1992) data on CEOs in the Forbes Executive Compensation Surveys from 1975 to 1991. We merge these data with hand-collected data on the exact dates of birth and death of 1,900 CEOs of large

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

U.S. firms (the “CEO Mortality Data Set”), and add information on pay, tenure, and firm characteristics.

In the analysis exploiting industry distress shocks, we estimate a hazard regression model. Controlling for a CEO’s chronological age, time trends, industry affiliation, and firm location, we show that industry distress increases CEOs’ mortality hazard by 15%. These results are robust to an array of alternative specifications, including models with CEO birth cohort fixed effects, additional firm and CEO controls, and birth cohort-specific age controls.

The estimated mortality effect is sizable: experiencing industry distress is equivalent to reducing a CEO’s chronological age by 1.1 years on average. To further put this result into perspective, we compare the estimated mortality effect to that of other known health threats. We find, for example, that smoking until age 30 is associated with a reduction in longevity by roughly one year, while lifelong smoking reduces longevity by 10 years (U.S. Department of Health and Human Services (2014), Jha et al. (2013)).

In the analysis exploiting the staggered passage of antitakeover laws, we restrict the sample to CEOs appointed before the laws were enacted to address selection concerns. We estimate significantly positive effects on CEO life expectancy. Specifically, using analogous hazard models, we find that one additional year under lenient governance decreases the CEO mortality rate by about 4%, which corresponds to a two-year increase in overall life expectancy for the average “protected” CEO in the sample. The slightly larger effect, compared to the effect of industry distress, may reflect the more permanent nature of changes in monitoring intensity, relative to the distress-induced changes in job demands.

The main results hold across a variety of robustness tests. For instance, our findings persist across sample splits and classifications of antitakeover laws designed to account for additional firm- or state-level antitakeover provisions and the exclusion of lobbying and opt-out firms, as well as data cuts based on firms’ industry affiliation or state of incorporation (see Cain, McKeon, and Solomon (2017), Karpoff and Wittry (2018)).

We also test for a compensating differential in the form of lower pay for CEOs as a result of being permanently protected from hostile takeovers. Our analysis of CEO pay builds on Bertrand and Mullainathan (1998) and on the predictions of the CEO market model in Edmans and Gabaix (2011). We find no evidence of a response in pay. This result may indicate that not all parties fully account for the health implications of job demands, although we note that prior literature generally struggles to find evidence of compensating differentials outside of select settings and carefully designed experiments (e.g., Mas and Pallais (2017), Lavetti (2020)).

Overall, our analysis establishes significant health consequences for CEOs arising from increases in job demands. The finding motivates further research on the interaction of job demands and CEO selection, compensation, and feedback on firm performance. For example, one might ask whether aspiring CEOs are (over-)confident about their health, or whether women are vastly underrepresented in the C-suite in part because they anticipate the health costs of

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

such positions. Another question is which job characteristics and hierarchy levels likely come with the highest personal cost. Although all comparisons in our analysis are within the CEO group, an important next step is to explore other hierarchy levels as well as other professions or population groups.

Our paper contributes to research examining CEOs and firms. Recent literature sheds light on CEOs' demanding job and time requirements (Bandiera et al. (2020), Bandiera et al. (2018), Porter and Nohria (2018)). Working long hours requires physical stamina, and consistent with our hypothesis, previous work documents that CEO health impacts performance. Bennedsen, Perez-Gonzalez, and Wolfenzon (2020) study the negative effect of CEO hospitalizations on firm performance. Keloharju, Knüpfer, and Tåg (2023) find that corporate boards in Scandinavia factor CEO health into CEO appointment and retention decisions. None of these papers, however, examines the effect of CEO job demands on CEOs' health trajectories. To the best of our knowledge, we are the first to explore quasi-random variation to establish significant health costs in terms of both mortality and visible aging. The only prior work on executives' health outcomes is Yen and Benham (1986), who compare the age-adjusted mortality rate of 125 executives in the banking industry to that of executives in other industries, and Nicholas (2023), who focuses on mortality patterns across organizational hierarchy levels at one large U.S. firm (white-collar employees at General Electric in the 1930s). Our significantly larger sample and quasi-experimental design allows us to control for industry-specific selection into job environments and to implement a rigorous survival analysis.

Our paper also contributes new quasi-experimental evidence to the literature on the health effects of stress, socioeconomic status, and recessions. A vast literature in psychology, medicine, and biology associates chronic stress with changes in hormone levels, brain function, cardiovascular health, DNA, and health outcomes (McEwen (1998), Epel et al. (2004), Sapolsky (2005)). This has led researchers outside of economics to identify stress, and the damage it causes, as the mechanism underlying many health disparities (Cutler, Deaton, and Lleras-Muney (2006), Cohen, Janicki-Deverts, and Miller (2007), Pickett and Wilkinson (2015), Puterman et al. (2016), Snyder-Mackler et al. (2020)). In health and labor economics, stress has been proposed as an explanation for, among other things, the effects of recessions on health (Ruhm (2000), Coile, Levine, and McKnight (2014)) as well as the association between job loss and higher mortality (Sullivan and Von Wachter (2009)).[8] In particular, the latter study examines job displacement in a population of male workers in the 1970s and 1980s (i.e., from similar birth cohorts as the CEOs we study), and finds

[8] Stress has also been linked to the efficacy of child-tax credits (Milligan and Stabile (2011)), the health benefits of the Earned Income Tax Credit (Evans and Garthwaite (2014)), unemployment insurance (Kuka (2020)), access to health care (Koijen and Van Nieuwerburgh (2020)), and early-life health disparities (Camacho (2008), Black, Devereux, and Salvanes (2016)). Relatedly, guaranteed, job-protected leave has been proposed to reduce adverse effects of mothers' job stress during pregnancy on infant health (Currie and Rossin-Slater (2015)). Stress is also implicated in the intergenerational persistence of poverty (Aizer, Stroud, and Buka (2016), Persson and Rossin-Slater (2018), East et al. (2017)).

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

that job displacement at age 40 increases the mortality hazard by 10% to 15% and reduces life expectancy by 1 to 1.5 years. The displacement shock, however, is different in nature than the CEO distress shock: it reduces time and effort spent at work (Krueger and Mueller (2012)), while industry crises induce CEOs to spend more time and effort at work.

Despite the importance of stress as a potential mediator of health, and the fact that the amount of stress experienced at work has grown steadily since at least the 1950s (Kaplan and Schulhofer-Wohl (2018)), few papers examine causal effects of job demands on health. Hummels, Munch, and Xiang (2016) document a negative impact of quasi-random trade shocks on workers' stress, injury, and illness. Evolving worker-firm interactions may have eroded protections from competition in the product market, likely exposing workers to higher levels of stress (Bertrand (2004)). Outside of economics, stress arising from social hierarchies (sometimes called psychosocial stress), especially in the workplace, has been examined as an explanation for the strong relationship between socioeconomic status and life expectancy (Marmot et al. (1991), Marmot (2005)). Quasi-experimental evidence on a causal effect of workplace promotions, however, is limited and reaches mixed conclusions (Boyce and Oswald (2012), Anderson and Marmot (2012), Johnston and Lee (2013)). Turning from the general population or poorer populations to wealthier populations, income appears to play a small role in health disparities among the already-wealthy, while Engelberg and Parsons (2016) document a link between stock market crashes and hospital admissions, especially for anxiety and panic disorders. Social factors, such as the prestige of winning a Nobel prize or an election, may be protective (Rablen and Oswald (2008), Cesarini et al. (2016), Borgschulte and Vogler (2019)). Our paper offers complementary evidence that work-related stressors impose long-term health costs, even for successful and wealthy individuals.

In the remainder of the paper, Section I describes the data and discusses the identifying variation. Section II presents our results on apparent aging and industry-wide distress shocks. Section III presents results on life expectancy and distress shocks, while Section IV presents results on life expectancy and corporate governance regulation. Section V concludes.

I. CEO Data Sets and Variation in CEO Job Demands

A. CEO Apparent Aging Data

To study visible signs of aging in CEOs' faces, we collect pictures of CEOs of firms in the 2006 Fortune 1000 list. Using a relatively recent CEO sample is necessary as picture availability and quality have increased substantially over time. We focus on the 2006 cohort to exploit differential exposure to industry shocks during the Great Recession.

We search for five images from the beginning of a CEO's tenure and two additional images every four years thereafter. The main challenge is finding *dated* images. Pictures from LinkedIn, for instance, do not satisfy this criterion

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

as they generally do not provide date information. In addition, we seek pictures that are taken in daily life, such as at social events or conferences, rather than posed pictures. The most useful source given these criteria is gettyimages.com, followed by Google Images. We are able to identify at least two such pictures from different points in time during or after their tenure for 453 CEOs. We refer to the resulting sample of 3,002 pictures as the CEO Apparent Aging Data Set. We note that the vast majority of CEOs in this sample are male and white.

Table I provides summary statistics for this data set, at both the image level (Panel A) and the CEO level (Panel B). The median picture is from 2009. On average, we find about seven images of a CEO. The average CEO is 57 years old in 2006 and has been in office for eight years. Approximately 65% of the CEOs in the data experienced an industry distress shock during the financial crisis (see Section I.C for details). Moreover, about one third of CEOs experienced pre-crisis industry shocks while in the top position, which we control for in our analyses. The majority of CEOs head firms in the manufacturing, wholesale and retail, transportation and electric services, and finance industries (Panel C). We discuss the remaining image-level characteristics from Panel A in Section II.B.

B. CEO Mortality Data

We collect mortality data for the universe of CEOs included in the Forbes Executive Compensation Surveys from 1975 to 1991, as originally collected by Gibbons and Murphy (1992).[9] These surveys are derived from corporate proxy statements and include the executives serving in the largest U.S. firms. We choose 1975 as the start year given the source of identifying variation in the third part of our analysis (i.e., the timing of antitakeover laws; see Section I.C), and in line with prior studies in this literature.[10] We include all firms with a PERMNO identifier in the Center for Research in Security Prices (CRSP) database. The initial sample comprises 2,720 CEOs employed by 1,501 firms.

We manually search for (i) the exact date of a CEO's birth, (ii) whether the CEO has died, and, if so, (iii) the date of death. All CEOs not identified as deceased by the cutoff date of October 1, 2017 are treated as censored. Our main source of birth and death information is Ancestry.com, which links historical birth and death records from the U.S. Census, the Social Security Death Index, birth certificates, and other historical sources. We validate Ancestry's information with online and newspapers searches, for example, on birth place, elementary school, or city of residence. Verifying that a person is alive turns out to be more difficult as there is little coverage of retired CEOs. We classify a CEO as alive whenever recent sources confirm the alive status,

[9] We are very grateful to Kevin J. Murphy for providing the data.

[10] Bertrand and Mullainathan (2003), Giroud and Mueller (2010), and Gormley and Matsa (2016) all start their sample in the mid-1970s. Our results are robust to varying the start year (see Section IV.D).

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table I

Summary Statistics for CEO Apparent Aging Data

Panel A presents image-level summary statistics. Panel B presents CEO-level statistics. Panel C contains information on the industry distribution of our sample. *Industry Distress (2007–2008)* is an indicator variable for distress experience during these years. *Industry Distress (pre-2007)* is an indicator variable for distress experience prior to 2007. All variables are defined in Section I of the Internet Appendix.

Panel A: Image Statistics

	N	Mean	*SD*	P10	P50	P90
Picture Year	3,002	2008.86	5.68	2003	2009	2016
Chronological Age	3,002	59.02	8.09	48.96	58.88	69.04
Industry Distress (2007-2008)	3,002	0.67	0.47	0	1	1
Apparent Age	3,002	55.14	7.00	45.71	55.85	63.35
Image Sharpness	3,002	2.57	0.74	1.55	2.58	3.54
Logo	3,002	0.19	0.39	0	0	1
Side Face	3,002	0.23	0.42	0	0	1
Professional Clothes	3,002	0.81	0.40	0	1	1
Magazine Shot	3,002	0.00	0.04	0	0	0
Magazine Quality	3,002	2.80	1.04	1	3	4
Natural Pose	3,002	0.67	0.47	0	1	1
Natural Lighting	3,002	0.18	0.38	0	0	1
Glasses	3,002	0.32	0.47	0	0	1
Facial Hair	3,002	1.19	0.56	1	1	2
Smile	3,002	1.69	0.67	1	2	3
Mood	3,002	1.76	0.69	1	2	3
Self-Confidence	3,002	2.22	0.65	1	2	3
Style	3,002	3.22	0.70	2	3	4

Panel B: CEO Statistics

	N	Mean	*SD*	P10	P50	P90
No. of Pictures per CEO	453	6.63	4.36	2	6	12
Chronological Age in 2006	453	56.68	6.96	48	57	65
Tenure (Pre-2007)	453	8.36	7.89	2	6	18
Industry Distress (2007-2008)	453	0.65	0.48	0	1	1
Industry Distress (pre-2007)	453	0.38	0.48	0	0	1

Panel C: Industry Distribution

Industry	No. of CEOs
Finance, Insurance, and Real Estate	66
Manufacturing	174
Services	44
Transportation, Communications, Electric, Gas, and Sanitary Services	69
Wholesale and Retail Trade	70
Other Industries	30

such as newspaper articles or websites that list the CEO as a board member, sponsor, donor, or chair of an organization or event.[11]

[11] We use sources dated January 2010 or later to infer alive status since recent coverage of a retired CEO makes it very likely that news outlets would also have reported their passing had

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

We obtain the birth and death information for 2,361 CEOs from 1,374 firms in the post-1975 sample, implying an identification rate of 87%. We refer to this data set as the CEO Mortality Data Set. We test and confirm that the availability of birth and death information is not correlated with our measures of variation in work-related stressors, namely, industry distress experience and incorporation in a state that passed a business combination (BC) law (see Internet Appendix Tables IA.XIII and IA.XV, respectively).[12]

We augment the CEO Mortality Data Set with several key variables. We first identify the historical states of incorporation during CEOs' tenure, which is needed to measure their exposure to antitakeover laws. Since CRSP/Compustat backfills the current state of incorporation, we obtain historical Comphist and Compustat Snapshot data as well as incorporation data recorded at issuance and merger events in the Securities Data Company (SDC) database. In the case of discrepancies, we rely on 10-Ks and other Securities and Exchange Commission (SEC) filings, legal documents, and news articles to identify the correct information. We correct the state of incorporation in 169 cases, or 6.7% of the initial sample with state-of-incorporation information (2,514 CEOs). Of the 2,361 CEOs for which we obtain birth and death information, we are able to identify the historical state of incorporation for 2,209 CEOs.

We collect tenure information for all individuals in the CEO Mortality Data Set to fill gaps and correct misrecorded data in the Forbes Executive Compensation Surveys. We use Execucomp, online searches, and especially the *New York Times* "Business People" section, which frequently reports executive changes in our sample firms. When the exact month of a CEO transition is missing, we use the "mid-year convention" (Eisfeldt and Kuhnen (2013)) motivated by the relatively uniform distribution of CEO starting months in Execucomp. We further restrict the sample to firms included in CRSP during the time of the CEO's tenure, which results in a main CEO Mortality Data Set of 1,900 CEOs.[13]

Finally, we address selection concerns with regard to antitakeover law passage. For example, our analyses would be confounded if less resilient managers, that is, those more prone to health ailments, were more likely to seek the CEO position when governance regulation relaxes CEO monitoring. To alleviate such concerns, we focus the antitakeover law analyses on CEOs appointed prior to the enactment of the BC laws (1,605 CEOs). That said, our results are robust to using the enlarged sample that includes CEOs who assume the CEO position after the passage of the BC laws (1,900 CEOs). Similarly, in the

it occurred by the cutoff date (October 1, 2017). Our results are robust to restricting the sample period to end in January 2010 for CEOs classified as alive as of October 2017, as we discuss in Sections III.D and IV.D).

[12] The Internet Appendix is available in the online version of this article on *The Journal of Finance* website.

[13] Relative to the previously mentioned restriction to firms with a PERMNO in CRSP, we drop CEOs who served, for instance, before their firm went public.

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table II

Summary Statistics for CEO Mortality Data

This table shows summary statistics for the CEO longevity analyses. *Industry Distress* is an indicator variable that equals 1 if a CEO experienced industry-wide distress during his tenure. *BC* denotes years of exposure to business combination laws. All variables are calculated at the CEO level and are defined in Section I of the Internet Appendix.

	N	Mean	*SD*	P10	P50	P90
Birth Year	1,900	1926.87	9.48	1915	1927	1940
Passed Away (by October 2017)	1,900	0.66	0.48	0	1	1
Year of Death	1,247	2003.72	9.83	1989	2006	2015
Age at Death	1,247	80.89	9.91	67	82	92
Age Taking Office	1,900	51.87	6.87	43	52	60
Year Taking Office	1,900	1978.74	8.04	1969	1979	1989
Tenure	1,900	10.04	6.69	2.5	8.75	19
Industry Distress	1,900	0.39	0.49	0	0	1
BC	1,605	2.21	4.20	0	0	8.24
$BC \mid BC > 0$	616	5.75	5.05	0.75	4.41	12.37

analysis exploiting industry distress, we consider CEOs appointed before the distress shock, regardless of whether they left their position during the crisis.

Table II presents summary statistics. The median CEO in this sample was born in 1927, became CEO at age 52, and served as CEO for nine years. The heterogeneity in tenure is relatively large, with an interdecile range of 16.5 years. Noninteger values result from CEOs starting or ending their tenure not at the end of the year. Turning to mortality, 66% of our CEOs passed away by the censoring date (October 1, 2017). The median CEO died at age 82, and passed away in 2006. About 40% of the CEOs witnessed industry distress during their tenure, but multiple distress shocks are rare—more than 80% of CEOs experienced no or at most one distress shock. Throughout, we employ a binary rather than a cumulative distress measure.[14] We further find that about 40% of the CEOs are protected by a BC law at some point during their tenure.

C. Variation in Job Demands

We exploit two sources of variation in job demands: industry-wide distress shocks and the implementation of state-level antitakeover protection.

Industry-Wide Distress Shocks. Industry distress shocks lead to a temporary increase in job demands. Similar to Opler and Titman (1994), Babina (2020), and Acharya, Bharath, and Srinivasan (2007), we define an industry as distressed in year t if the median firm's two-year stock return (forward-looking) is less than −30%. As in Babina (2020), we generate an annual industries-in-distress panel (i) restricting attention to single-segment CRSP/Compustat

[14] The indicator also helps avoid endogeneity from picking up additional industry shocks long into a CEO's tenure. Long-serving CEOs are associated with longer lifespans in the data.

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

firms, that is, dropping firms with multiple reported segments in the Compustat Business Segment Database, (ii) dropping firms if the reported single segment sales differ from those in Compustat by more than 5%, (iii) restricting attention to firms with sales of at least $20 million, and (iv) excluding industry-years with fewer than four firms. This annual distress panel serves as the foundation for our mortality analysis (Section III). For the apparent-aging analysis of the 2006 Fortune 1000 CEO cohort, we specifically examine industry distress during the Great Recession (see Section II for additional details). Following prior work, we use three-digit SIC classifications to identify industry affiliation and we rely on historical SIC codes for the firms in our sample.

Antitakeover Laws. Antitakeover statutes increase the hurdles for hostile takeovers and help protect a CEO's job. They therefore induce a shift in the opposite direction of industry distress, and they are more permanent in nature.

Following prior literature, we focus on the second generation of antitakeover laws, which states started passing in the mid-1980s after the first-generation laws were struck down by courts in the 1970s and early 1980s (Cheng, Nagar, and Rajan (2004), Cain, McKeon, and Solomon (2017)). The statutes included BC laws, control share acquisition, fair price, and directors' duties laws, as well as poison pills. We follow prior literature and focus on BC laws as the most potent type of statutes, but we return to the other types of laws in Section IV.D.

BC laws significantly reduced the threat of hostile takeovers by imposing a moratorium on large shareholders conducting certain transactions with the firm, usually for a period of three to five years. The constitutionality of BC laws was established in a 1989 ruling by the U.S. Seventh Circuit Court of Appeals (*Amanda Acquisition Corp. v. Universal Foods Corp.*). From an identification standpoint, an important assumption is that firms' BC law coverage is plausibly exogenous. As Karpoff and Wittry (2018) write, "for most firms the laws can be treated as exogenous" (p. 678) as there was no widespread corporate lobbying for the laws. At the same time, Karpoff and Wittry (2018) identify 46 firms that *did* lobby for the adoption of second-generation laws. As we discuss below, our results are robust to various tests related to lobbying firms, firm-level defenses, and opt-out provisions, among others, proposed in Karpoff and Wittry (2018). We refer the reader to Bertrand and Mullainathan (2003) and Karpoff and Wittry (2018) for a more detailed discussion of the political economy of antitakeover laws.

An advantage of using antitakeover laws as a source of identifying variation is that these laws apply based on the state of incorporation, not the state of firms' headquarters or operations. The frequent discrepancies between a firm's location and state of incorporation enables us to assess the impact of the laws while controlling for shocks to the local economy. Figure 1 depicts the staggered introduction of BC laws across states.[15] The map illustrates the variation across both time and states. As can be seen, 33 states passed a BC law between 1985 and 1997, with most laws passed in 1987 to 1989. As in

[15] Internet Appendix Figure IA.9 contains a similar map based on the earliest enactment of any of the five types of second-generation antitakeover laws listed above.

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

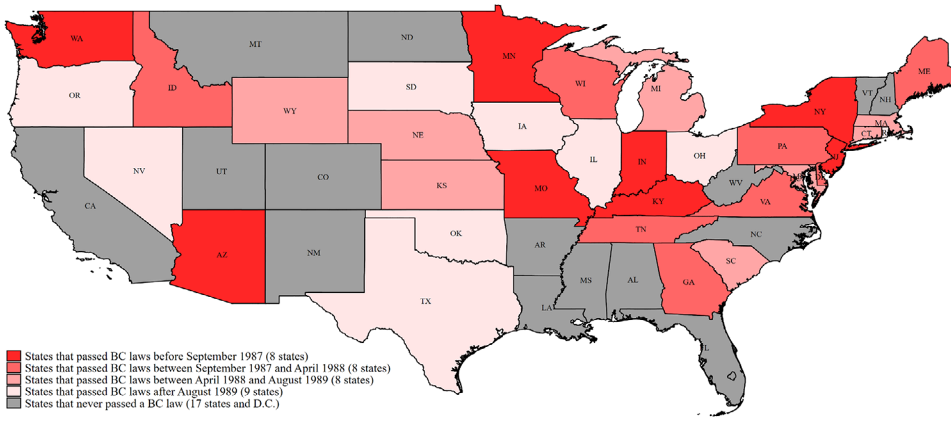

Figure 1. Introduction of business combination laws over time. The map omits the states of Alaska and Hawaii, which never passed a BC law. (Color figure can be viewed at wileyonlinelibrary.com)

prior work, the most common state of incorporation in our data is Delaware. Other common states include New York and Ohio.

II. Industry-Wide Distress Shocks and Apparent Aging

In our first analysis, we focus on visible manifestations of adverse health effects in CEOs' faces. Research in medicine and biology has established numerous links between stress and visible signs of aging, such as hair loss (Choi et al. (2021)), hair whitening (Zhang et al. (2020)), and inflammation, which accelerates skin aging (Heidt et al. (2014), Kim et al. (2013)). Moreover, these visible signs of aging predict mortality and other adverse health outcomes in longitudinal studies. For example, the apparent age of Danish twins, rated from facial photographs, predicts short-term mortality over the next two years (Christensen et al. (2004)) and long-term survival of twins aged 70 and older (Christensen et al. (2009)). Christensen et al. (2009) also establish strong correlations between apparent age and physical functioning (e.g., strength and endurance), cognitive functioning (e.g., verbal fluency and recall), and leucocyte telomere length (which is associated with aging-related diseases and mortality).

We test whether experiencing industry distress predicts accelerated apparent aging in the CEO Apparent Aging Data Set. We exploit CEOs' differential exposure to industry shocks during the Great Recession in a difference-in-differences framework.

A. Apparent-Age Estimation

To analyze visible CEO aging, we make use of recent advances in ML. While earlier generations of age-estimation software focused on a person's

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

chronological or "true" age (Antipov et al. (2016)), recent developments aim to estimate a person's apparent age or how old a person looks. This distinction is important. As the medical literature shows, differences between assessed age and chronological age can be large, they are recorded even when the physician conducting the assessment knows the chronological age, and they are highly predictive of illness and mortality (Hwang et al. (2011)). Accordingly, we use the difference between a CEO's apparent or perceived and their chronological age as our main outcome variable in the first part of the analysis.

The algorithmic implementation of age assessments, and thus the construction of the age gap variable, has been made possible by the development of deep learning and convolutional neural networks (CNNs) as well as the increased availability of large data sets of facial images with associated true and apparent ages, where the apparent ages are estimated by people. A CNN is a neural network that employs the method of convolution, that is, of transforming the data by sliding (or convolving) over it using a slider matrix, to abstractly determine intermediate features about the data such as edges or corners. (We provide a detailed discussion of CNNs in Section II.A of the Internet Appendix.) We use ML-based software (Antipov et al. (2016)) that has been specifically developed for estimation of apparent age. This software, which is based on Oxford's Visual Geometry Group deep CNN architecture, was the winner of the 2016 Looking At People apparent-age estimation competition.

In a first step, the software was trained on more than 250,000 images with information on people's true age from both the Internet Movie Database and Wikipedia. In a second step, it was fine-tuned for apparent-age estimation using a newly available data set of 5,613 facial images, each of which was rated by at least 10 people in terms of the person's age. The addition of fine-tuning using these human estimates of age is particularly important, as it led to the software's largest improvement in accuracy (of more than 20%) in the apparent-age estimation of the competition data (see table II in Antipov et al. (2016) and Section II.A of the Internet Appendix). Both the distribution of true ages used for training and the human age estimations used for fine-tuning the software cover people from all age groups, including elderly people. The neural network produces a 100×1 vector of probabilities associated with apparent ages from 0 to 99 years. The apparent-age point estimate is the expected value of the software output. A more detailed description appears in Section II.A of the Internet Appendix.

As indicated above, the software has been successfully validated in an apparent-age competition against other ML-trained apparent-aging software. Nevertheless, we further validate it within our CEO context by comparing it against human assessments. We create 250 random pairs of CEO images such that each pair involves CEOs of similar chronological age (five-year bins), and for each pair we ask a team of research assistants to indicate which person looks older. The software agrees with the median human assessment in approximately 70% of cases, and in almost 90% of cases when the software-based apparent-age difference between the two images is in the upper tercile of the distribution.

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

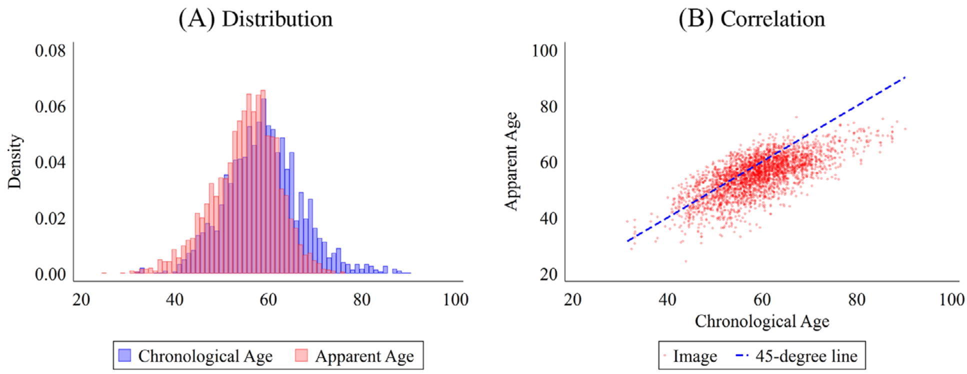

Figure 2. CEO apparent age and chronological age. The figure plots apparent and chronological ages for our sample of 3,002 CEO images. Panel A shows the CEO apparent-age distribution in red, and the chronological-age distribution in blue, with the overlapping areas appearing as purple. Panel B shows a scatter plot of CEOs' apparent age against chronological age. The dotted line represents the 45° line. (Color figure can be viewed at wileyonlinelibrary.com)

Figure 2 plots the distributions and correlation between chronological age and apparent age for the 3,002 images in the CEO Apparent Aging Data Set. Panel A shows that the distributions of apparent age and chronological age largely overlap, although the apparent-age distribution is shifted to the left. That is, consistent with a large prior literature on the "looks," stature, and health-related measures of CEOs and other high-earning individuals,[16] the software estimates CEOs as looking younger than their chronological age. (See also Table II discussed in Section I.B.) We note that our analyses do not rely on comparisons between CEOs and the general population, but rather focus on *within*-CEO comparisons and account for chronological age.

The scatter plot of CEOs' apparent age against chronological age in Panel B confirms both the high correlation and the shift in apparent age relative to chronological age, with a greater mass below the 45° line. In this figure and in the regression analysis below, we trim the sample at the top and bottom 0.5% of the apparent-age gap distribution, that is, the distribution of the difference between apparent and chronological age, to ensure that outliers in age estimation do not affect the results.

It is worth reiterating that the difference between chronological age and apparent age should not be thought of as a "mistake". By design, the ML software is first trained to predict chronological age and then fine-tuned to match human age assessment. As the medical literature shows, the differences between human assessment and chronological age can be large,

[16] See Hamermesh and Biddle (1994), Persico, Postlewaite, and Silverman (2004), Loh (1993), Steckel (1995), and Averett and Korenman (1996). See also Chetty et al. (2016) on better access to health care, healthier nutrition, and higher life expectancy of individuals with high socioeconomic status.

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Figure 3. Sample images (James Donald, CEO of Starbucks from 2005 to 2008). The left picture was taken on December 8, 2004. The right picture was taken on Monday, May 11, 2009. Chronological ages based on data from Ancestry.com (date of birth March 5, 1954): 50.76 years and 55.18 years, respectively. Apparent ages based on aging software: 53.47 years and 60.45 years, respectively. (Color figure can be viewed at wileyonlinelibrary.com)

and, importantly, these differences are highly predictive of illness and mortality.[17]

B. Illustrative Example and Potential Confounds from Image Heterogeneity

To illustrate the link between industry shocks and aging, we first discuss a specific example. James Donald was the CEO of Starbucks from April 2005 until January 2008, when he was fired after Starbucks' stock plunged by more than 40% over the preceding year. Figure 3 presents two images of Donald: the left one from December 8, 2004, before his appointment at Starbucks, and the right one 4.42 years later, on May 11, 2009, after his dismissal. Donald was 50.76 years old in the first image and 55.18 years in the second. The ML-based aging software estimates his apparent age in the earlier image as 53.47 years and in the later image as 60.45 years. Thus, the software estimates that he aged by 6.98 years, or, 2.5 years more than the amount of time that had passed.

This example is also useful to discuss concerns one may have about image heterogeneity. One noticeable difference between the two images is that Donald smiles in the image in which he looks younger but not in the other one. Hence, one potential identification concern is that photographers and newspaper editors might select different types of images during good and bad times, in a way that is correlated with firm or industry performance. Other differences between the two images include possible variations in lighting in the two images, and the left image may have been taken in a more staged setting. Researchers have noted that accounting for image context and facial

[17] See, for example, Hwang et al. (2011). Other medical research that documents a positive relationship between apparent age in facial images and life expectancy and health status includes Gunn et al. (2016) and Dykiert et al. (2012).

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

positioning may be important in related settings, such as in assessments of an individual's character, attractiveness, or sexual orientation from facial images (Wang and Kosinski (2018), Dotsch, Hassin, and Todorov (2016), Agüera y Arcas, Todorov, and Mitchell (2018)).

The image-processing software is designed to account for such "picture management". In particular, the image pre-processing and fine-tuning steps help account for image heterogeneity as described in Section II.A of the Internet Appendix. Nevertheless, we go a step further and manually assess all images in our sample along thirteen dimensions: logo, side face, professional clothes, magazine shot, magazine quality, natural pose, natural lighting, glasses, facial hair, smile, mood, self-confidence, and style. Section I of the Internet Appendix provides definitions of these variables, which are all indicator or categorical variables. To highlight a few definitions, *smile* assesses facial expression (smile, frown, or neither), *mood* assesses mood (happy, grim, or neutral), *self-confidence* assesses the degree of portrayed self-confidence (not very, normal, or very), and *style* assesses the predicted amount of time the CEO spent getting their face styled and ready in the morning. By controlling for these variables in our estimations, we further alleviate concerns about spurious aging effects. As we will see, our results are not affected (and sometimes strengthened) by the inclusion of the additional controls.

C. Difference-in-Differences Results

We formalize our analysis of job-induced apparent aging in a difference-in-differences design, analyzing differences between CEOs whose industry was in distress during the 2007 to 2008 financial crisis and those whose industry was not in distress. As we detail in Section I.C, we use three-digit SIC codes and a 30% decline in equity value criterion to identify firms that experienced an industry shock during the crisis years. This approach classifies 78 out of 146 industries represented in the CEO Apparent Aging Data Set as distressed during at least one of the two crisis years. Industries classified as distressed during these years include real estate and banking. Nondistressed industries include agriculture, food products, and utilities.

To account for potential selection bias due to CEOs departing from their job during the Great Recession, we identify treated CEOs based on intended exposure. That is, the treatment variable $Industry\ Distress_j$ is equal to 1 if CEO j 's firm operates in an industry that was distressed in 2007, 2008, or both years, regardless of whether the CEO stepped down between 2006 and 2008. For example, $Industry\ Distress_j$ is equal to 1 for a CEO departing in 2007 and whose industry was distressed in 2008.[18]

Graphical Evidence. We start by plotting the difference in aging trends between distressed and nondistressed CEOs in Figure 4. For this purpose, we bin our sample of images into eight roughly equal-sized and equal-spaced groups

[18] Regressing actual industry shock exposure in 2007 or 2008 on intended exposure yields a coefficient of 0.92 (t-statistic of 41.17).

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

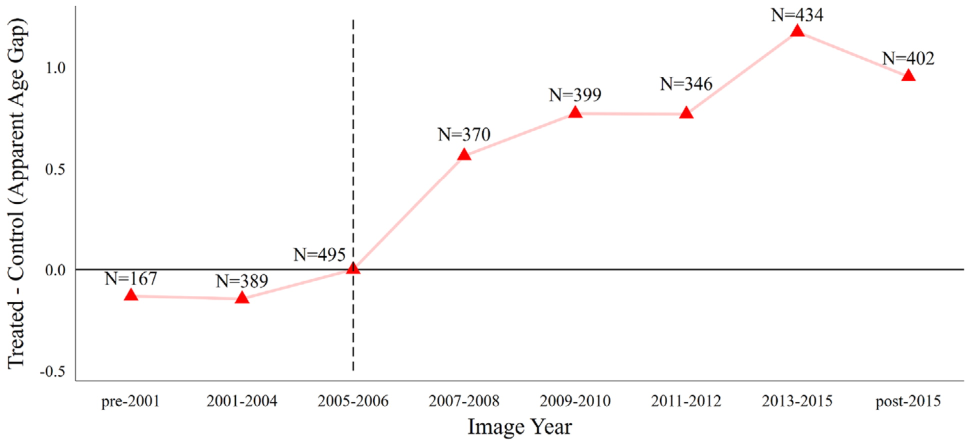

Figure 4. Differences in apparent aging between CEOs with and without industry distress exposure during the Great Recession. This figure depicts the estimated coefficients from $\boldsymbol{\beta_1}$ on the interaction terms between the time-period indicators and the *Industry Distress* indicator from model (1), where *Industry Distress* is equal to 1 if the CEO's firm was exposed to industry-wide distress during 2007 or 2008. *Apparent-Age Gap* is the difference between apparent and chronological age. Observations are weighted by image sharpness. N denotes the number of images in each time bin. (Color figure can be viewed at wileyonlinelibrary.com)

over the sample period, $t \in T = \{\text{pre-2001}, \text{2001-2004}, \ldots, \text{post-2015}\}$, and estimate the difference-in-differences model

$$\begin{aligned} Apparent\ Age\ Gap_{i,j,t} = \ & \beta_0 \\ & + \sum_{\substack{t \in T,\\ t \neq 2005\text{-}06}} \beta_{1,t}\, Industry\ Distress_j \times \mathbb{1}_t + \boldsymbol{\beta_2'} \boldsymbol{X_{i,j,t}} + \delta_t + \theta_j \\ & + \varepsilon_{i,j,t}, \end{aligned} \tag{1}$$

where i denotes an image, j a CEO, and t a time bin, $Apparent\ Age\ Gap_{i,j,t}$ is the difference between CEO j's apparent age in image i as assessed by the aging software and their chronological age at time t when the picture was taken, and $\mathbb{1}_t$ are time indicators, where the t^{th} indicator is equal to 1 for pictures taken in time bin t. We interact the time indicators with $Industry\ Distress_j$, so that the interaction is equal to 1 if the firm of CEO j shown in image i was distressed in 2007 or 2008. For the graphical presentation, we normalize against the pre-crisis bin ($t = 2005$–2006).

The vector of control variables $\boldsymbol{X_{i,j,t}}$ includes time-varying controls for a CEO's pre-2007 industry shock experience and pre-2007 CEO tenure as well as extensive controls for image setting and characteristics discussed above and a control for image sharpness. We measure sharpness using an image's Laplacian, that is, the second spatial derivative of an image, as described in Section II.B of the Internet Appendix. Note that for any of these image controls

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

to affect the results in the first place, they would have to systematically affect the software's age estimate and be correlated with industry distress experience. (We discuss such potential concerns in Section II.D.)

We also include CEO fixed effects θ_j and time fixed effects δ_t. The CEO fixed effects absorb any time-invariant CEO facial characteristics such as facial shape. The CEO fixed effects also account, for example, for CEO-specific aging and determinants of aging such as risk attitudes and selection into riskier industries. The time fixed effects absorb time trends, such as improving image quality. While the aging software was trained on a large number of faces and images of differing quality, these fixed effects tighten the identification and absorb the main effects of the time-industry shock interaction in the regression.

We weight observations by image sharpness, that is, images in which detail is rendered more clearly receive larger weight. We discuss robustness to other weighting choices below with the regression results.

Figure 4 plots the estimated components of vector $\boldsymbol{\beta_1} = (\beta_{1,\text{pre-2001}}, \ldots, \beta_{1,t}, \ldots, \beta_{1,\text{post-2015}})$. They capture differences in the gap between apparent and chronological age between the treated group and the control group at different points in time, after controlling for covariates and normalizing against the pre-crisis bin ($t = 2005\text{-}2006$). The difference in apparent-age gap between future distressed and nondistressed CEOs is small and stable over time before the crisis, consistent with aging in both groups following parallel pre-trends. In particular, there is no evidence that CEOs who experience an industry downturn during the Great Recession age faster than control CEOs before the crisis. After the onset of the Great Recession, however, the difference in the apparent-age gap increases markedly, first to about half a year, then to about 0.75 years around 2010, then to a full year around 2013. The difference stabilizes at a level of about one year after 2015. In other words, the graphical evidence indicates that exposure to industry distress accelerates apparent aging starting around the time of exposure and levels off after a few years to a persistent difference of one year.

We note that the rapid onset of accelerated aging and full realization after a few years are consistent with biological mechanisms linking the hormone responses to cellular damage during periods of chronic stress exposure. For example, a similar time horizon stretching over two to three years has been found for the relationship between stress and mortality in a population with a similar age-cohort distribution to our mortality sample and with access to health care (Nielsen et al. (2008), Rutters et al. (2014)).

Regression Model. We next turn to estimating the full difference-in-differences regression model, using a specification similar to model (1) above:

$$\begin{aligned} \mathit{Apparent\ Age\ Gap}_{i,j,t} = {} & \beta_0 + \beta_1\, \mathit{Industry\ Distress}_j \times \mathbb{1}_{\{t>2006\}} + \boldsymbol{\beta_2' X_{i,j,t}} + \delta_t + \theta_j \\ & + \varepsilon_{i,j,t}. \end{aligned} \tag{2}$$

As before, i denotes an image and j a CEO, but t now represents a calendar year. All variable definitions remain as specified for equation (1), and we include the same set of control variables and fixed effects. We also continue to

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table III

Industry Distress and CEO Aging

This table shows OLS estimates of the effect of industry distress during the Great Recession on CEO apparent aging, as identified from CEOs' facial images. The dependent variable is the apparent-age gap, that is, the difference between apparent and chronological age. *Industry Distress* is equal to 1 if the CEO's firm was exposed to industry-wide distress during 2007 or 2008. Observations are weighted by image sharpness. All variables are defined in Section I of the Internet Appendix. Standard errors, clustered at the industry level, are shown in brackets. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)
Industry Distress × $\mathbb{1}_{\{t>2006\}}$	0.806**	0.883**		
	[0.382]	[0.382]		
Industry Distress × $\mathbb{1}_{\{2006<t<2012\}}$			0.634	0.670*
			[0.386]	[0.396]
Industry Distress × $\mathbb{1}_{\{t\geq 2012\}}$			1.049**	1.183***
			[0.462]	[0.448]
CEO FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
CEO Controls	Y	Y	Y	Y
Picture Controls		Y		Y
No. of CEOs	453	453	453	453
Observations	3,002	3,002	3,002	3,002

weight observations by image sharpness. Internet Appendix Table IA.II shows the robustness to other weighting choices and treatments of outliers. Internet Appendix Table IA.III shows that our measure of image sharpness is uncorrelated with industry distress exposure during the Great Recession. We cluster standard errors at the three-digit SIC code level, at which industry shocks are defined (Abadie et al. (2017)). The key coefficient of interest is β_1, which gives the change in the apparent-age gap after the start of the crisis and during the post-crisis years ($t > 2006$) if the CEO's firm experienced industry shocks during 2007 to 2008.

Table III presents the regression results. In column (1), the coefficient on the interaction term between *Industry Distress* and the post-2006 indicator $\mathbb{1}_{\{t>2006\}}$ is 0.806 (significant at the 5% level). This indicates that CEOs look about 0.8 years older for a given chronological age if their firm has experienced an industry distress shock between 2007 and 2008. In column (2), we add the extensive set of image controls for smile versus frown, mood, portrayed self-confidence, etc. The coefficient on the post-treatment interaction term is very similar (now 0.883, again significant at the 5% level).

In columns (3) and (4), we split the post-period into two subperiods, 2007 to 2011 and 2012 onward. The estimates indicate that longer horizon effects are driving the results. Consistent with Figure 4, we estimate a distress-induced apparent-aging effect of around 0.65 years over the earlier five-year horizon that is insignificant or only marginally significant, but an effect of 1 to 1.2 years over the later horizon, which is significant at the 5% or 1% level. The estimated effects are similar whether we include the additional image controls or not.

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

The long-term persistence of the distress-induced aging effects ameliorates potential concerns about "picture management". If the media or firms engage in picture selection in a manner that is correlated with distress exposure, it could affect the apparent-age estimates. However, such differential image management is unlikely to occur years after the distress crisis. We further discuss these and other remaining identification concerns in detail in the next subsection.

Overall, the apparent-aging analysis provides robust evidence that increased job demands in the form of industry distress accelerate visual aging. In Section III below, we further show that the effects of industry distress on CEO mortality are very similar in magnitude. Hence, the appearance of aging may presage a shorter lifespan for CEOs whose industries experienced downturns in the Great Recession.

D. Robustness Tests

In this section, we perform a series of robustness tests. All figures and tables are relegated to Section II.E of the Internet Appendix.

CEO Appearance Management. One potential confound of our results is that CEOs may engage in "appearance management". For example, given their public status, young CEOs may prefer to grow some facial hair to look older, whereas older CEOs may prefer to dye their hair to look younger. Such behavior, while plausible, is unlikely to affect our estimates for two reasons. First, there is no difference in chronological age between distressed and nondistressed CEOs as of 2006, the year prior to treatment assignment (Internet Appendix Table IA.IV). Thus, general appearance management incentives should not differ by treatment status. Consistent with this view, both groups have parallel aging pre-trends, as shown in Figure 4. Second, image-type control variables such as the facial hair and style controls help alleviate this concern.

Differential Selection of Images During Good and Bad Times. Another potential confound is that newspaper editors may select more grim-faced (and possibly older-looking) CEO images during the crisis, particularly if the firm is in distress. We address this concern in three ways. First, we point to the stability of the aging effect. Our main result holds after five years and throughout the 2010s, when news about the industry's distress and possible criticism of the CEO would have subsided. In these later images such selection is unlikely to be at work (see Figure 4). Moreover, the results are robust to including image heterogeneity controls, including assessed smile versus frown, happy versus grim, and the degree of the CEO's self-confidence.

Second, we show directly that CEOs' facial expressions in our sample are not correlated with treatment. That is, when we use facial expression as the outcome variable (with $+1$ = smiling, 0 = neutral, and -1 = frowning) and test whether industry distress exposure predicts the outcome, we fail to reject the null hypothesis of no significant relationship. This result continues to hold when we interact industry distress with a post dummy to restrict the

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

comparison to pictures from 2007 onward (see Panel A of Internet Appendix Table IA.V).

We do find, however, that the apparent-age gap is correlated with facial expressions (see Panel B of Internet Appendix Table IA.V). More precisely, we estimate no significant relation when controlling for the full slate of control variables, but there is a significantly positive relation with the frowning indicator when we omit the mood controls (happy versus grim), which are correlated with the smile controls (smiling versus frowning).

In light of these findings, we go a step further in addressing the role of smiling versus frowning and use artificial intelligence (AI)-based image manipulation techniques to change facial expression. Specifically, we use software that creates natural-looking transformations of faces using ML and neural network techniques to change grim expressions toward happier expressions (neutral and even faint smiles). We discuss these manipulations in detail in Section II.C of the Internet Appendix. We then include the 341 resulting "fake images" in our analysis and apply the apparent-age software to reestimate our model. As shown in Internet Appendix Table IA.VI, we replicate our findings.

Differential Image Selection Due to CEO Departures. A further concern is that CEO departure rates may differ by industry distress experience, which might then lead to differences in the type of images we can find. For example, news of CEO departures is often accompanied by photos of a more grim-faced CEO, and after stepping down, CEOs may assume less prestigious positions with fewer incentives for appearance management. This could drive the differential patterns in apparent aging, even in the long run.

To address this concern, our analysis includes controls for "magazine quality" (which assesses the degree to which an image can be used in a magazine) and "style" (which assesses the time an individual spent styling their face in the morning). In addition, we show that our results are not driven by differential finding rates of post-crisis images depending on whether CEOs experienced distress during the crisis (Internet Appendix Figure IA.6 and Internet Appendix Table IA.VII).

To further address this concern, we collect information on the departure date and post-departure career trajectory of each CEO in our sample. We then reestimate the results on the subsample of CEOs who remain in the position until 2010 or thereafter.[19] As we show in more detail in Section II.D of the Internet Appendix, in this subsample CEO departure rates and image "types" (in-office, post-departure but nonretired, retired) are similar across distressed and nondistressed CEOs. This result mitigates concerns related to departure-driven image heterogeneity and selection. Moreover, our aging results continue to go through (Internet Appendix Table IA.VIII).

Alternative Empirical Specification. We also replicate our results when using apparent age as the outcome variable and chronological age as an

[19] Of course, whether CEOs remain in office until 2010 is endogenous. Selection from this conditioning likely works against identifying the effect of distress, as distressed CEOs who remain in office are presumably more "resilient".

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

additional control variable (Internet Appendix Table IA.IX), rather than using the apparent-age gap as the outcome variable.

Alternative Combination of Trained Neural Networks. Precisely speaking, the software forms the primary apparent-age estimate by averaging estimates across eleven separately trained sub-models (see Section II.A of the Internet Appendix for details), an approach akin to bootstrap-aggregating or "bagging" (Breiman (1996)). Our results are not sensitive to how the 11 trained neural nets are combined. The results remain unchanged when we use the median, rather than the average, apparent-age estimate across the trained sub-models in the regressions (Internet Appendix Table IA.X).

E. Possible Mechanisms

As discussed earlier, the rapid onset of visible signs of aging is consistent with the medical literature on stress responses. Cortisol and other immediately triggered "flight-or-fight" hormonal reactions to chronic stress are plausibly linked to our finding of accelerated aging. In particular, Harvanek et al. (2021) find that higher insulin resistance (which can be caused by excess cortisol) positively predicts a person's epigenetic age, which is a strong predictor of mortality (see Föhr et al. (2021)).

In light of these plausible biomedical underpinnings of our results, we explore ways to tease out related physical changes from the image sample. First, we consider changes in body mass index (BMI). Biochemically, chronic stress increases cortisol levels (Van der Valk, Savas, and van Rossum (2018)), which slows metabolism and triggers a desire for "comfort foods". Both can lead to weight increases. In addition, excessive work demands triggered by the crisis may by themselves induce unhealthy eating due to time constraints and adversely affect exercise behavior. These behavioral changes can evolve into unhealthy habits in the long run, even after heightened job demands subside.

Accordingly, we retrieve ML-based estimations of the BMI from facial images (Sidhpura et al. (2022)). Applying these estimation techniques to our CEO image data, we find suggestive, albeit insignificant, evidence of higher BMI levels among treated CEOs over time (Internet Appendix Table IA.XI). While more data and less noisy estimates would be needed to draw conclusive evidence, the estimates are suggestive of a slow-moving, long-run behavior change.

In addition to poor diet and lack of exercise, stress might induce other behavior changes that can accelerate aging, including lack of sleep and excess alcohol consumption. To test for such channels, we have constructed measures of the degree of puffy eyes, red eyes, dark areas under eyes, and red face. We find no evidence that these facial aspects are significantly related to industry distress exposure (Internet Appendix Table IA.XII). Although it is possible that a larger sample and refined definitions of the above features would allow for the detection of a statistically significant relationship, the null effect is consistent with such features more likely reflecting very recent sharp changes in behavior.

In summary, our CEO Apparent Aging Data Set does not allow us to identify specific biomedical or behavioral channels beyond the main result on visible

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

signs of aging, which are a widely used indicator in medicine. Our additional results here are suggestive of changes in BMI, which are consistent with hormonal responses to stress as well as worse diet and exercise behavior.

III. Industry-Wide Distress Shocks and Life Expectancy

In the remaining two parts of the analysis, we move from apparent aging to mortality as the outcome variable. In this section, we examine the link between mortality and industry distress, and in Section IV we examine the link between mortality and governance regulation. In both sets of analyses, we use the longer and earlier CEO Mortality Data Set described in Section I.B, which allows us to analyze mortality outcomes and accommodates the timing of variation in antitakeover laws.

A. Empirical Strategy

We employ stratified Cox (1972) proportional hazards models to estimate the effect of variation in the exposure to industry distress on longevity. CEOs enter the analysis ("become at risk") in the year they are appointed, and they exit at death or the censoring date. Specifically, we estimate

$$\ln \lambda(t|\mathit{Industry\,Distress}_{i,t}, X_{i,t}) = \ln \lambda_{0,j}(t) + \beta\, \mathit{Industry\,Distress}_{i,t} + \boldsymbol{\delta' X_{i,t}}, \quad (3)$$

where λ and $\lambda_{0,j}$ are the hazard rate and the baseline hazard rate, respectively, with the latter allowed to vary across the Fama and French (1997) 49 industries j, and $\mathit{Industry\ Distress}_{i,t}$ is an indicator variable equal to 1 if CEO i has experienced distress by year t, that is, if in year t or a prior year during the CEO's tenure, the forward-looking two-year stock return of the median firm in the industry is less than −30%. Note that when a CEO steps down, the value of the distress indicator remains constant at its value at departure. Control variables are contained in vector $\boldsymbol{X_{i,t}}$. In our baseline specifications, the controls include a CEO's chronological age, time trends (linear or fixed effects), and location fixed effects. The location fixed effects are based on firms' state of headquarters and absorb state-level characteristics such as general business conditions and pollution to the extent that such factors are time-invariant. We also present specifications with birth-cohort fixed effects. We cluster standard errors at the three-digit SIC code level, at which industry shocks are defined (Abadie et al. (2017)).

B. Graphical Evidence

Before presenting the main estimation results, we provide graphical evidence on the mortality effects of CEOs' exposure to industry distress. Figure 5 plots Kaplan-Meier survival graphs, with the vertical axis showing the survival rate and the horizontal axis the time elapsed (in years) since becoming CEO, split by whether CEOs experienced industry distress during their tenure. The nonparametric Kaplan-Meier estimator discretizes time into inter-

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

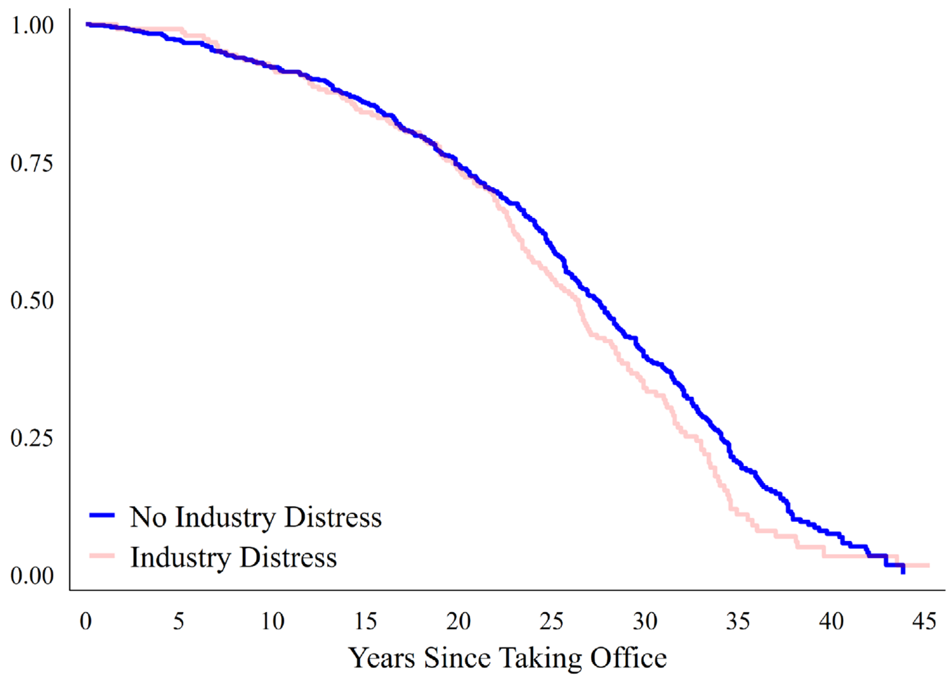

Figure 5. Kaplan-Meier survival estimates. This figure shows Kaplan-Meier survival plots of the relation between industry distress experience and longevity. The vertical axis shows the fraction of CEOs who are still alive. The horizontal axis reflects time elapsed (in years) since a person became CEO. The figure compares the survival of CEOs who never experienced industry-wide distress during their tenure (dark blue) to that of CEOs who did experience such distress (light red). The figure focuses on CEOs appointed up to 10 years prior to the retirement age of 65 and stepping down up to 10 years after the retirement age. (Color figure can be viewed at wileyonlinelibrary.com)

vals $t_1, \ldots, t_J$ and is defined as $\widehat{\lambda_j^{KM}} = \frac{f_j}{r_j}$, where f_j is the number of spells ending at time t_j and r_j is the number of spells at risk at the beginning of time t_j.

For the graphical presentation, we restrict the sample to CEOs who were appointed no earlier than 10 years prior to the retirement age of 65 and who stepped down no later than 10 years after the retirement age.[20] This restriction increases similarity with respect to age among CEOs and thus accounts indirectly for age being a strong predictor of both mortality and treatment (due to the fact that once treated, CEOs remain classified as treated in subsequent years). In the univariate Kaplan-Meier survival graphs, we cannot control for age directly since these graphs plot survival unadjusted for covariates. In our

[20] Internet Appendix Figure IA.7 plots the retirement hazard for CEOs in our main sample. The figure confirms a large spike in retirements at age 65, consistent with the evidence in Jenter and Lewellen (2015). Although CEOs may continue to work after stepping down, few (32 in total) become CEO at another firm in our sample.

Table IV
Industry Distress and Mortality

This table shows hazard coefficients estimated from a Cox (1972) proportional hazards model. The dependent variable is an indicator that equals 1 if the CEO dies in a given year. The main independent variable *Industry Distress* is an indicator of a CEO's exposure to industry distress shocks. All variables are defined in Section I of the Internet Appendix. Standard errors, clustered at the industry level, are shown in brackets. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
Industry Distress	0.108**	0.103*	0.147**	0.140**	0.137**	0.178***
	[0.053]	[0.055]	[0.058]	[0.059]	[0.061]	[0.063]
Age	0.119***	0.119***	0.121***	0.117***	0.117***	0.125***
	[0.006]	[0.006]	[0.007]	[0.006]	[0.006]	[0.007]
ln(*Pay*)				−0.005	−0.011	0.011
				[0.045]	[0.046]	[0.047]
ln(*Assets*)				−0.078	−0.084*	−0.091*
				[0.047]	[0.048]	[0.052]
ln(*Employees*)				0.029	0.033	0.038
				[0.049]	[0.049]	[0.051]
Year	−0.003			0.001		
	[0.005]			[0.006]		
FF49 Strata	Y	Y	Y	Y	Y	Y
Location FE	Y	Y	Y	Y	Y	Y
Year FE		Y			Y	
Birth Year FE			Y			Y
No. of CEOs	1,900	1,900	1,900	1,818	1,818	1,818
Observations	58,034	58,034	58,034	55,796	55,796	55,796

Cox (1972) regressions below, we are able to directly control for age as a covariate in the model.

Figure 5 shows that the survival line for CEOs who were exposed to industry distress during their tenure is visibly left-shifted at longer horizons, that is, distressed CEOs have significantly worse long-run survival patterns than nondistressed CEOs. For example, about 67% of distressed CEOs passed away within 30 years of their appointment, whereas this percentage is only reached after approximately 32 years in the nondistressed CEO group. The hazard coefficient on industry distress corresponding to the survival patterns in Figure 5 is 0.178, which is in the ballpark of the Cox (1972) regression estimates that we discuss next. The survival plot offers initial, suggestive evidence that experiencing industry distress as CEO is associated with adverse consequences in terms of life expectancy. Our hazard analysis below formalizes the observed patterns.

C. Main Results

Table IV presents the hazard model results on the relationship between industry distress and CEOs' mortality rates, based on equation (3) and stratified by industry. All columns show the estimated hazard coefficients (β, δ). A

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

coefficient greater than zero indicates that the risk of failure (death) is positively associated with a given variable.

The specification in column (1) estimates the model with the industry distress indicator, a linear control for age, a linear control for time trends, and location fixed effects based on firms' state of headquarters, which absorb state-level characteristics such as general business conditions and pollution to the extent that such factors are time-invariant. In column (2), we replace the linear time control with year fixed effects, and in column (3), we include CEO birth-year fixed effects instead of year fixed effects. Columns (4) to (6) reestimate columns (1) to (3), including as additional control variables CEO pay (from Gibbons and Murphy (1992)) and firm size (assets and employees from Compustat). These controls are available for 96% of sample observations.

Across specifications, we estimate a robust and statistically and economically significant effect of industry distress on the mortality hazard. Averaging the estimates across columns, distress experience increases CEOs' log mortality hazard by 0.136, that is, given a hazard ratio of $\exp(0.136) = 1.145$, the mortality hazard increases by 14.5%.[21]

Turning to the control variables, the effect of age is significantly positive across specifications, reflecting the fact that older people have a higher risk of dying. Note that the linear age term is motivated by the Gompertz (1825) "law of mortality," the empirical regularity that the risk of dying follows a geometric increase after middle age (Olshansky and Carnes (1997)). We obtain virtually identical estimates when including higher order age terms. The linear time control in columns (1) and (4) is close to zero and insignificant, suggesting no general time trends in the survival of CEOs over the sample period.

Economic Significance. One way to evaluate the magnitude of the estimated distress effect on longevity is relative to other predictors, in particular, relative to age: what increase in chronological age does the effect of distress exposure on mortality correspond to? Averaging across all columns, the estimated effect of age on the log mortality hazard is 0.120. This means that the effect of industry distress exposure corresponds to the effect of being 1.1 years older $(0.136/0.120 \approx 1.1)$.

This "in-sample" comparison has the advantage that it is based on data from the sample CEOs, who have a higher baseline life expectancy. Alternatively, we can compare the estimated mortality hazard with mortality statistics of the general U.S. population. For example, at age 57 (the median CEO age in our sample), the one-year mortality rate of a male American born in 1927 (the median birth year in our sample) is 1.337% (Human Mortality Database (2019)). Industry distress experience while CEO pushes this rate up to 1.532%, which is roughly the mortality rate of a male born in 1927 at age 59, that is, when two years older.

[21] Results using firm distress instead of industry distress find coefficients of a smaller magnitude, although within the confidence intervals of the industry distress estimates. A possible reason could be that robust CEOs select into vulnerable firms. Another possibility is that industry-wide shocks bring about a broader set of stressors than those arising from own-firm performance, such as lenders being less willing to support firms in a declining industry.

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Finally, we can compare our mortality estimates to the estimated effect of other economic stressors in different populations. For example, in Sullivan and Von Wachter (2009), job displacement increases the mortality hazard by 10% to 15% and reduces life expectancy by 1 to 1.5 years. This effect is similar to our industry distress point estimates, although as already noted, job displacement reduces time and effort spent at work (Krueger and Mueller (2012)), whereas industry distress leads CEOs to spend more time and effort at work. Nicholas (2023) estimates larger mortality differences in his sample of General Electric employees, finding that working as an executive was associated with a three- to five-year reduction in longevity compared to lower hierarchy employees.

Another benchmark for comparison are other known health threats. For example, smoking until age 30 is associated with a reduction in longevity of roughly one year (Jha et al. (2013)). The reduction in life expectancy from industry distress exposure is thus slightly larger than the reduction from smoking in the first three decades of one's life.

In sum, unexpected changes in the work environment and in the job demands of CEOs arising from industry-wide distress have substantial health consequences not only in terms of short- to medium-term visible aging, but also in terms of long-term mortality.

D. Robustness Tests and Mechanisms

We perform several additional robustness tests, with all figures and tables relegated to Section III of the Internet Appendix.

First, to further examine potential confounds around heterogeneity in life expectancy over time, and this heterogeneity being correlated with industry distress exposure, Internet Appendix Table IA.XIV estimates alternative specifications that allow the effect of age on mortality to be cohort-specific. Specifically, we sort CEOs into quintiles based on birth year and allow for separate age estimates. Although there are small differences in age effects across CEO cohorts, the industry distress coefficients are little affected and remain statistically and economically significant.

Second, we reestimate the effect of industry distress when varying the censoring year for CEOs' alive status. This check alleviates concerns that we may have failed to identify some deaths, thereby granting "extra years" of life to these CEOs[11]. The coefficients remain stable as we gradually move the censoring date for CEOs identified as alive as of October 2017 from October 1, 2017 to December 31, 2010 (Internet Appendix Figure IA.8).

Third, we explore specific recession periods similar to the analysis in Section II, such as the 1987 stock-market downturn or the recession of 1981–1982. However, fewer than 5% of the CEOs in our sample experienced either of these shocks so we lack statistical power when applying the same methodology. The corresponding estimates indicate that CEOs who experienced these specific shocks tend to have a higher mortality hazard, but they are generally not statistically significant.

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

We also explore the availability of data on the causes of death, as they might elucidate the mechanisms relating industry downturns to mortality. We find that cause of death is sometimes reported in CEOs' obituaries and in news articles, albeit less commonly than date of death, and it is never reported on Ancestry.com, one of our primary sources for death dates. We are able to extract cause of death information for 493 of the 1,247 CEOs who passed away in our sample. Within this relatively small and possibly selected sample, industry distress is associated with a higher frequency of deaths due to heart disease or stroke, and a lower frequency of deaths due to cancer or Alzheimer's disease. We lack power, however, to rule out that these differences are due to chance.

In summary, while the results are robust to a wide range of mortality specifications, the data do not allow us to pin down specific crises or specific medical causes of mortality.

IV. Corporate Monitoring and Life Expectancy

In our final analysis, we exploit the staggered passage of antitakeover laws across U.S. states in the mid-1980s as the source of identifying variation to study CEO mortality effects.

A. Empirical Strategy

Our main analysis continues to use the Cox (1972) proportional hazards model, again stratified by industry. First, we estimate a modified version of equation (3):

$$\ln\ \lambda(t|BC_{i,t}, \boldsymbol{X_{i,t}}) = \ln\ \lambda_{0,j}(t)\ + \beta\, I(BC_{i,t}) + \boldsymbol{\delta}'\boldsymbol{X_{i,t}}, \tag{4}$$

where $I(BC_{i,t})$ is an indicator variable equal to 1 if CEO i in industry j has been exposed to a BC law by year t. As in Section III.A, in the baseline models $\boldsymbol{X_{i,t}}$ includes chronological age, time trends (or fixed effects), and state-of-headquarters fixed effects. We also verify again that all of our results are robust to specifications that account for CEO birth cohorts. Furthermore, we add as an additional control an indicator variable capturing a CEO's exposure to first-generation antitakeover laws to all specifications. Karpoff and Wittry (2018) emphasize the importance of accounting for the historical political economy of the BC laws and therefore include a control for first-generation laws in their empirical tests. In Section IV.D, we also implement a host of further robustness tests proposed by Karpoff and Wittry (2018).

Second, we test for differential effects depending on BC law exposure intensity. Given that the laws led to a permanent corporate governance regime change, rather than a temporary exposure (as in the case of industry distress), we replace the indicator $I(BC_{i,t})$ with a measure $BC_{i,t}$ that counts the exposure

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

length in years until year t:[22]

$$\ln\ \lambda(t|BC_{i,t},\boldsymbol{X_{i,t}}) = \ln\ \lambda_{0,j}(t)\ + \beta\, BC_{i,t} + \boldsymbol{\delta}'\boldsymbol{X_{i,t}}. \tag{5}$$

Relative to the binary measure, the cumulative exposure measure is more prone to endogeneity concerns for long-serving CEOs. We address this concern in Section IV.D, where we examine initial versus incremental exposure as well as predicted exposure length.

As with the distress indicator in the previous section, the values of the BC law indicator and BC law exposure length variables remain constant once a CEO has stepped down. We now cluster standard errors at the state-of-incorporation level, given that the BC laws apply based on firms' state of incorporation (Abadie et al. (2017)).

B. Graphical Evidence

We again start by plotting Kaplan-Meier survival graphs. As in Figure 5, we focus on CEOs who started and ended their tenure within $+/-10$ years around the retirement age of 65, so that the univariate plots account for CEO age to some degree.

Panel A of Figure 6 plots the survival lines of this set of CEOs, comparing those who became CEO in the 1970s and were never shielded by a BC law, those who became CEO in the 1980s and were not shielded by a BC law, and those who became CEO in the 1980s and were insulated by BC law protection during their tenure.[23]

Two results emerge. First, the survival patterns of the 1970s and 1980s cohorts without BC exposure are remarkably similar, allaying concerns that our BC law–mortality results pick up *general* changes in survival patterns between the 1970s and 1980s. Second, the survival line for the 1980s cohorts with BC exposure is visibly right-shifted compared to the no-BC-cohorts. For example, 20 years after their appointment, about 25% of CEOs in the 1980s cohorts without BC exposure had died, whereas it takes closer to 25 to 30 years for a similar share of CEOs in the 1980s cohorts with BC exposure to die.

To address concerns about systematic differences between BC and non-BC states affecting the results, Panel B reshuffles CEOs in Panel A's no-BC-cohorts, grouping them by whether their state eventually enacted a BC law after the CEO stepped down (light blue) or not (dark blue). The survival lines for these groups are virtually identical. Only CEOs in BC states with BC exposure (light red) show a more beneficial survival curve. Thus, there is

[22] In these specifications, we also replace the indicator for first-generation law exposure with an exposure length measure. In both cases, we calculate exposure length up to daily precision. For example, Delaware's BC law was adopted on Feburary 2, 1988, and a CEO's exposure in Delaware in 1988 is calculated as $BC_{i,1988} = \frac{365-\text{doy}(2/2/1988)}{365} = 0.92$.

[23] For the 1970s cohorts, maximum elapsed time since our sample start is $t = 47.75$ (time elapsed between January 1, 1970 and the censoring date, October 1, 2017). Similarly, for the 1980s cohorts, maximal elapsed time is $t = 37.75$. We restrict the graph to periods when at least 10 CEOs in either cohort group are uncensored, explaining the slightly differential ends of the survival lines.

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

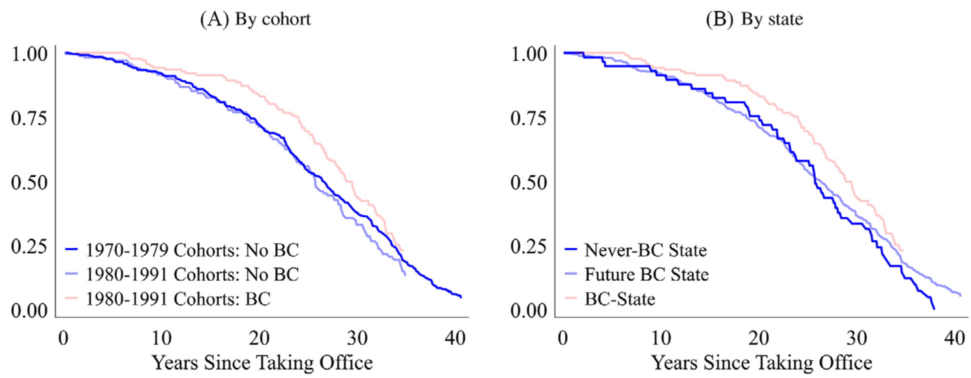

Figure 6. Kaplan-Meier survival estimates. This figure shows Kaplan-Meier survival plots for the relation between antitakeover law protection and longevity. The vertical axis shows the fraction of CEOs who are still alive. The horizontal axis reflects time elapsed (in years) since a person became CEO. Panel A compares the survival of CEOs starting in the 1970s who never served under a BC law (dark blue) to those who became CEO in the 1980s and never served under a BC law (light blue) and those who became CEO in the 1980s and were eventually exposed to a BC law (light red). Panel B splits the CEOs from Panel A based on whether their state never passed a BC law (dark blue), passed a BC law after the CEO stepped down (light blue), or passed a BC law while in office (light red). As in Figure 5, both panels focus on CEOs appointed up to 10 years prior to the retirement age of 65 that had stepped down up to 10 years after the retirement age. (Color figure can be viewed at wileyonlinelibrary.com)

no evidence of BC states being inherently different prior to BC enactment. We also note that all estimations below include location fixed effects and are robust to using state-of-incorporation fixed effects.

The survival plots suggest significant adverse consequences in terms of life expectancy associated with serving under more stringent corporate governance regimes. The underlying hazard coefficient on BC law exposure is −0.228, which is very similar to the Cox (1972) hazard model results we turn to next.

C. Main Results

Table V shows the hazard estimates based on empirical model (4) in the first four columns and based on model (5) in the last four columns, that is, in columns (1) to (4) we summarize the total effect of BC law exposure with the indicator $I(BC_{i,t})$, which is equal to 1 if CEO i had been exposed to a BC law by time t, and in columns (5) to (8) we estimate the linear effect in years of exposure, $BC_{i,t}$. We include fixed effects and controls as in the Table IV specifications with year controls (linear or fixed effects), in addition to the control for first-generation law exposure.

Across all columns, we estimate a statistically and economically strong effect of BC law protection on mortality. For the BC indicator in columns (1) to (4), the hazard coefficient ranges from −0.198 to −0.234. For the cumulative BC exposure measure in columns (5) to (8), the coefficient ranges from −0.037 to −0.040. Averaging the latter estimates across columns, a one-year increase in

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table V
Business Combination Laws and Mortality

This table shows hazard coefficients estimated from a Cox (1972) proportional hazards model. The dependent variable is an indicator that equals 1 if the CEO dies in a given year. The main independent variables are a binary indicator of BC law exposure, $I(BC)$, in the left four columns and a count variable of years of exposure, BC, in the right four columns. All variables are defined in Section I of the Internet Appendix. Standard errors, clustered at the state-of-incorporation level, are shown in brackets. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(*BC*)	−0.234***	−0.229***	−0.208**	−0.198**				
	[0.086]	[0.083]	[0.085]	[0.081]				
BC					−0.040***	−0.039***	−0.038***	−0.037***
					[0.006]	[0.006]	[0.008]	[0.008]
I(*FirstGen*)	−0.035	−0.101**	−0.036	−0.109**				
	[0.048]	[0.047]	[0.042]	[0.043]				
FirstGen					−0.016	−0.024*	−0.012	−0.020*
					[0.014]	[0.014]	[0.011]	[0.011]
Age	0.111***	0.112***	0.111***	0.112***	0.108***	0.108***	0.109***	0.109***
	[0.004]	[0.004]	[0.005]	[0.005]	[0.004]	[0.004]	[0.005]	[0.005]
ln(*Pay*)			0.001	0.001			−0.009	−0.008
			[0.035]	[0.035]			[0.040]	[0.040]
ln(*Assets*)			−0.030	−0.040			−0.007	−0.015
			[0.035]	[0.035]			[0.032]	[0.032]
ln(*Employees*)			0.004	0.008			−0.013	−0.012
			[0.032]	[0.032]			[0.033]	[0.034]
Year	−0.001		−0.001		−0.003		−0.002	
	[0.005]		[0.005]		[0.006]		[0.006]	
FF49 Strata	Y	Y	Y	Y	Y	Y	Y	Y
Location FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE		Y		Y		Y		Y
No. of CEOs	1,605	1,605	1,553	1,553	1,605	1,605	1,553	1,553
Observations	50,530	50,530	49,052	49,052	50,530	50,530	49,052	49,052

exposure to more lenient governance is estimated to reduce a CEO's mortality risk by 3.8%. For a CEO with typical BC law exposure, both BC exposure measures imply very similar effects on longevity.[24]

The estimated effects of control variables on mortality rates mirror those in Table IV, with the linear time control being insignificant and age strongly predicting mortality rates. The coefficients on the first-generation antitakeover controls are negative throughout, pointing to health benefits also arising also from first-generation law protection. These estimates are not reliably significant, however, and their magnitudes fluctuate across specifications.

Economic Significance. The estimates pertaining to the BC exposure variables imply meaningful effect sizes. First, we again use the "in-sample" comparison to other CEOs. Based on the average hazard coefficient estimates from the specifications with the BC indicator variable (−0.217 for BC exposure and

[24] The cumulative measure estimates a 16% shift in mortality hazard associated with the median BC exposure of 4.41 years, close to the 18% to 21% shift estimated with the BC indicator.

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

0.112 for age), the effect of BC law protection on mortality is equivalent to being about two years younger. This effect size is of a similar order of magnitude as the 1.1-year increase estimated for exposure to industry distress. The somewhat larger mortality effect, compared to the industry shock experience, might reflect the more permanent nature of the BC law experience.

Second, we again use the general U.S. population life tables to assess the magnitude of the estimate. Here, the median exposure to lenient governance of 4.41 years pushes the 1.337% mortality rate of males born in 1927 down to 1.128%, which is roughly the mortality rate of males born in 1927 at age 54.5, that is, when 2.5 years younger.

As with the industry distress analysis, we also collect data on the causes of death. We are able to locate information for 450 of the pre-BC law CEOs, which accounts for about 35% of passed CEOs in the pre-BC-law sample. The data do not allow us to detect a specific cause of death as the driver of the relationship between BC laws and lifespan, although the frequency of strokes is somewhat higher in the high-job-demands (i.e., non-BC) subsample, as in the industry distress analysis.

Overall, we find variation in job demands based on antitakeover laws to be associated with substantial mortality effect sizes.

D. Robustness Tests

Our results are robust to a series of additional tests, some analogous to the robustness checks of the distress–longevity relation in Section III.D, and some specific to the use of antitakeover laws as a source of identifying variation. We provide a brief overview of the tests here; we present a detailed discussion of the tests in Section IV of the Internet Appendix.

Other Specifications and Sample Choices. We first test and confirm that our results are robust to using birth-year fixed effects, using the same specification as in columns (3) and (6) in the industry distress regressions in Table IV (Internet Appendix Table IA.XVI). Mirroring the robustness test in Section III.D, the results also hold with age-by-birth-cohort controls (Internet Appendix Table IA.XVII).

Next, as in Section III.D, our results are robust to different censoring date choices (Internet Appendix Figure IA.10).

Finally, while it is standard in the BC law literature to assign location fixed effects based on firms' headquarters (Gormley and Matsa (2016)), the results are robust to using state-of-incorporation fixed effects (Internet Appendix Table IA.XVIII). The stability of the estimates suggests that firm locations do not affect the relationship between governance and longevity. Alternatively, the results are robust to keeping state of headquarters fixed effects but dropping CEOs who stepped down significantly before the passage of the BC laws (Internet Appendix Figure IA.11), which further ameliorates concerns specific to the BC law results around differences between BC-protected and nonprotected CEOs.

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Other Antitakeover Laws. The results are also robust to using the first-time enactment of any of the five second-generation antitakeover laws as a source of identifying variation (Internet Appendix Table IA.XIX). This test highlights that our results should be interpreted more broadly, applying to different corporate governance mechanisms rather than narrowly to BC laws.

Karpoff-Wittry and Related Tests. All results are robust to the extensive robustness checks proposed in Karpoff and Wittry (2018). We account for firms lobbying for the passage of BC laws or opting-out, as well as confounding effects of firm-level defenses, and further restrictions based on the first-generation antitakeover laws (Internet Appendix Tables IA.XX and IA.XXI). Additionally, the results are robust to data cuts based on state of incorporation and industry affiliation (Internet Appendix Table IA.XXII).

Nonlinear Exposure Effects and Predicted Length of Exposure. The final two robustness checks address concerns that the cumulative BC specification in equation (5) picks up CEOs' endogenous selection into a long tenure. We note that this concern does not apply to the indicator strategy, and thus does not threaten our main findings in Table V; it only relates to the magnitude of the per-year estimates in columns (5) to (8).

We first address this concern by separately examining the mortality effects of initial years and incremental years of BC law exposure. Columns (1) and (2) in Internet Appendix Table IA.XXIII reestimate columns (5) and (6) of Table V, but with $BC_{i,t}$ split into below- and above-median exposure, $BC_{i,t}^{(\text{min-}p50)}$ and $BC_{i,t}^{(p51\text{-max})}$. Here, the below-median exposure variable counts exposure years up to the sample median (conditional on exposure) of 4.41 years, and the above-median exposure variable records incremental exposure.[25] In both columns, the hazard coefficient on below-median BC exposure is strongly significant. By contrast, the coefficient on above-median BC exposure is close to zero and insignificant. These results imply that the estimated survival gains are driven by the initial years of reduced monitoring, rather than by the tails of long-tenured CEOs.

Second, we estimate a hazard model using a CEO's predicted rather than true length of BC exposure. The prediction model only uses information from prior to the BC law passage to predict CEOs' remaining tenure over time, from which predicted BC exposure is derived; see Section IV of the Internet Appendix for full details. The results are reported in columns (3) and (4) of Internet Appendix Table IA.XXIII. The hazard coefficient estimates of -0.042 in both columns are very similar to those in Table V, while the standard errors, now bootstrapped (since we use a generated regressor), are larger.[26]

[25] For example, for a CEO with a current BC exposure of four years, $BC_{i,t}^{(\text{min-}p50)}$ would take the value of 4 and $BC_{i,t}^{(p51\text{-max})}$ the value of 0. In the following year $(t+1)$, $BC_{i,t+1}^{(\text{min-}p50)}$ would be set to 4.41 and $BC_{i,t+1}^{(p51\text{-max})}$ to 0.59. In year $t+2$, $BC_{i,t+2}^{(\text{min-}p50)}$ would remain at 4.41, and $BC_{i,t+2}^{(p51\text{-max})}$ would increase to 1.59.

[26] A regression of true BC exposure on predicted exposure yields a coefficient of 1.215, which indicates that the prediction well approximates the true exposure. The estimated effects remain sizable if we divide them by 1.215, amounting to $-0.042/1.215 = -0.035$.

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

In Section IV of the Internet Appendix, we also analyze how tenure responds to antitakeover laws. We find evidence of increases in tenure under BC laws, consistent with the laws affecting managers' perceptions of job demands.

E. Business Combination Laws and CEO Pay

The permanent corporate governance regime changes induced by BC laws also lend themselves to studying the extent to which managers account for the health implications of their jobs, for example, in negotiating pay. We conduct a simple calibration exercise that builds on the literature on the value of a statistical life (Viscusi and Aldy (2003)). (See Section IV of the Internet Appendix for details.) We estimate that, if CEO pay reflects working conditions, then a reduction in mortality risk of 4.0% per year of BC exposure (as estimated in column (5) of Table V) would imply a change in CEO pay between −2.5% and −10%.[27] By contrast, when we turn from the theoretical calibration to the empirical relationship between BC law protection and pay, we estimate a positive albeit statistically insignificant effect of BC law passage on pay (Internet Appendix Table IA.XXIV). The estimates indicate a pay increase of around 4.5% to 7.6%.[28] The apparent lack of a compensating differential casts doubt on whether all parties fully account for the health implications of different governance regimes.

V. Conclusion

In this paper, we assess the health consequences of being exposed to increased job demands and a more stressful work environment while in a high-profile CEO position. We analyze the consequences for CEOs' aging and mortality using two sources of variation in job demands, namely, industry-wide distress shocks and the staggered introduction of antitakeover laws.

We first show that industry distress is reflected in short- to medium-term signs of adverse health consequences—faster visible aging. To the best of our knowledge, we are the first to collect and use panel data of facial images and apply ML-based apparent-age estimation software in social science research. Implementing a difference-in-differences design that exploits variation in industry distress during the Great Recession, we estimate that CEOs who experienced industry distress during the 2007 to 2008 financial crisis look roughly one year older than those whose industry did not suffer the same level of distress. The effect of distress on aging becomes slightly larger over time, increasing to 1.18 years if we analyze images from 2012 and afterward.

Using an earlier CEO sample, we next document more long-term adverse health outcomes associated with strenuous job demands. CEOs who

[27] We thank Xavier Gabaix for suggesting this calibration exercise.

[28] In comparing the results to the earlier work (Bertrand and Mullainathan (1998)), who estimate a (more significant) 5.4% pay increase, it is important to note that our analysis is conducted on our CEO Mortality Data Set, a CEO-level sample, and restricts the sample to incumbent pre-BC CEOs.

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

experienced periods of industry-wide distress during their tenure die significantly earlier. We estimate a mortality effect corresponding to that of a 1.1-year increase in chronological age. In line with these results, we observe significant improvements in life expectancy for CEOs who became shielded by an antitakeover law during their tenure.

In sum, our results indicate that financial distress and stricter corporate governance regimes—the latter of which are generally viewed as desirable and welfare-improving—impose significant personal health costs on CEOs. Although we lack direct physical or medical measures of heightened stress, the evidence implies a substantial personal cost for CEOs in terms of their health and life expectancy. As such, our findings also contribute to the literature on the trade-offs between managerial incentives and private benefits arising from the separation of ownership and control. We document and quantify a previously unnoticed yet important cost—personal health cost—associated with serving under strict corporate governance.

Our findings suggest further avenues of investigation. One open question is whether managers fully account for these personal health costs as they progress in their careers, and how these costs affect selection into service as a CEO. Are some high-ability candidates for a Forbes-level CEO career more aware of these consequences than others and select out? Alternatively, candidates might differ in their preferences, with some embracing the "wild ride" of a CEO career and others aiming for a healthier and more balanced life.

Another important question is which jobs and hierarchy levels come with the largest adverse health consequences. For the reasons discussed in the introduction, the highest tier of management is important to study because of their impact on firm outcomes and the identification opportunities it offers. But managers just one tier below might be more affected by work-related stressors, and workers at the bottom might suffer the most, also in light of looming financial hardships. Going beyond the realm of corporations, we might hypothesize that minimum wage and temporary workers with rigid schedules, such as delivery drivers, suffer even more. Or, it could be the case that people in "life-or-death" jobs, such as emergency room doctors and airline pilots, have more adverse health consequences. In all cases, it would be important to understand the health consequences and explore whether any dimension of compensation responds to these job demands.

Finally, another promising avenue is the more fine-grained identification of stressors. Which aspects of individual job situations and which decisions tend to have the largest adverse health consequences, for either management or regular employees? In the context of CEOs, our results on the mortality-improving effects of takeover protection point to a role for shareholder scrutiny and disciplining mechanisms. Our results on accelerated aging and mortality in response to industry distress suggest that recession-triggered "tough" decisions such as downsizings and layoffs may also be particularly relevant.[29]

[29] We also explore whether the adverse health outcomes in response to industry-wide equity-value declines vary with CEO compensation structures. We find no evidence that the mortality or

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Consistent with a mechanism related to layoffs, Guenzel, Hamilton, and Malmendier (2025) find evidence of a personal cost for CEOs associated with firing employees. Furthermore, heightened workplace stress can also adversely affect other aspects of life, including marriage, divorce, and parenting. We leave these topics for future research.

Initial submission: March 17, 2022; Accepted: September 26, 2023
Editors: Stefan Nagel, Philip Bond, Amit Seru, and Wei Xiong

REFERENCES

Abadie, Alberto, Susan Athey, Guido W. Imbens, and Jeffrey Wooldridge, 2017, When should you adjust standard errors for clustering? NBER Working Paper No. 24003.

Acharya, Viral V., Sreedhar T. Bharath, and Anand Srinivasan, 2007, Does industry-wide distress affect defaulted firms? Evidence from creditor recoveries, *Journal of Financial Economics* 85, 787–821.

Agüera y Arcas, Blaise, Alexander Todorov, and Margaret Mitchell, 2018, Do algorithms reveal sexual orientation or just expose our stereotypes? *Medium*, January 11.

Aizer, Anna, Laura Stroud, and Stephen Buka, 2016, Maternal stress and child outcomes: Evidence from siblings, *Journal of Human Resources* 51, 523–555.

Anderson, Michael, and Michael Marmot, 2012, The effects of promotions on heart disease: Evidence from Whitehall, *Economic Journal* 122, 555–589.

Antipov, Grigory, Moez Baccouche, Sid-Ahmed Berrani, and Jean-Luc Dugelay, 2016, Apparent age estimation from face images combining general and children-specialized deep learning models, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 96–104.

Atanassov, Julian, 2013, Do hostile takeovers stifle innovation? Evidence from antitakeover legislation and corporate patenting, *Journal of Finance* 68, 1097–1131.

Averett, Susan, and Sanders Korenman, 1996, The economic reality of the beauty myth, *Journal of Human Resources* 31, 304–330.

Babina, Tania, 2020, Destructive creation at work: How financial distress spurs entrepreneurship, *Review of Financial Studies* 33, 4061–4101.

Bandiera, Oriana, Renata Lemos, Andrea Prat, and Raffaella Sadun, 2018, Managing the family firm: Evidence from CEOs at work, *Review of Financial Studies* 31, 1605–1653.

Bandiera, Oriana, Andrea Prat, Stephen Hansen, and Raffaella Sadun, 2020, CEO behavior and firm performance, *Journal of Political Economy* 128, 1325–1369.

Bennedsen, Morten, Francisco Perez-Gonzalez, and Daniel Wolfenzon, 2020, Do CEOs matter? Evidence from hospitalization events, *Journal of Finance* 75, 1877–1911.

Bertrand, Marianne, 2004, From the invisible handshake to the invisible hand? How import competition changes the employment relationship, *Journal of Labor Economics* 22, 723–765.

Bertrand, Marianne, and Sendhil Mullainathan, 1998, Corporate governance and executive pay: Evidence from takeover legislation, NBER Working Paper No. 6830.

Bertrand, Marianne, and Sendhil Mullainathan, 2001, Are CEOs rewarded for luck? The ones without principals are, *Quarterly Journal of Economics* 116, 901–932.

Bertrand, Marianne, and Sendhil Mullainathan, 2003, Enjoying the quiet life? Corporate governance and managerial preferences, *Journal of Political Economy* 111, 1043–1075.

Black, Sandra E., Paul J. Devereux, and Kjell G. Salvanes, 2016, Does grief transfer across generations? Bereavements during pregnancy and child outcomes, *American Economic Journal: Applied Economics* 8, 193–223.

aging results differ by the degree of a CEO's cash compensation or salary relative to performance-contingent pay, which speaks against a channel related to changes in material well-being induced by distress shocks as an important driver of our findings.

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Borgschulte, Mark, and Jacob Vogler, 2019, Run for your life? The effect of close elections on the life expectancy of politicians, *Journal of Economic Behavior & Organization* 167, 18–32.
Borkan, Gary A., and Arthur H. Norris, 1980, Assessment of biological age using a profile of physical parameters, *Journal of Gerontology* 35, 177–184.
Boyce, Christopher J., and Andrew J. Oswald, 2012, Do people become healthier after being promoted? *Health Economics* 21, 580–596.
Breiman, Leo, 1996, Bagging predictors, *Machine Learning* 24, 123–140.
Brondolo, Elizabeth, Kahaema Byer, Peter J. Gianaros, Cindy Liu, Aric A. Prather, Kamala Thomas, Cheryl L. Woods-Giscombé, Lula A. Beatty, Patricia DiSandro, and Gwendolyn Puryear Keita, 2017, Stress and health disparities: Contexts, mechanisms, and interventions among racial/ethnic minority and low socioeconomic status populations, Working group report, American Psychological Association (APA).
Cain, Matthew D., Stephen B. McKeon and Steven Davidoff Solomon, 2017, Do takeover laws matter? Evidence from five decades of hostile takeovers, *Journal of Financial Economics* 124, 464–485.
Camacho, Adriana, 2008, Stress and birth weight: Evidence from terrorist attacks, *American Economic Review* 98, 511–515.
Cesarini, David, Erik Lindqvist, Robert Östling, and Björn Wallace, 2016, Wealth, health, and child development: Evidence from administrative data on Swedish lottery players, *Quarterly Journal of Economics* 131, 687–738.
Cheng, Shijun, Venky Nagar, and Madhav V. Rajan, 2004, Identifying control motives in managerial ownership: Evidence from antitakeover legislation, *Review of Financial Studies* 18, 637–672.
Chetty, Raj, Michael Stepner, Sarah Abraham, Shelby Lin, Benjamin Scuderi, Nicholas Turner, Augustin Bergeron, and David Cutler, 2016, The association between income and life expectancy in the United States, 2001-2014, *JAMA* 315, 1750–1766.
Choi, Sekyu, Bing Zhang, Sai Ma, Meryem Gonzalez-Celeiro, Daniel Stein, Xin Jin, Seung Tea Kim, Yuan-Lin Kang, Antoine Besnard, Amelie Rezza, Laura Grisanti, Jason D. Buenrostro, Michael Rendl, Matthias Nahrendorf, Amar Sahay, and Ya-Chieh Hsu, 2021, Corticosterone inhibits GAS6 to govern hair follicle stem-cell quiescence, *Nature* 592, 428–432.
Christensen, Kaare, Maria Iachina, Helle Rexbye, Cecilia Tomassini, Henrik Frederiksen, Matt McGue, and James W. Vaupel, 2004, "Looking old for your age": Genetics and mortality, *Epidemiology* 15, 251–252.
Christensen, Kaare, Mikael Thinggaard, Matt McGue, Helle Rexbye, Jacob v. B. Hjelmborg, Abraham Aviv, David Gunn, Frans van der Ouderaa, and James W. Vaupel, 2009, Perceived age as clinically useful biomarker of ageing: Cohort study, *BMJ* 339, b5262. https://doi.org/10.1136/bmj.b5262.
Cohen, Sheldon, Denise Janicki-Deverts, and Gregory E. Miller, 2007, Psychological stress and disease, *JAMA* 298, 1685–1687.
Coile, Courtney C., Phillip B. Levine, and Robin McKnight, 2014, Recessions, older workers, and longevity: How long are recessions good for your health? *American Economic Journal: Economic Policy* 6, 92–119.
Cox, David R., 1972, Regression models and life tables, *Journal of the Royal Statistical Society: Series B* 34, 187–202.
Currie, Janet, and Maya Rossin-Slater, 2015, Early-life origins of life-cycle well-being: Research and policy implications, *Journal of Policy Analysis and Management* 34, 208–242.
Cutler, David, Angus Deaton, and Adriana Lleras-Muney, 2006, The determinants of mortality, *Journal of Economic Perspectives* 20, 97–120.
Dotsch, Ron, Ran R. Hassin, and Alexander Todorov, 2016, Statistical learning shapes face evaluation, *Nature Human Behaviour* 1, 1–6.
Dykiert, Dominika, Timothy C. Bates, Alan J. Gow, Lars Penke, John M. Starr, and Ian J. Deary, 2012, Predicting mortality from human faces, *Psychosomatic Medicine* 74, 560–566.
East, Chloe N., Sarah Miller, Marianne Page, and Laura R. Wherry, 2017, Multi-generational impacts of childhood access to the safety net: Early life exposure to medicaid and the next generation's health, NBER Working Paper No. 23810.

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Easterbrook, Frank H., and Daniel R. Fischel, 1981, The proper role of a target's management in responding to a tender offer, *Harvard Law Review* 94, 1161–1204.

Edmans, Alex, and Xavier Gabaix, 2011, The effect of risk on the CEO market, *Review of Financial Studies* 24, 2822–2863.

Eisfeldt, Andrea L., and Camelia M. Kuhnen, 2013, CEO turnover in a competitive assignment framework, *Journal of Financial Economics* 109, 351–372.

Engelberg, Joseph, and Christopher A. Parsons, 2016, Worrying about the stock market: Evidence from hospital admissions, *Journal of Finance* 71, 1227–1250.

Epel, Elissa S., Elizabeth H. Blackburn, Jue Lin, Firdaus S. Dhabhar, Nancy E. Adler, Jason D. Morrow, and Richard M. Cawthon, 2004, Accelerated telomere shortening in response to life stress, *Proceedings of the National Academy of Sciences of the United States of America* 101, 17312–17315.

Evans, William N., and Craig L. Garthwaite, 2014, Giving mom a break: The impact of higher EITC payments on maternal health, *American Economic Journal: Economic Policy* 6, 258–290.

Fama, Eugene F., and Kenneth R. French, 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153–193.

Föhr, Tiina, Katja Waller, Anne Viljanen, Riikka Sanchez, Miina Ollikainen, Taina Rantanen, Jaakko Kaprio, and Elina Sillanpää, 2021, Does the epigenetic clock grimage predict mortality independent of genetic influences: An 18-year follow-up study in older female twin pairs, *Clinical Epigenetics* 13, 1–9.

Franceschi, Claudio, Paolo Garagnani, Paolo Parini, Cristina Giuliani, and Aurelia Santoro, 2018, Inflammaging: A new immune–metabolic viewpoint for age-related diseases, *Nature Reviews Endocrinology* 14, 576–590.

Ganster, Daniel C., and Christopher C. Rosen, 2013, Work stress and employee health: A multidisciplinary review, *Journal of Management* 39, 1085–1122.

Garvey, Gerald T., and Todd T. Milbourn, 2006, Asymmetric benchmarking in compensation: Executives are rewarded for good luck but not penalized for bad, *Journal of Financial Economics* 82, 197–225.

Gibbons, Robert, and Kevin J. Murphy, 1992, Optimal incentive contracts in the presence of career concerns: Theory and evidence, *Journal of Political Economy* 100, 468–505.

Giroud, Xavier, and Holger M. Mueller, 2010, Does corporate governance matter in competitive industries? *Journal of Financial Economics* 95, 312–331.

Gompertz, Benjamin, 1825, On the nature of the function expressive of the law of human mortality, and on a new mode of determining the value of life contingencies, *Philosophical Transactions of the Royal Society of London* 115, 513–583.

Gormley, Todd A., and David A. Matsa, 2016, Playing it safe? Managerial preferences, risk, and agency conflicts, *Journal of Financial Economics* 122, 431–455.

Guenzel, Marius, Clint Hamilton, and Ulrike Malmendier, 2025, Prosociality and layoffs, Working paper, University of Pennsylvania, University of California, Berkeley.

Gunn, David Andrew, Lisbeth Aagaard Larsen, Jaspal Singh Lall, Helle Rexbye, and Kaare Christensen, 2016, Mortality is written on the face, *Journals of Gerontology Series A: Biomedical Sciences and Medical Sciences* 71, 72–77.

Hamermesh, Daniel S., and Jeff E. Biddle, 1994, Beauty and the labor market, *American Economic Review* 84, 1174–1194.

Harvanek, Zachary M., Nia Fogelman, Ke Xu, and Rajita Sinha, 2021, Psychological and biological resilience modulates the effects of stress on epigenetic aging, *Translational Psychiatry* 11, 601.

Heidt, Timo, Hendrik B. Sager, Gabriel Courties, Partha Dutta, Yoshiko Iwamoto, Alex Zaltsman, Constantin von Zur Muhlen, Christoph Bode, Gregory L. Fricchione, John Denninger, Charles P. Lin, Claudio Vinegoni, Peter Libby, Filip K. Swirski, Ralph Weissleder, and Matthias Nahrendorf, 2014, Chronic variable stress activates hematopoietic stem cells, *Nature Medicine* 20, 754.

Human Mortality Database, 2019, USA, 1x1 cohort mortality rates, University of California, Berkeley (USA) and Max Planck Institute for Demographic Research (Germany).

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Hummels, David, Jakob Munch, and Chong Xiang, 2016, No pain, no gain: The effects of exports on effort, injury, and illness, NBER Working Paper No. 22365.

Hwang, Stephen W., Mina Atia, Rosane Nisenbaum, Dwayne E. Pare, and Steve Joordens, 2011, Is looking older than one's actual age a sign of poor health? *Journal of General Internal Medicine* 26, 136–141.

Jenter, Dirk, and Fadi Kanaan, 2015, CEO turnover and relative performance evaluation, *Journal of Finance* 70, 2155–2184.

Jenter, Dirk, and Katharina Lewellen, 2015, CEO preferences and acquisitions, *Journal of Finance* 70, 2813–2852.

Jha, Prabhat, Chinthanie Ramasundarahettige, Victoria Landsman, Brian Rostron, Michael Thun, Robert N. Anderson, Tim McAfee, and Richard Peto, 2013, 21st-century hazards of smoking and benefits of cessation in the United States, *New England Journal of Medicine* 368, 341–350.

Johnston, David W., and Wang-Sheng Lee, 2013, Extra status and extra stress: Are promotions good for us? *ILR Review* 66, 32–54.

Kaplan, Greg, and Sam Schulhofer-Wohl, 2018, The changing (dis-)utility of work, *Journal of Economic Perspectives* 32, 239–258.

Karpoff, Jonathan M., and Michael D. Wittry, 2018, Institutional and legal context in natural experiments: The case of state antitakeover laws, *Journal of Finance* 73, 657–714.

Keloharju, Matti, Samuli Knüpfer, and Joacim Tåg, 2023, CEO health, *Leadership Quarterly* 34, 101672.

Kennedy, Brian K., Shelley L. Berger, Anne Brunet, Judith Campisi, Ana Maria Cuervo, Elissa S. Epel, Claudio Franceschi, Gordon J. Lithgow, Richard I. Morimoto, Jeffrey E. Pessin, Thomas A. Rando, Arlan Richardson, Eric E. Schadt, Tony Wyss-Coray, and Felipe Sierra, 2014, Geroscience: Linking aging to chronic disease, *Cell* 159, 709–713.

Kim, So Ra, Yu Ri Jung, Hye Jin An, Dae Hyun Kim, Eun Ji Jang, Yeon Ja Choi, Kyoung Mi Moon, Min Hi Park, Chan Hum Park, Ki Wung Chung, Ha Ram Bae, Yung Whan Choi, Nam Deuk Kim, and Hae Young Chung, 2013, Anti-wrinkle and anti-inflammatory effects of active garlic components and the inhibition of mmps via NF- κ B signaling, *PloS One* 8, e73877.

Koijen, Ralph S. J., and Stijn Van Nieuwerburgh, 2020, Combining life and health insurance, *Quarterly Journal of Economics* 135, 913–958.

Krueger, Alan B., and Andreas I. Mueller, 2012, Time use, emotional well-being, and unemployment: Evidence from longitudinal data, *American Economic Review* 102, 594–599.

Kuka, Elira, 2020, Quantifying the benefits of social insurance: Unemployment insurance and health, *Review of Economics and Statistics* 102, 490–505.

Lavetti, Kurt, 2020, The estimation of compensating wage differentials: Lessons from the deadliest catch, *Journal of Business & Economic Statistics* 38, 165–182.

Lazarus, Richard S., and Susan Folkman, 1984, *Stress, Appraisal, and Coping* (Springer Publishing Company, New York, NY).

Loh, Eng Seng, 1993, The economic effects of physical appearance, *Social Science Quarterly* 74, 420–438.

Marmot, Michael, 2005, *Status Syndrome: How Your Social Standing Directly Affects Your Health* (A&C Black, London).

Marmot, Michael G., Stephen Stansfeld, Chandra Patel, Fiona North, Jenny Head, Ian White, Eric Brunner, Amanda Feeney, and G Davey Smith, 1991, Health inequalities among British Civil servants: The Whitehall II Study, *Lancet* 337, 1387–1393.

Mas, Alexandre, and Amanda Pallais, 2017, Valuing alternative work arrangements, *American Economic Review* 107, 3722–3759.

McEwen, Bruce S., 1998, Protective and damaging effects of stress mediators, *New England Journal of Medicine* 338, 171–179.

Milligan, Kevin, and Mark Stabile, 2011, Do child tax benefits affect the well-being of children? Evidence from Canadian child benefit expansions, *American Economic Journal: Economic Policy* 3, 175–205.

Nicholas, Tom, 2023, Status and mortality: Is there a Whitehall Effect in the United States? *Economic History Review* 76, 1191–1230.

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Nielsen, Naja Rod, Tage S. Kristensen, Peter Schnohr, and Morten Grønbæk, 2008, Perceived stress and cause-specific mortality among men and women: Results from a prospective cohort study, *American Journal of Epidemiology* 168, 481–491.

Olshansky, S. Jay, and Bruce A. Carnes, 1997, Ever since Gompertz, *Demography* 34, 1–15.

Opler, Tim C., and Sheridan Titman, 1994, Financial distress and corporate performance, *Journal of Finance* 49, 1015–1040.

Persico, Nicola, Andrew Postlewaite, and Dan Silverman, 2004, The effect of adolescent experience on labor market outcomes: The case of height, *Journal of Political Economy* 112, 1019–1053.

Persson, Petra, and Maya Rossin-Slater, 2018, Family ruptures, stress, and the mental health of the next generation, *American Economic Review* 108, 1214–1252.

Pickett, Kate E., and Richard G. Wilkinson, 2015, Income inequality and health: A causal review, *Social Science & Medicine* 128, 316–326.

Porter, Michael E., and Nitin Nohria, 2018, How CEOs manage time, *Harvard Business Review* 96, 42–51.

Puterman, Eli, Alison Gemmill, Deborah Karasek, David Weir, Nancy E. Adler, Aric A. Prather, and Elissa S. Epel, 2016, Lifespan adversity and later adulthood telomere length in the nationally representative U.S. health and retirement study, *Proceedings of the National Academy of Sciences* 113, E6335–E6342.

Rablen, Matthew D., and Andrew J. Oswald, 2008, Mortality and immortality: The Nobel prize as an experiment into the effect of status upon longevity, *Journal of Health Economics* 27, 1462–1471.

Ruhm, Christopher J., 2000, Are recessions good for your health? *Quarterly Journal of Economics* 115, 617–650.

Rutters, Femke, Stefan Pilz, Anitra D. Koopman, Simone P. Rauh, Saskia J. Te Velde, Coen D. Stehouwer, Petra J. Elders, Giel Nijpels, and Jacqueline M. Dekker, 2014, The association between psychosocial stress and mortality is mediated by lifestyle and chronic diseases: The Hoorn Study, *Social Science & Medicine* 118, 166–172.

Sapolsky, Robert M., 2005, The influence of social hierarchy on primate health, *Science* 308, 648–652.

Scharfstein, David, 1988, The disciplinary role of takeovers, *Review of Economic Studies* 55, 185–199.

Sidhpura, Jiten, Rudresh Veerkhare, Parshwa Shah, and Surekha Dholay, 2022, *Face to BMI: A deep learning based approach for computing BMI from face, 2022 International Conference on Innovative Trends in Information Technology (ICITIIT)*, IEEE, pp. 328–336.

Snyder-Mackler, Noah, Joseph Robert Burger, Lauren Gaydosh, Daniel W. Belsky, Grace A. Noppert, Fernando A. Campos, Alessandro Bartolomucci, Yang Claire Yang, Allison E. Aiello, Angela O'Rand, Kathleen Mullan Harris, Carol A. Shively, Susan C. Alberts, and Jenny Tung, 2020, Social determinants of health and survival in humans and other animals, *Science* 368, eaax9553.

Steckel, Richard H.,1995, Stature and the standard of living, *Journal of Economic Literature* 33, 1903–1940.

Sullivan, Daniel, and Till Von Wachter, 2009, Job displacement and mortality: An analysis using administrative data, *Quarterly Journal of Economics* 124, 1265–1306.

U.S. Department of Health and Human Services, 2014, The health consequences of smoking: 50 years of progress. A report of the Surgeon General. U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, National Center for Chronic Disease Prevention and Health Promotion.

van der Valk, Eline S., Mesut Savas, and Elisabeth F. C. van Rossum, 2018, Stress and obesity: Are there more susceptible individuals? *Current Obesity Reports* 7, 193–203.

Viscusi, W. Kip, and Joseph E. Aldy, 2003, The value of a statistical life: A critical review of market estimates throughout the world, *Journal of Risk and Uncertainty* 27, 5–76.

Wang, Yilun, and Michal Kosinski, 2018, Deep neural networks are more accurate than humans at detecting sexual orientation from facial images, *Journal of Personality and Social Psychology* 114, 246.

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Yen, Gili, and Lee Benham, 1986, The best of all monopoly profits is a quiet life, *Journal of Health Economics* 5, 347–353.

Zhang, Bing, Sai Ma, Inbal Rachmin, Megan He, Pankaj Baral, Sekyu Choi, William A. Goncalves, Yulia Shwartz, Eva M. Fast, Yiqun Su, Leonard I. Zon, Aviv Regev, Jason D. Buenrostro, Thiago M. Cunha, Isaac M. Chiu, David E. Fisher, and Ya-Chieh Hsu, 2020, Hyperactivation of sympathetic nerves drives depletion of delanocyte stem cells, *Nature* 577, 676–681.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.

15406261, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.13497 by University Of Pennsylvania, Wiley Online Library on [08/09/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License