Title: The tension between worker safety and organization survival

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Abstract: This research addresses the fundamental question of whether providing a safe workplace improves or hinders organizational survival, because there are conflicting predictions on the relationship between worker safety and organizational performance. The results, based on a unique longitudinal database covering over 100,000 organizations across 25 years in the U.S. state of Oregon, indicate that in general organizations that provide a safe workplace have significantly ***lower*** odds and length of survival. Additionally, the organizations that would in general have better survival odds, benefit most from not providing a safe workplace. This suggests that relying on the market does not engender workplace safety.

Introduction

The pursuit of profit can lead to job creation, innovation, and enhanced prosperity. But when organizations cannot or will not provide a safe workplace, there are costs to workers and society. This research exploits unique longitudinal data to address a fundamental question: Does providing a safe workplace improve or hinder organizational survival?

We address this question because there are conflicting predictions on the relationship between worker safety and organizational performance, making it difficult to provide coherent policy recommendations or create effective safety regulation. Safety regulation and policy are intended to prevent harm at work. But the implications for regulation and policy if it is profitable to provide a safe workplace are very different than if it is more profitable not to provide a safe workplace.

Managerial research posits that improving worker safety and wellbeing will improve profits (e.g. Pagell et al., 2015; Gubler et al., 2018). The argument that a safer workplace will increase profits is as follows. Building and leveraging human capital to develop unique capabilities is a key enabler for creating long-term competitive advantage (e.g. Becker 1993; Hatch and Dyer, 2004). When the work environment is not safe, human capital is being harmed, not built. Workers in unsafe environments engage in self-protection and are not motivated to improve the organization's operations (Das et al., 2008). However, workers in safe environments do not have to dedicate resources to self-protection and can be motivated to engage in improving the organization's operations; safety provides a necessary condition to leverage human capital into the development of unique capabilities and long-term competitive advantage (Das et al., 2008). Organizations that harm their human capital cannot build these capabilities and will be less likely to survive. This suggests that market mechanisms alone should eliminate poor safety.

However, classical economics suggest that safety regulation exists because organizations would not provide a safe workplace on their own volition. The supposition that regulation that provides a communal good (in this case a safe workforce) is burdensome or costly for employers is often referred to as the 'costly regulation hypothesis' (Palmer et al., 1995; Levine et al., 2012).

The literature on occupational safety is generally in line with the costly regulation hypothesis, with some safety researchers positing that organizations make trade-offs between being safe and being productive (e.g. Das et al., 2008; Zohar, 2008). The safety literature notes that a key way to increase productivity is by producing more output from the same workers. As the pace of work increases and buffers or slack decrease, productivity increases, but so does the likelihood of accidents and other harm to workers (Diwas and Terwiesch, 2009; Kuntz et al., 2015; Wiengarten et al., 2017).

From this perspective, organizations that do not provide a safe workplace gain an economic advantage by avoiding burdensome costs and being more productive, which may explain why even proponents of “it pays to be safe” provide evidence that numerous organizations are not safe (Pagell et al., 2015). Similarly, many organizations have accidents and harm their workers without being sanctioned by regulators (BLS, 2019b). And, organizations that do get inspected could conclude that the fines for non-compliance are miniscule (Bradbury, 2006). If there are incentives for organizations to ignore safety, then market mechanisms alone will not eliminate poor safety.

The veracity of the costly regulation hypothesis has been the subject of much debate and empirical study in economics since Porter and van der Linde (1995) controversially claimed that well designed environmental regulations increase innovation, offsetting the costs of regulation and increasing profitability. This prediction finds limited support, but the debate continues (Rassier and Earnhart, 2015; Earnhart and Rassier, 2016). The same debate is salient to safety regulation. Levine et al. (2012) found that inspections (regulatory oversight) decrease accidents in the short-term, while not affecting organization survival. However, the research linking regulation to improved safety indicates that the impact of an inspection is short-term and that inspections do not improve safety in the long-term (Haviland et al., 2012; Tompa et al., 2016). Similarly, research also indicates that when inspections do not lead to sanctions, the likelihood of future accidents either stays the same (Tompa et al., 2016) or increases (Scholz & Gray, 1997). Finally, with a few exceptions such as Levine et al. (2012), studies of the effectiveness of safety regulation only focus on safety outcomes, not profits or survival.

Similarly, many studies in the managerial literature linking workplace safety to improved organizational performance have been hamstrung by cross-sectional analyses, small and biased samples, and poor proxies. For instance, the sample in Pagell et al. (2015) was limited to manufacturing facilities with at least 100 employees, when most organizations are much smaller and not engaged in manufacturing (BLS, 2019c). While there is compelling evidence to support the perspective of either the costly regulation hypothesis or the managerial literature concluding it pays to be safe, neither is conclusive.

We further this discussion by directly exploring organizational survival and safety outcomes across 25 years of quarterly data on all organizations in the U.S. state of Oregon. Directly exploring safety is important for two reasons. First, many organizations have accidents and harm their workers without facing regulatory sanctions (BLS, 2019b). Second, worker safety, not regulatory compliance is both the desired outcome of regulation and what leads to the development of human capital or unique capabilities (Pagell et al., 2015). Our data include the cost of all safety-related claims for each organization, as well as its entry date and how long it survived. Additionally, the data allow us to explore the role of contextual factors such as industry, and an organization's size, age, output-per-worker and growth. Our research explores these competing predictions in the context of modern regulations:

1. Providing a safe workplace increases organizational survival, in line with the managerial literature on safety.

2. Providing a safe workplace reduces organizational survival, in line with the costly regulation hypothesis.

We perform separate analyses to examine short and long-term survival because it is possible that the relationship between workplace safety and organizational survival depends on the time horizon. Short-term survival, survival in the immediate future, may be enhanced by not taking on the costs of providing a safe-workplace; for instance by decreasing costs by eliminating safety training. However, over the long-term, the same organizational conduct could increase the severity and frequency of claims and destroy rather than build human capital.

The results of both analyses are consistent with the costly regulation hypothesis. In general, organizations significantly ***decrease*** their odds and length of survival by providing a safe workplace. This effect is most pronounced for organizations that are older, larger and/or have zero to moderate levels of growth. Organizations that are young, small, and or are growing at a negative or fast rate, gain the least from having claims and are most likely to see high claims costs harm survival. These findings suggest that relying on the market to make workplaces safe is inadequate and that current regulations do not achieve their aims, because they are not sufficiently incentivizing organizations to protect their workers.

Data and Methods

Oregon has a diversified economy with a mix of natural resources, agriculture, manufacturing, services and high technology (SOS, 2019). The State's safety regulations have met or exceeded U.S. federal guideline since being approved in 1982 (OSHA, 2019b), before the beginning of our data. The Oregon Department of Consumer and Business Services (DCBS), which administers laws and rules governing workplace safety and health in Oregon, provided data on the cost of all disabling claims made in the state from 1989-2014. Disabling claims are those where a worker suffers temporary disability, defined as requiring three or more days off work, or the expectation of permanent disability[1].

DCBS also provided employment data for all organizations operating in Oregon, which originally came from the BLS' Quarterly Census of Employment and Wages (QCEW). The QCEW compiles quarterly employment and wage data for 8.9 million U.S. organizations, representing 98% of non-farm, payroll organizations (BLS, 2019c). While this data is publicly available in aggregate form, individual organizational records are not publicly available due to privacy concerns (BLS, 2019a). DCBS provided unique IDs allowing us to anonymously link the QCEW and claims data.

The population included 386,179 organizations with establishments in the state between 1989 and 2014. Two samples of organizations with over 5 employees at some point in their lifetime and sufficient data were constructed. For the short-term analysis, a sample (ST sample) of 103,906 organizations was available; for the long-term analysis, a sample (LT sample) of 122,570 organizations was available. The appendix provides additional detail on the data and the composition of each sample.

While individual worker behaviors lead to some accidents, the literature shows that the systems, climate and culture that an organization creates and maintains have a large influence on worker behaviors and the likelihood of accidents (Christian et al., 2009; Clark, 2013). Hence, we treat providing a safe workplace as an organizational responsibility. We operationalize providing a safe workplace based on an

[1] DCBS did not provide data on fatalities because these are very rare events (BLS 2019b). For instance, from 2010-2014 there were 136 fatalities in Oregon (CBS 2019a) and 93,721 disabling claims (CBS 2019b)

organization's short and long-term cost of claims history, both because cost is a good proxy for the severity of a claim (Lebeau et al., 2014) and because as costs go up either the claims are more numerous and/or more severe. A count of claims is less refined and does not capture severity. However, because the distribution of claims is highly skewed, the robustness checks also explore two alternative operationalizations of providing a safe workplace; a count of claims and the presence of claim(s) vs. no claims.

For the short-term analysis, the independent variable is short-term claims costs (STCC) and the dependent variable is risk of failure in the current quarter. For the long-term analysis the independent variable is long-term claims cost (LTCC) and the dependent variable is time-to-failure. Because there is evidence that the relationship between social and economic performance could be non-linear (e.g. Barnett and Salomon, 2006; Lioui and Sharma, 2012) we explore both the linear and non-linear relationship between claims costs and failure. Controls were growth, output-per-worker, employee turnover, industry, organization age, employment, year and quarter of entry, year and quarter of claim. The appendix provides additional detail on measurement.

STCC were captured in each quarter as a time varying covariate. Defined as the mean cost of claims per 100 workers per quarter per organization in the past two years, STCC was log transformed due to extreme positive skew. STCC was top-coded at the 99th percentile to reduce the influence of very large claims (e.g. Levine et al., 2012; Elfenbein et al., 2010). Mean STCC after top-coding was \$ 4,264 (SD= \$ 16,014), or 1.95 (SD=3.71) log STCC.

LTCC was calculated as mean claims costs per 100 workers per quarter, across the portion of an organization's lifetime in the data (between 1989 and 2014). LTCC was log transformed and top-coded in the same manner as STCC. Mean LTCC after top-coding was $4,575(SD= $13,284), or 3.16 (SD=4.13) log LTCC.

The literature on organizational survival and failure is vast but disjointed (e.g. Josefy et al., 2017). Failure or survival has been operationalized multiple ways including ongoing operations, solvency or bankruptcy, or continuity of ownership (e.g. Josefy et al., 2017). We follow the U.S. Bureau of Labor Statistics (BLS) and define survival as ongoing operations (Sadeghi, 2008) even in the face of an ownership change. Failure occurs when operations cease. This definition posits that management (as opposed to ownership), technology, and the operational workforce remain if operations continue. In addition, because the literature suggests that both characteristics of the competitive environment and the organization impact an organization's likelihood of failure (e.g. Knaup and Piazza, 2007) we address both in the analysis.

To examine the effects of STCC on risk of failure in the current quarter, organizations were dummy coded as "failed" or "ongoing" in each quarter. To examine the effects of LTCC on time-to-failure in quarters, survival was calculated as exit time minus entry time in quarters. To distinguish between organizations that failed and those that were still in operation in the last quarter of the data, organizations were dummy coded as "failed" or "ongoing" at the last time point of the QCEW dataset (2014 quarter 4).

Organizational growth has been shown to be associated with increases in organizational survival (Philips & Kirchloff, 1989) and occupational accident rates (Fernández-Muñiz et al., 2018). Therefore, we included organizational growth as a control variable in the models. Short-term growth was operationalized as the mean quarterly change in employment for the previous two years. Long-term growth was operationalized as the mean quarterly change in employment from entry to exit. Moderate organizational growth was anticipated to be positively associated with survival, but very high growth has been argued to be negatively associated with organizational survival (Sterman et al., 2007); hence we control for the polynomial effect of growth.

The safety literature and safety regulation assume that as workers produce more, they have greater exposure to risk (Zohar, 2008). Similarly, increases in working hours, especially overtime working hours, also increase workers' risk exposure (Dembe et al., 2005). However, increased output-per-worker is also associated with an increased likelihood of organizational survival (e.g. Jovanovic, 1982). Furthermore, while working more hours may not be an indication of being busier, working fewer hours or not being busy would reduce organizational survival. Because we do not have data that directly measures production, hours worked or sales, we coarsely control for these factors by including wages-per-employee (relative to industry mean) as a proxy for output-per-worker.

Increased turnover of workers is associated with poorer organizational performance (e.g. Koys, 2001) and increased harm to workers, because new hires are more likely to get injured (e.g. Khanzode et al., 2012; Burt, 2016). While we do not have a direct measure of turnover, we included the standard deviation of employment per quarter as a proxy for turnover. Both output-per-worker and turnover were calculated over the past two years for the short-term analysis, and across the lifetime of the organization for the long-term analysis. The remaining controls are described in the appendix.

Analysis and results

We examined the relationship between log STCC and risk of failure in the current quarter employing the ST sample (103,906 organizations / 4,046,312 observations) using a conditional cox proportional hazards model that deals with left truncation (Guo, 1993; Yang and Aldrich, 2012). Primary results are in Table 1 and Figs. 1 and 2, with full results, including control variables in supplement Table S3. The relationship is non-linear (u-shaped); hazard may be predicted as -0.0852 (0.0071) log STCC + 0.0079 (7e-04) log $STCC^2$. The model significantly predicted hazard, χ^2 (125)= 84907.

Increases in STCC (log STCC + log $STCC^2$) are associated with a reduction in quarterly risk of failure by up to 20.52 % (10.98 %, 29.28 %)[2] relative to an organization with zero STCC (Fig. 1; Table 2)[3]. The largest reduced risk of failure occurs above the 75th percentile of log STCC, and claims do not relate to a predicted increased risk of failure until they reach the 90th percentile of log STCC. For an organization with 100 employees, the 90th percentile corresponds to more than 3.45 mean-sized claims per quarter (Table 2).

The predictions in the managerial literature are premised on building and then leveraging human capital (Das et al., 2008; Pagell et al., 2015) which takes time (Becker, 1993). Hence, we also examined whether long-term claims costs predict time to organizational failure. Specifically, we perform a set of linear regression analyses on the LT sample (122,570 organizations). Primary results are in Table 3 and Fig. 3. The results are similar to the short-term analysis. Increased log LTCC is associated with increased time to failure and the effect is non-linear (inverse u-shaped).

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[2] Results reported in parentheses are 95% confidence intervals unless otherwise noted

[3] We use organizations with zero STCC as the comparison for all analysis because this was the most common outcome, claims costs (or counts) cannot go below zero forming a natural minimum and most importantly this is the goal of policy and regulation.

Increasing log LTCC (log LTCC + log LTCC^2) is associated with an increase in survival of up to 22.05 (20.19, 23.92) quarters (Table 3 Main Effect; Table 4; Fig. 3A), representing a 56% longer lifespan relative to the mean lifespan of 39.59 quarters. The greatest increase in time to failure occurs above the 65th percentile of log LTCC, and claims do not relate to decreased time to failure until they reach the 90th percentile of log LTCC: an organization with 100 employees could have up to 22.86 mean-sized claims per quarter before their time to failure was less than an organization with zero claims (Table 4).

To further explore the results, we ran analyses with subsets of the data. Specifically, we created groups by size, growth, industry, turnover, and output-per-worker in both the short and long-term models. We did the same for age in the short-term models. We did not create age groupings for the long-term models, because the dependent variable for the long-term models is time to failure / length of survival.

Z-tests were used to test whether the coefficients for the different groups were significantly different from each other for the given variables. The z-tests made it possible to determine if the benefits from increased claims costs; in terms of reducing risk of failure (ST analysis - Tables S4-6) or increasing time to failure (LT analysis- Tables S8-10), differed significantly by group. For groups where effects differed significantly (according to a z-test) and consistently, we discuss the differences between the curves.

We report the results for age, size and growth in the paper's main body. Age provides additional insight into the short-term models while size and growth are consistent across the short and long-term in an insightful manner. The results for industry, turnover and output-per-worker are not reported in the main body because while there are some significant differences between groups, there are no clear patterns. Please refer to the supplement (pages 3-8) for the full results.

The reduced risk of failure associated with increased STCC is amplified with age (Table 1 Age; Fig. 2A; Table S4). Younger organizations benefit less from having claims and are more susceptible to large claims harming survival (Table 2). For example, the youngest organizations (3-7 years) benefit from STCC only up to \$7,130, compared to \$48,280 for all organizations or \$157,776 for organizations between 23 and 27 years old.

The reduced risk of failure due to increased claims is also amplified with organizational size[4] for both STCC (Table 1 Size; Fig. 2B; Table S4) and LTCC (Table 2 Size; Fig. 3B; Table S10). In the short-term, the smaller organizations (6-10 and 10-30 workers) get no or minimal benefits from claims, while the largest organizations (over 100) benefit from having claims up until STCC reaches \$9,042,459 (Table 2). In the long-term the smaller organizations (6-10 and 10-30) reap significantly lower benefits from having claims relative to the larger organizations (30-100, > 100) and the larger organizations see benefits from LTCC until they reach extremely high levels (Table 4).

The results for growth in the short-term (Table 1 Growth; Fig 2C; Table S4) and long-term (Table 3, Growth; Table 4; Fig 3C; Table S10) provide important insight. In both the short and long-term, the organizations that see the greatest benefit from increased claims costs are those that have zero to moderate levels of growth (quartile 3) while

[4] Because we excluded organizations that never reached 6 employees, we do not discuss the results for observations where the organization had less than 6 employees. This is because only organizations that at one time had six or more employees would be included in this group, making interpretation difficult and inconsistent with other size groupings. Please see the appendix for more details.

those with the most negative growth (quartile 1) gain few if any benefits from increased claims. Interestingly, the organizations growing the fastest (quartile 4) are most susceptible to very large claims harming survival.

The results indicate that on average an increase in claims costs is associated with an increase in survival. This effect is amplified for older and larger organizations as well as for organizations that have zero to moderate levels of growth. On the contrary, organizations already facing greater survival risks, those that are young, have few employees, and or have negative or fast growth, are most likely to see high levels of claims harm survival.

A number of additional analyses were conducted to test alternative explanations for the results (Table 5). These analyses show that the results are robust to alternative operationalizations of providing a safe workplace, the analytical approach, the choice of time lag, the exclusion criteria used to create the samples, the form of the relationship between claims costs and failure, and the operationalizations of industry and failure.

Discussion

The research asked if providing a safe workplace improved or hindered organizational survival. The results indicate that providing a safe workplace generally hindered organizational survival, in line with the costly regulation hypothesis. Organizations with claims survive longer than their peers without claims. This effect is magnified for organizations that are older, larger and or that have zero to moderate levels of growth; those that already have the best survival prospects (e.g. Knaup and Piazza, 2007). These organizations are most likely to have the resources to dedicate to protecting the workforce and will have the least incentive to do so.

Similarly, organizations facing more precarious survival prospects, organizations that are young, small or facing other risks due to negative or fast growth (e.g. Knaup and Piazza, 2007), gain the least from having claims and are most likely to see high claims costs harm survival. These organizations, that may have an incentive to protect the workforce, will be least likely to have the resources to do so.

In the United States OSHA was created "to ensure safe and healthful working conditions for working men and women" (OSHA, 2019a) while the mission of the HSE in the United Kingdom is to "prevent work-related death, injury and ill health" (HSE, 2019). Both are aligned with the occupational health and safety conventions of the International Labour Organization (the United Nation's agency that sets labor standards and policies) which have been adopted by 68 countries; these conventions have prevention as the ultimate goal (ILO, 2019). Safety regulation and policy are intended to prevent harm at work. Yet the results predict that for most organizations enhanced survival will conflict with the goal of protecting the workforce. Market mechanisms alone will not eliminate poor safety and our results imply that the regulations of a developed economy are not enough to incent the elimination of poor safety.

The data set is both the key strength and key limitation of the research. The dataset captures almost all organizations that engaged in economic activity in the state of Oregon over 25 years, but the dataset provides no information on actual managerial practices. Hence, the analysis is predictive not explanatory. Still the analysis does provide some direction both to start to explain the results and to guide future research.

First, the analysis directly addressed many of the potential alternative explanations for the results. Most of the characteristics of the competitive environment or the organization that the literature suggests could impact survival or having claims were controlled or tested. The analysis controls for industry (e.g. Knaup and Piazza, 2007) and economic conditions (e.g. Geroski et al, 2010); the later through year dummies. The regulatory and political environment (e.g. Hiatt et al., 2014) also impacts survival and was controlled for by having data from a single U.S. state. At the organizational level; growth, productivity, turnover, size, and age (e.g. Ohlson, 1980; Knaup and Piazza, 2007) have all been linked to both survival and accidents and all were controlled for in the analysis. In addition, the robustness checks suggest that the results are not due to the operationalization of providing a safe workplace, the analytical approach, or if the timeframe is short, medium or long-term.

However, there is a considerable body of literature that examines survival based on financial indicators such as debt and cash flow (e.g. Keener, 2013). Similarly, issues such as board composition (e.g. Bermis et al., 2015) and managerial background (e.g. Chadwick et al., 2016) have also been linked to survival. Given our data we could not control for these factors, which is a limitation that future research will need to address.

Another area to explore is alternative measures of providing a safe workplace. While near misses and minor accidents have been linked to future severe accidents in the safety literature (Manuele, 2011), the links are tenuous (Bellamy, 2015; Manuele, 2011; Marshall et al., 2018). Exploring only disabling claims, which are quite severe hopefully eliminated the noise from minor incidents and allowed us to target only serious harm to workers. In addition, with minor accidents, under-reporting is a possibility (Pransky et al., 1999). This is much less likely with disabling claims, relative to non-disabling claims due to their severity. The wide range of medical and non-medical costs associated with these claims needs to be paid, typically by an insurance company for the organizations in this data, which can only occur if the claims are reported. Hence, worker compensation databases are viewed as providing a robust measure of work injuries (Oleinick & Zaidman, 2004). Future research needs to test this supposition by exploring the same questions with alternative measures of providing a safe workplace, which could include fatalities, both disabling and non-disabling claims, near misses, and regulatory sanctions.

The data does not allow the level of detail required to explain the mechanism that makes having claims generally superior for organizational survival. We can say that our results do not support the prediction that providing a safe workplace will enhance competitiveness. This does not mean that there are not organizations that can simultaneously provide a safe workplace and improve their competitiveness, as has been documented in the literature (e.g. Pagell et al., 2015), but it does mean that such organizations are not the norm. Consistent with the costly regulation hypothesis we posit that many organizations approach safety management from the standpoint of minimizing the cost of being in compliance with regulation. These organizations have fewer accidents than those who are out of compliance; some even have none. But viewing safety as a cost to be minimized rather than an opportunity to build human capital, means they cannot leverage protecting the workforce into other capabilities (e.g. Das et al., 2008). Similarly, from the perspective of the costly regulation hypothesis they have taken on the costs of compliance, while some competitors with accidents seemingly have not. In other words, treating compliance as a cost, and trying to comply, is more expensive than not complying and having accidents. However, this approach does not build any of the capabilities that theory (though not our results) suggests could offset these costs. This is speculative and needs to be explored in future research.

Finally, future research needs to focus on testing the effectiveness of policies and regulations that incentivize organizations to protect their workforce. Pagell and Gobeli (2009) found two paths to high operational performance. The first group with high operational performance minimized their harm to workers and the environment. However, there was a second group of organizations with high operational performance that effectively ignored or externalized their harm to workers and the environment. Pagell and Gobeli (2009) concluded that future research needed to explore if the gains from externalizing this harm to workers and the environment was short lived.

The current research suggests not. It provides clear evidence that many organizations are presently benefiting in the short and long-term from externalizing their costs of poor safety on society. For safety regulators and policy makers to achieve their goal of preventing harm to workers they need to create incentives that reward the organizations who are safe and productive. Organizations seeking to maximize their own survival are unlikely to intentionally harm workers. But our results indicate that they are, on average, also correct in concluding that the costs of preventing all harm is higher than the costs of not doing so. In addition, the organizations most likely to have the resources to dedicate to protecting their workforce, currently have the least incentive to do so. Hence, we paraphrase Porter and van der Linde (1995) and suggest that future safety regulation and policy needs to be crafted and enforced in a manner that rewards innovations that simultaneously improve the safety of the workforce and the organization's likelihood of survival.

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Appendix

Data

The data provided by the Oregon Department of Consumer and Business Services (DCBS) come from organizations with workers covered by state unemployment insurance (UI) laws and federal workers covered by the Unemployment Compensation for Federal Employees (UCFE) program. Any organization that:

a. pays $1,000 or more to employees in a calendar quarter;
b. pays $20,000 or more in cash wages in a calendar quarter and employs agricultural workers; or
c. has 10 or more employees in each of 20 weeks during a calendar year

is required to pay unemployment insurance (Oregon Employment Department, 2017). While these data are publicly available in aggregate form, individual organizational records are not publicly available due to privacy concerns (BLS, 2018b).

The claims and QCEW datasets allowed us identify organizations using unique IDs to preserve anonymity. Matching these datasets allowed us to examine the effects of claims costs on organizational failure and length of survival. In our original sample, 9.21% of organizations had multiple establishments in the state of Oregon in their lifetime, but we treat them as a single organization. As our data only cover establishments in the state, we are unaware of whether employers have out-of-state establishments, a limitation of the dataset.

Samples

The population (based on QCEW data, which cover all organizations, even those without claims) totaled 386,179 organizations with Oregon operations between 1989 and 2014. We created separate subsamples for the short-term (ST sample) and long-term (LT sample) analyses. We used the following elimination criteria to create both sub-samples:

1. Organizations that never employed more than five workers at a time, in their lifetime (64.61% of original population).
2. Government (state, local or federal) organizations (.35% of original population); government employers do not experience the same competitive pressures as business and other non-governmental organizations.
3. Organizations with an invalid industry (NAICS) code (.13% of original population).

In addition, to examine the effect of short-term claims costs (STCC) on risk of organizational failure, organizations with fewer than two years of records in the QCEW (8.02% of original population) were eliminated to construct the ST sample; the measure constructed to assess short-term claims costs requires at least two years of data. The ST sample consisted of 103,906 organizations, with a total of 4,046,312 observations (quarter-organizations); 3,128,095 of which do not have claims (77.31%). Observations without claims were kept for the analysis. Descriptive statistics and correlations for the ST sample are in Table A1.

To examine the effect of long-term claims costs (LTCC) on time to organizational failure (length of organizational survival), organizations with only one quarter in the QCEW (3.17% of original population) were eliminated to construct the LT sample; a minimum of two quarters is needed for the long-term analysis. The LT sample consisted of 122,570 organizations, with a total of 122,570 observations (organizations), 75,084 of which do not have claims (61.26%). Observations without claims were kept for the analysis. Descriptive statistics and correlations for the LT sample are in Table A2.

The first elimination criterion means that both samples excluded organizations that never exceeded 5 employees, while maintaining organizations that at any point were very small (<5), but at some point had 6 or more employees. Hence, in the short-term analysis there were many observations with 1-5 employees. But these are only for organizations that exceeded 5 employees at some point in their lifetime, they exclude organizations that never exceeded 5 employees. Similarly, the long-term analysis included organizations whose average employment over their lifetime was less than 6, but which exceeded 5 for at least one quarter. Hence, when discussing the results for small organizations, we exclude organizations with less than 5 employees. This subsample of the smallest organizations only includes those that grew to more than 5 employees at some point in their lifetime and therefore is incomplete making interpretation difficult and not consistent with other size groupings. The robustness checks (Table 5 and Supplement p 20-22) indicate that this exclusion criterion did not drive the results.

In some quarters the claims rate calculation was impossible because of missing values for employment (.16% of all organization-quarters), or cases where an organization had a claim but had zero employees (.06% of all organization-quarters), or cases where an organization reported wages paid but zero employees (.25% of all organization-quarters). For these observations, the number of employees was imputed based on employment in preceding and/or subsequent quarters.

<u>Operationalizing ongoing operations and potential sampling bias</u>

We operationalize survival as ongoing operations, even in the face of an ownership change. We define organizational exit (when operations cease) as the year of the last record of an organization in the QCEW dataset, consistent with definitions used in previous research (e.g. Mata et al., 1995; Phillips and Kirchloff 1989). An organization is assigned a new ID when it changes owners, legal status or industry. However the new and old IDs are linked across the datasets, allowing us to treat these as ongoing, not new organizations. This is in line with previous research (e.g. Knaup and Piazza, 2007), as well as the practice of the BLS, as they do not classify mergers or acquisitions (United States Census Bureau, 2017) or other changes in status, as exits (see Sadeghi, 2008).

Exiting the dataset means that the last ID associated with an organization has left the dataset. In other words, exits are really exits rather than changes of ownership, legal status or industry. 19.98% of organizations in the ST sample, and 17.6% of organizations in the LT sample, have multiple IDs- indicating a change in legal entity, ownership or industry at some point in their history.

We compared our exit data with exit data from the US Census Business Dynamics Statistics (BDS), for the state of Oregon. We chose the BDS data because exit rates were available at the State level, whereas they were not available at the State level from the BLS. We compared exit rates between 1989 and 2013 because our data end 2014, so all organizations are censored at that point. Our exit rate is slightly above that of the BDS' reported rate for the state of Oregon for the period (United States Census Bureau, 2017). Specifically, our annual mean exit rates average 1.5% higher than those reported by the census bureau (with a range from 4.65% above (1990) to 1.95% below (2006).

The small difference may arise because the Census Bureau data derives from Longitudinal Business Database (LBD) data, whereas our data come from the QCEW. The LBD are constructed from the Census Bureau's Business Register, based on survey and administrative data, whereas the QCEW is based on unemployment insurance data. Further, the census bureau data uses several smoothing algorithms to account for processing delays.

It is possible that some of this difference could be due to organizations closing their establishments in Oregon but remaining in business elsewhere. Given the small difference between our exit rate and that from other sources, we argue that that is not a major concern. And, it does not seem likely that out-of-state organizations would systematically close their safer operations, which would be necessary to bias our results. Finally, while mergers and acquisitions with entities outside of the state of Oregon could potentially account for some of the difference, announced mergers/acquisitions for the period of our data account for only 2.58% of total exits at the national level (Institute For Mergers, Acquisitions and Alliances, 2017). In sum, our treatment of exit, and our observed exit rate are in line with those reported elsewhere using the same or similar data, and we do not expect any bias due to treating multi-state entities closing their Oregon establishments as exits.

<u>Short-term analysis: variable definitions</u>

To assess the effect of STCC on risk of failure**,** STCCs were captured at each time point (quarter) as a time-varying covariate (Fisher and Lin, 1999). For each organization-quarter, these were defined as the mean claims cost per 100 workers per quarter in the past two years; for instance, the mean claims costs of quarters 1-8 would be used to predict risk of failure in quarter 9. STCC was log transformed due to extreme positive skew. To avoid losing 0 values in the transformation, a 1 was added prior to transformation. STCC was top coded at the 99th percentile to reduce the influence of very large claims (e.g. Levine et al., 2012; Elfenbein et al., 2010). Mean STCC after top coding was $4,263.68 (SD= $16,013.83); mean log STCC was 1.95 (SD=3.71). The log mean does not convert directly to the dollar mean, because the mean of logged values is less influenced by high values than the mean of dollar values. Mean of dollar values was calculated as mean (exp(log STCC) -1)), while mean of log values was calculated as mean (log STCC).The mean claim cost was $13,910.0, thus an organization of 100 employees averaged .304 average-sized claims per quarter.

Organizations are considered to have entered the dataset on their first appearance in the QCEW data (e.g. Fisher and Lin, 1999; Knaup & Piazza, 2007; Mata et al., 1995; Phillips and Kirchoff, 1989). Organizations entering the dataset in the first quarter of the dataset (1989 quarter 1) may have been founded prior to entering the dataset and could be left truncated. To deal with left-truncated organizations, a conditional likelihood approach was adopted (Guo, 1993; Yang & Aldrich, 2012) using organizational age as start times.

Age for organizations that entered the dataset in quarter 1 of 1989 was identified using the dates of initial liability (DOL) provided by the DCBS. The DOL is the point at which an establishment becomes liable for unemployment insurance. The QCEW dataset is based on unemployment insurance, thus the DOL provides the same information as first entry date. Organizations "exit" the dataset at their last record (Dunne et al., 1989; Phillips & Kirchoff, 1989). Age, in quarters, at time t was calculated as t - DOL. For example, consider an organization that enters the QCEW dataset in quarter 1 of 1989 with a DOL in quarter 1 of 1987. Age in quarter 2 of 1990 may be calculated as 1990 Q2 - 1987 Q1= 13 quarters.

Organizations exiting the dataset in the last quarter of the dataset (2014 quarter 4) were considered right censored. Organizations were considered to have "failed" at a given time point if they left the dataset for more than two consecutive quarters and did not return. To examine the effects of STCC on risk of organizational failure in the current quarter, organizations were dummy coded as "failed" or "ongoing".

Major industry group was included as a control variable because industries vary in their level of danger to workers (BLS, 2017) and likelihood of going out of business (Stearns et al., 1995). We use two-digit North American Industry Classification System (NAICS) 2012 codes to indicate major industry groups. Organizations initially classified using NAICS 2002, 2007, or Standard Industrial Classification 1987 systems were converted into NAICS 2012. Each organizational was assigned a single NAICS 2012 code. For organizations that used multiple industry codes during their lifetime, one NAICS 2012 code was selected based on the highest employment level. Industry code was derived from QCEW data, as this contains the entire population. The referent category in the analysis was NAICS 54 (Professional, Scientific, and Technical Services) because this industry has the lowest STCC (mean of $2.68 STCC per 100 employees per quarter, SD=$4.23, N=7563).

Mean employment per organization also was included as a control variable as larger organizations have more claims and are more likely to survive (Evans, 1987). To examine the effects of STCC on risk of failure, mean employment per organization per quarter in the last two years was included as a time-varying covariate.

Growth also was included as a control variable because economic growth is associated with increases in organizational survival (Philips & Kirchloff, 1989) and occupational accident rates (Fernández-Muñiz et al., 2018). To examine the impact of short-term growth (growth) on risk of failure**,** growth was captured at each time point (quarter) as a time-varying covariate (Fisher & Lin, 1999). Growth was defined in the short-term for each organization i in quarter t as the logarithmic difference in employees from two years previous (Bird & Zellwegger, 2018; Daunfeldt & Halvarsson, 2015; Brush et al., 2000)A constant of .01 was added to employment at t and to employment at t-2 years, to avoid losing zero values prior to calculation. (Zero values are rare in this data). Logged growth was divided by 8, to provide a quarterly growth rate. Growth was top coded at the 99th percentile and bottom coded at the 1st percentile to reduce the influence of extreme growth. Mean growth after top and bottom coding was -0.0033 (SD=0.1371).

We include wages-per-employee (relative to industry average in each quarter) as a control variable; it serves as a proxy for output-per-worker. The economics literature indicates that wages and productivity are linked (e.g. Hellerstein et al., 1999; Haltiwangerer et al., 2007) and using wages as a proxy for productivity is common in health economics (e.g. Connolly et al., 2017). When an organization's workers earn more than average, they are typically either more productive or working more hours; output-per-worker then should be higher. For the short-term analysis, this is calculated as the mean over the preceding 8 quarters, at each timepoint. Mean output-per-worker was $7120.751 (SD=21796.96).

We included the standard deviation of employment as a proxy for employee turnover, with the assumption that while some variance in employment could be due to seasonal fluctuations, more variance indicated an increased likelihood of hiring and firing and hence the presence of new workers. For the short-term analysis, this is calculated as the mean over the preceding 8 quarters, at each timepoint. Mean turnover was 2.81 (SD=5.46).

To control for changes in the relative risk of starting a business over time, the entry year and quarter that each organization entered the QCEW dataset also was included as a covariate.

To control for the overall business environment, as well as for changes in legislation that might affect claims costs over time, each time-point (each quarter between quarter 1 of 1989 and quarter 4 of 2014) was dummy-coded and included as a covariate.

<u>Long-term Analysis: variable definitions</u>

To test the effect of long-term claims cost (LTCC) on time to failure, LTCC was calculated as mean claims costs per 100 workers per quarter per organization, calculated across the lifetime of each organization. Long-term claims cost was log transformed due to extreme positive skew. To avoid losing 0 values in the transformation, 1 was added prior to transformation. LTCC was top coded at the 99th percentile to reduce the influence of extremely large claims. Mean LTCC was $4,575.09 (SD=$13,036.18), or 3.16 (SD=4.13) log LTCC. The log mean does not convert directly to the dollar mean, because the mean of logged values is less influenced by high values than the mean of dollar values. Mean of dollar values was calculated as mean (exp(LTCC) -1), mean of log values was calculated as mean (log LTCC).The average claim cost was $13,910.0, meaning an organization of 100 employees averaged .329 average-sized claims per quarter.

To examine effects of LTCC on time to failure, organizations were dummy coded as "failed" or "ongoing" at the last timepoint of the QCEW dataset (2014 quarter 4). Time to failure in quarters was calculated as exit time minus entry time in quarters. To deal with left-truncated organizations, age at dataset entry was included in the model as a control covariate.

To assess the effect of long-term growth (growth) on time to failure**,** growth for organization i in its final quarter (t final) was captured as the log of the number of employees in its final quarter minus the log of the number of employees in the first quarter. A constant of .01 was added to employment in the final quarter and to employment in first quarter prior to calculation, to avoid losing zero values. Logged growth was divided by the total number of quarters between the first and final quarters. Growth was again top-coded at the 99th percentile and bottom coded at the 1st percentile to reduce the influence of extreme growth. Mean growth after top and bottom coding was -.04 (SD=.26).

We include wages-per-employee (relative to industry average) as a proxy for output-per-worker. For the long-term analysis, this is calculated over the organization lifetime. Mean quarterly wages-per-employee were \$ 7,085.99 (SD= \$43,592.65).

We included the standard deviation of employment as a proxy for employee turnover. For the long-term analysis, this is calculated over the organization lifetime. Mean turnover was 7.14 (SD= 43.08).

Also included as control variables were major industry group and entry year and quarter, as well as mean employment per organization, calculated across the organizational lifetime.

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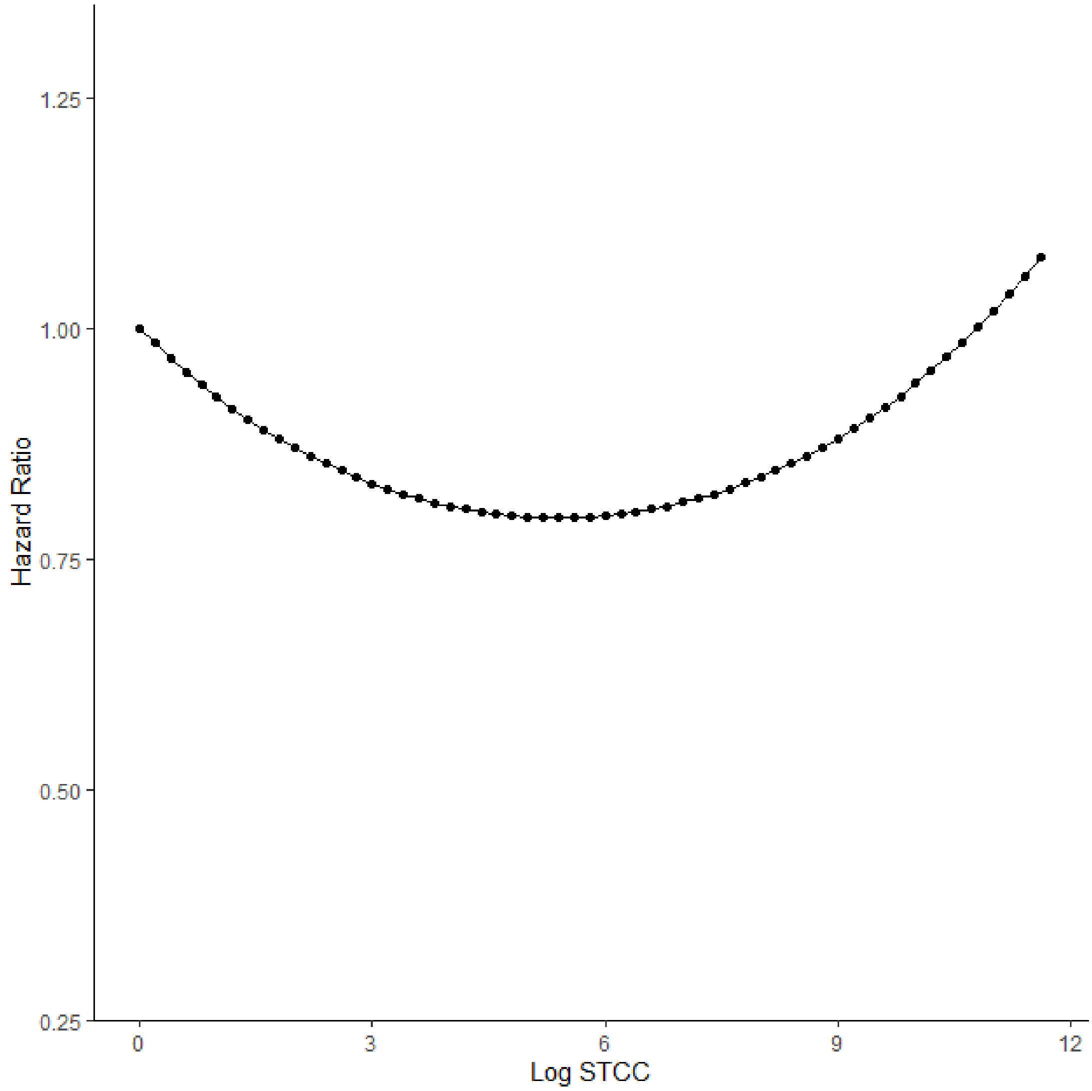

Fig. 1. Graph depicting predicted values of Hazard Ratio (risk of failure relative to employers with $0 STCC, with all covariates held constant) vs. log STCC, for all organizations.

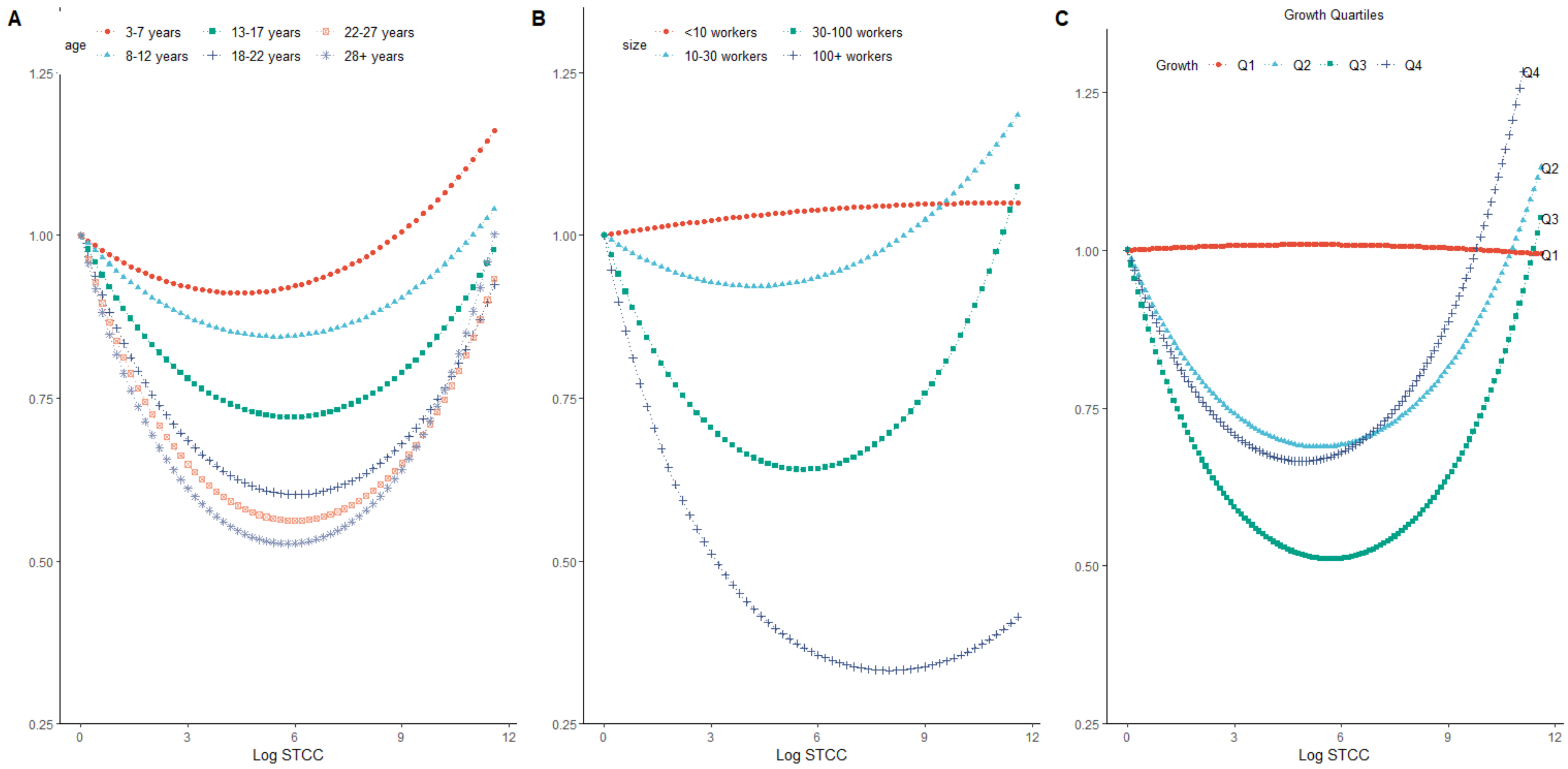

Fig. 2. Graph depicting predicted values of Hazard Ratio (risk of failure relative to employers with $0 STCC, with all covariates held constant) vs. log STCC, grouped by organizational age in years (A; Table 1 Age; Table 2; also see Table S4) and grouped by organizational size (B; Table 1 Size; Table 2; also see Table S4), and organizational growth (C; Table 1 Growth; Table 2; also see Table S4). There is a substantial non-linear effect which is greater for older (A), larger (B), and moderately fast growing organizations (C).

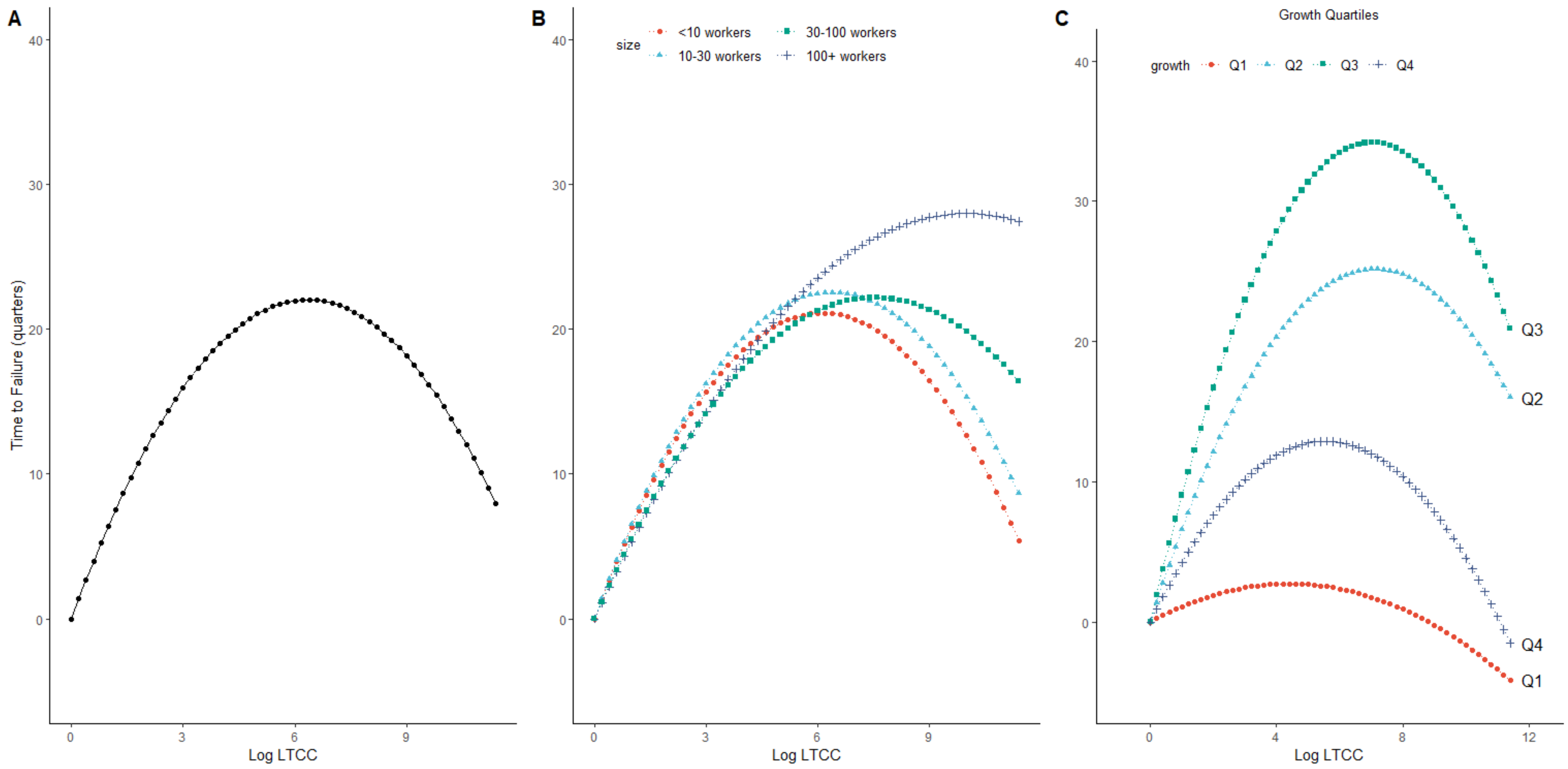

Fig. 3. Graph depicting predicted survival (quarters between organization entry and exit relative to a firm with $0 LTCC) vs. log LTCC, for all organizations (A; Table 3 Main effect; also see Table 4), for organizations grouped by size (B; Table 3 Size; Table 4; also see Table S10), for organizations grouped by growth (C; Table 2 Growth; Table 4; also see Table S10). There is a substantial non-linear effect (A), which is greater for larger (B), and moderately growing organizations (C).

Table 1. Conditional cox proportional hazards models show that increasing STCC reduces hazard but the effect is non-linear. The dependent variable for all models was risk of failure at time t (hazard).

The Main Effect model tests the polynomial effects of log STCC. The Age model tests the polynomial effects of STCC grouped by organization age. The Size model tests the polynomial effects of STCC grouped by organization size. The Growth model tests the polynomial effects of STCC grouped by organization growth quartiles.

The following control variables were included in all models: year and quarter, entry year and quarter, mean employment per quarter in the last two years, growth, turnover, output-per-worker and industry dummy variables.

Coefficients are rounded to four digits and p<.001 unless otherwise specified. Standard errors are in brackets.

Independent Variable Specification	**Main Effect**	**Age**	**Size**	**Growth**	**% of total obs.**
Controls	Included	Included	Included	Included	
Log STCC	-0.0852 (0.0071)				
Log STCC^2	0.0079 (7e-04)				
Log STCC: 3-7 years		-0.0417 (0.0099)			34.46
Log STCC: 8-12 years		-0.0616 (0.0149)			20.89
Log STCC: 13-17 years		-0.111 (0.0192)			15.42
Log STCC: 18-22 years		-0.168 (0.0256)			10.6
Log STCC: 23-27 years		-0.1927 (0.0325)			6.91
Log STCC: 28+ years		-0.2214 (0.0246)			11.72
Log STCC^2: 3-7 years		0.0047 (0.001)			
Log STCC^2: 8-12 years		0.0056 (0.0015)			
Log STCC^2: 13-17 years		0.0094 (0.002)			
Log STCC^2: 18-22 years		0.0139 (0.0026)			
Log STCC^2: 23-27 years		0.0161 (0.0033)			
Log STCC^2: 28+ years		0.0191 (0.0025)			
Log STCC: < 10 workers			0.0088 (0.0109), p=0.4191		60.8
Log STCC: 10-30 workers			-0.0388 (0.0116)		25.68
Log STCC: 30-100 workers			-0.1597 (0.018)		9.74
Log STCC: 100+ workers			-0.2755 (0.0355)		3.78
Log STCC^2: < 10 workers			-4e-04 (0.0011), p= 0.6954		
Log STCC^2: 10-30 workers			0.0046 (0.0012)		
Log STCC^2: 30-100 workers			0.0143 (0.0019)		
Log STCC^2: 100+ workers			0.0172 (0.0038)		
Log STCC: growth quartile 1				0.0036 (0.0084), p=0.6712	24.85
Log STCC: growth quartile 2				-0.1388 (0.0228)	17.19
Log STCC: growth quartile 3				-0.236 (0.0207)	32.93[5]
Log STCC: growth quartile 4				-0.1664 (0.0207)	25.02
Log STCC^2: growth quartile 1				-3e-04 (8e-04), p=0.679	
Log STCC^2: growth quartile 2				0.0129 (0.0024)	
Log STCC^2: growth quartile 3				0.0207 (0.0021)	
Log STCC^2: growth quartile 4				0.017 (0.0021)	
Likelihood Ratio Test	$\chi2$ (125)= 84907	$\chi2$ (135)= 85122	$\chi2$ (131)= 82956	χ^2 (131)= 45286	

[5] The growth quartiles are unbalanced because Q3 contains all organizations with 0 growth

Table 2. Values of log STCC and associated with maximum hazard reduction, and increased hazard relative to organizations with zero STCC, grouped by growth quartiles.

Column (1) Maximum Reduction in Hazard, %: Column 1 refers to the percentage reduction in hazard between a firm with zero claims and one at the vertex (minimum) of the polynomial relationship between STCC and hazard of failure. Columns (2) and (3) provide the log(STCC) and the STCC at which this vertex occurs: This refers to the values of log(STCC) [col 2] and STCC [col 3] at which employers reduce their likelihood of failure the most by having claims, relative to a firm with no claims.

Columns (4) and (5) refer to values of log(STCC) [col 4] and STCC [col 5] above which hazard of failure is predicted to be greater than that of organizations with zero STCC. This refers to the point at which employers increase their likelihood of failure by having claims. 95% confidence intervals are in brackets.

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Max. reduction in hazard	**Value of STCC/log(STCC) at which this max. reduction occurs**		**Increased hazard**	
All organizations	20.52 %	5.39	219.73	10.78	48280.81
	(10.98 % , 29.28 %)	(3.86 , 7.67)	(46.57 , 2147.23)	(7.72 , 15.34)	(2261.63 , 4614906.99)
3- 7 years	8.83 %	4.44	83	8.87	7130.95
	(-3.35 % , 19.42 %)	(1.66 , 10.95)	(4.28 , 56964.99)	(3.33 , 21.9)	(26.92 , 3245123850.76)
8- 12 years	15.58 %	5.5	244	11	59873.14
	(-8.42 % , 34.44 %)	(1.89 , 17.78)	(5.62 , 52717096.43)	(3.78 , 35.56)	(42.84 , 2779092361042351)
13- 17 years	27.94 %	5.9	366	11.81	134390.26
	(-2.9 % , 49.55 %)	(2.77 , 13.39)	(14.95 , 650916.56)	(5.54 , 26.77)	(253.39 , 423693676041.08)
18- 22 years	39.81 %	6.04	420	12.09	177428.91
	(1.55 % , 63.1 %)	(3.09 , 12.38)	(20.96 , 238135.78)	(6.18 , 24.76)	(481.44 , 56709124164.05)
23- 27 years	43.82 %	5.98	396	11.97	157776.97
	(-4.03 % , 69.56 %)	(2.85 , 13.3)	(16.23 , 598249.28)	(5.69 , 26.6)	(295.73 , 357903400476.32)
27 +years	47.35 %	5.8	328	11.59	108186.71
	(18.09 % , 66.25 %)	(3.62 , 9.52)	(36.21 , 13609)	(7.23 , 19.04)	(295.73 , 185232112.78)
<10 workers	*ns*	*ns*	*ns*	*ns*	*ns*
10-30 workers	7.86 %	4.22	67	8.43	4603.47
	(-5.76 % , 19.76 %)	(1.15 , 13.9)	(2.17 , 1083036.58)	(2.31 , 27.79)	(9.03 , 1172970395290.05)
30-100 workers	35.97 %	5.58	265	11.17	70814.43
	(12.53 % , 53.09 %)	(3.46 , 9.17)	(30.74 , 9586.52)	(6.92 , 18.34)	(1006.4 , 91920610.33)
100+ workers	66.82 %	8.01	3006	16.02	9042459.37
	(5.85 % , 88.25 %)	(4.16 , 17.77)	(62.83 , 52043640.84)	(8.31 , 35.54)	(4073.38 , 2708540656360314)
Growth quartile 1	*ns*	*ns*	*ns*	*ns*	*ns*
Growth quartile 2	31.16 %	5.38	216	10.76	47083.07
	(-0.32 % , 52.76 %)	(2.67 , 11.19)	(13.48 , 72674.02)	(5.35 , 22.39)	(208.78 , 5281659055.4)
Growth quartile 3	48.96 %	5.7	298	11.4	89407.07
	(26.48 % , 64.57 %)	(3.94 , 8.34)	(50.29 , 4180.89)	(7.88 , 16.68)	(2629.9 , 17488219.69)
Growth quartile 4	33.45 %	4.89	133	9.79	17821.83
	(10.42 % , 50.56 %)	(2.98 , 8.03)	(18.68 , 3077.3)	(5.96 , 16.06)	(386.18 , 9475931.83)

Table 3. Linear regression models show that increasing LTCC increases survival, but the effect is non-linear. The dependent variable for all models was survival, in quarters.The Main Effect model tests for the polynomial effects of LTCC. The Size model examines the polynomial effects of LTCC grouped by organization size.

The Growth model examines the polynomial effects of LTCC grouped by organization growth quartiles. The following control variables were included in all models: entry year and quarter, mean employment per quarter, industry dummy variables, age at entry, growth, turnover, and output-per-worker.

Coefficients are rounded to four digits and p<.001 unless otherwise specified. Standard errors are in brackets.

Independent Variable Specification	**Main effect**	**Size**	**Growth**	**% of total firms**
Controls	Included	Included		
Log LTCC	6.9621 (0.0894)			
Log LTCC²	-0.5495 (0.0096)			
Log LTCC: < 10 workers		6.9064 (0.1221)		79.1
Log LTCC: 10-30 workers		7.0637 (0.1499)		27.59
Log LTCC: 30-100 workers		5.8796 (0.2517)		8.57
Log LTCC: 100+ workers		5.6116 (0.469)		2.72
Log LTCC²: < 10 workers		-0.5642 (0.013)		
Log LTCC²: 10-30 workers		-0.5529 (0.0168)		
Log LTCC²: 30-100 workers		-0.3895 (0.0288)		
Log LTCC²: 100+ workers		-0.281 (0.0538)		
Log LTCC: growth quartile 1			1.2356(0.1761)	25
Log LTCC: growth quartile 2			7.0724(0.1645)	21.29
Log LTCC: growth quartile 3			9.731(0.1449)	28.7[6]
Log LTCC: growth quartile 4			4.6498(0.1846)	25
Log LTCC²: growth quartile 1			-0.1402(0.0187)	
Log LTCC²: growth quartile 2			-0.4971(0.0183)	
Log LTCC²: growth quartile 3			-0.6924(0.0162)	
Log LTCC²: growth quartile 4			-0.4195(0.0201)	
R^2	R^2 = .35, F(31, 122530) = 2114, p < .001.	R^2 = .35, *F*(37, 122524) = 1787 *p* < .001.	R^2 = .4, *F*(37, 122524) = 2210, *p* < .001.	

[6] The growth quartiles are unbalanced because Q3 contains all organizations with 0 growth

Table 4. Values of log LTCC associated with the maximum survival, and with reduced survival relative to organizations with 0 LTCC.

Column (1) Maximum Increase in Survival (quarters): Column 1 refers to the increase in survival time (in quarters) between a firm with zero claims and one at the vertex (maximum) of the polynomial relationship between LTCC and survival.

Columns (2) and (3) provide the log(LTCC) and the LTCC at which this vertex occurs: This refers to the values of log(LTCC) [col 2] and LTCC [col 3] at which employers increase their survival time the most by having claims, relative to a firm with no claims.

Columns (4) and (5) refer to values of log(LTCC) [col 4] and LTCC [col 5] above which survival is predicted to be less than that of organizations with zero LTCC. This refers to the point at which employers reduce their survival by having claims. 95% confidence intervals are in brackets.

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Max. Increase in Survival	**Value of LTCC/log(LTCC) at which this max. reduction occurs**		**Survival < 0**	
All organizations	22.05	6.33	711.44	12.67	507573.3
	(20.19 , 23.92)	(5.97 , 6.72)	(428.32 , 1242.4)	(11.94 , 13.45)	(184315.75 , 1546042.73)
<10 workers	21.14	6.12	454	12.24	207118.1
	(18.72 , 23.55)	(6.63 , 5.65)	(758.09 , 284.18)	(13.26 , 11.31)	(576221.18 , 81329.35)
10-30 workers	22.56	6.39	594	12.78	353530.54
	(19.34 , 25.78)	(7.07 , 5.78)	(1180.93 , 322.13)	(14.15 , 11.56)	(1396957.69 , 104412.62)
30-100 workers	22.19	7.55	1895	15.1	3595702.87
	(15.25 , 29.13)	(9.57 , 6.04)	(14291.25 , 418.52)	(19.13 , 12.08)	(204268505.43 , 175999.53)
100+ workers	28.02	9.99	21699	19.97	470876664.77
	(8.32 , 47.71)	(18.6 , 6.07)	(119744443.1 , 432.17)	(37.2 , 12.14)	(14338731893414168 , 187638.99)
Growth quartile 1	2.72	4.41	81	8.81	6720.89
	(0.49 , 4.96)	(7.63 , 2.52)	(11.4, 2064.16)	(15.27 , 5.03)	(4264880.62 , 152.69)
Growth quartile 2	25.16	7.11	1228	14.23	1509543.41
	(21.05 , 29.26)	(8.02 , 6.33)	(561.53 , 3029.18)	(16.03 , 12.66)	(9182000.34 , 316438.69)
Growth quartile 3	34.19	7.03	1126	14.05	1269348.37
	(30.63 , 37.75)	(7.58 , 6.52)	(679.48 , 1957.01)	(15.16 , 13.05)	(3833790.21 , 463052.63)
Growth quartile 4	12.88	5.54	254	11.08	65129.47
	(9.67 , 16.1)	(6.59 , 4.67)	(105.92 , 728.55)	(13.18 , 9.34)	(532241.6 , 11430.53)

Table 5. Robustness Checks. The table below summarizes the consistency of the direction and significance of the linear and squared terms with the main analyses. Details of these analyses and the corresponding results are provided in the online supplement.

- In tests 1-4, we tested whether the results were consistent when we operationalized providing a safe workplace as either a count of claims or a binary claims / no claims measure, rather than cost of claims.
- In test 5, we tested whether the results are robust to an alternative modelling method (discrete time hazard models; e.g. Box-Steffensmeier & Jones 2011).
- In test 6 we extended the time lag from the short-term analysis from 1 quarter to 1 year, to ensure that the results are not driven by the particular time lag in the short-term analysis.
- In test 7, we predict failure in the long-term sample using logistic regression to ensure that the main long-term results are not unique to the prediction of time to failure.
- In tests 8-9, we split claims costs into quartiles and deciles to test the u shaped functional form of the relationship between claims costs and failure.
- In tests 10-11, we excluded organizations that never exceeded 10 employees in their lifetime in order to rule out that small organizations (which exceed 5 but not 10 employees) drive the results.
- In tests 12-13, we tested whether the results were consistent when we operationalized industry as either a 4 digit NAICS code or as the accident rate at the 4 Digit NAICS level rather, than as a 2 digit NAICS code

The results are robust to alternative operationalizations of providing a safe workplace, the analytical approach, the choice of time lag, the exclusion criteria used to create the samples, the form of the relationship and the operationalization of failure.

Test #	Test	IV	DV	Model†	Sample††	Consistent with main analysis †††	Supplement pp
1	Alternative operationalizations of claims	Count of claims	Hazard	CCPH	ST	Yes	8
2			Time to Failure	MR	LT	Yes	10
3		Binary claims	Hazard	CCPH	ST	Yes	11
4			Time to Failure	MR	LT	Yes	12
5	Discrete time hazards models	Cost of Claims	Hazard	DTHM	ST	Yes	13
6	Medium Term analysis	Cost of Claims	Hazard	CCPH	MT	Yes	15
7	Predicting Failure instead of time to failure	Cost of Claims	Log odds of failure	LR	LT	Yes	17
8	Alternative Functional Forms (deciles and quartiles)	Cost of Claims	Hazard	CCPH	ST	Yes	18
9			Time to Failure	MR	LT	Yes	19
10	Exclusion criteria (<=10 vs. <=5 employees)	Cost of Claims	Hazard	CCPH	ST	Yes	20
11			Time to Failure	MR	LT	Yes	21
12	Alternative operationalizations of industry	Cost of Claims	Hazard	CCPH	ST	Yes	22
13			Time to Failure	MR	LT	Yes	24

† CCPH: conditional cox proportional hazards model; DTHM: discrete time hazards model; MR: multiple regression; LR: logistic regression;
†† ST: short-term sample; LT: long-term sample; MT: medium-term sample
††† $p < 0.001$

Table A1. Descriptive statistics and correlations for ST sample (short-term analysis).

	Variables	mean	sd	min	max	[1]	[2]	[3]	[4]	[5]	[6]
[1]	*Log STCC*	1.95	3.71	0.00	11.66	1					
[2]	*Mean employment per quarter in the past 2 years*	26.23	166.42	0.00	17861.17	0.148	1				
[3]	*Quarterly growth*	0.00	0.14	-1.49	1.63	-0.001	0.005	1			
[4]	*Output-per-worker*	0.00	1.00	-2.51	50.99	0.057	0.044	0.012	1		
[5]	*Turnover*	2.81	5.46	0.00	39.44	0.303	0.408	-0.005	0.048	1	
[6]	*Entry year and quarter*	1993.72	5.87	1989.00	2012.75	-0.105	-0.050	0.034	-0.075	-0.047	1

Table A2. Descriptive statistics and correlations for LT sample (long-term analysis).

	Variables	mean	sd	min	max	[1]	[2]	[3]	[4]
[1]	*Log LTCC*	3.16	4.13	0.00	11.42	1			
[2]	*Mean employment per quarter*	18.28	101.08	0.09	11790.21	0.103	1		
[3]	*Quarterly growth*	-0.04	0.26	-1.40	0.76	0.040	0.016	1	
[4]	*Output-per-worker*	-0.09	0.72	-1.92	35.65	0.077	0.062	0.021	1
[5]	*Turnover*	7.14	43.08	0.00	5913.87	0.095	0.831	-0.003	0.065
[6]	*Entry year and quarter*	1996.89	7.77	1989.00	2014.50	-0.204	-0.052	0.058	-0.07
[7]	*Time to Failure*	39.59	32.29	1.00	103.00	0.339	0.077	0.140	0.155
[8]	*Age at Entry*	10.67	26.59	-3.00	319.00	0.161	0.109	-0.020	0.124

Supplementary Materials for

The tension between worker safety and organization survival

Contents

Short-term analysis and results

To examine the effects of log STCC on risk of failure, a series of conditional cox proportional hazards models were performed on the ST sample (103,906 organizations). Table S1 shows the distribution of the ST sample by industry and Table S2 shows descriptive statistics of claims, by year.

A conditional proportional hazards model was selected for several reasons. It allows for the assessment of hazard (risk of failure) and does not make assumptions about the shape of the survival function (Cox, 1972). It accounts for censoring (Evans, 1987) and left truncation (Guo, 1993). It allows covariates to vary over time (Fisher and Lin, 1999). Cox proportional hazards regression models estimate the effect of covariates on hazard of experiencing an event, in this case organizational failure (Cox, 1972). Because the models are conditional, start times are defined using organizational age at each time point. Hazard coefficients measure the impact of each covariate; a coefficient greater than 0 implies an increase in risk of failure, whereas a coefficient less than 0 implies a decrease in risk of failure. Hazard ratios (exponentiated hazard coefficients) indicate the percent change in likelihood of failure per covariate unit increase, with a ratio greater than 1 implying an increase in risk of failure and a ratio less than one implying a decrease. Survival probabilities are not calculated for the conditional cox model, because of the use of time varying covariates (e.g., Thomas and Reyes, 2014).

As shown in Tables S3, 6 conditional cox proportional hazards models were constructed. Model 1 includes only the control variables (see Table S3). Model 2 includes control variables and log STCC. Increases in log STCC are associated with a lower risk of failure, as indicated by the negative coefficient for log STCC, improving model fit over the control variables alone ($\chi 2(1) = 51.47$). Model 2 predicts that a one-unit increase in log STCC is associated with a 0.94 % (0.68 %, 1.19 %)[7] lower risk of failure in the current quarter relative to organizations with no short-term claims (see Table S3). Risk of failure relative to organizations with no claims, holding all other covariates constant, may be calculated as exp (-0.0094 (0.0013) *log STCC) (standard errors in brackets).

Model 3 (Table S3) tests whether there is a substantial non-linear component by including a polynomial term ((log STCC)^2) as an independent variable. We note that the third-order polynomial model was non-significant, and as such no polynomial terms beyond the squared term were included. The formula is as follows:

$$H(t)=h0(t)\times exp(\text{entry year and quarter} + \text{mean employment per quarter in the last two years} + \text{industry dummy variables} + \text{year and quarter} + \text{growth} + \text{growth}^2 + \text{output-per-worker} + \text{turnover} + \text{Log STCC} + (\text{log STCC})^2)$$

where $H(t)$is the hazard function and $h0(t)$ is the baseline hazard.

The positive coefficient for the log STCC squared term implies a U-shaped curve (see Table S3 Model 2; and Table 1 and Fig. 1 in the main body). Including this term improved model fit, $\chi 2(1) = 122.15$. The minimum of the curve does occur in the range of log STCC in the data. In Model 3, having claims is associated with up to a 20.52 % (10.98 %, 29.28 %) lower risk of failure relative to organizations with zero STCC (see also Table 2 in the main body;

[7] Results reported in parentheses are 95% confidence intervals unless otherwise noted

and Table S3 for complete results). When STCCs are very high, the curve crosses H(t)=0, implying that claims are associated with an increased risk of failure when compared to organizations with no claims. For the full sample, this occurs when log STCC = 10.78 (7.72, 15.34), above the 90th percentile. Risk of failure relative to organizations with no claims, holding all other covariates constant, may be calculated as exp (-0.0852 *log STCC + 0.0079*(log STCC)^2.

Model 3 (Table S3) may violate the assumption of proportional hazards if the effects vary over time (organizational age in the models) potentially causing model misspecification (Schemper,1992) and loss of power (Schemper, 1992; Lagakos and Schoenfeld, 1984). Therefore in Model 4, the polynomial effects of log STCC on hazard are grouped by organizational age (3-7 years, 8-12 years, 13-17 years, 18-22 years, 23-27 years, 28 years or more) when examining the effect of log STCC on risk of failure (Table S3; see also Table 1, Table 2 and Fig. 2 in the main body). We used z-tests to compare the equality of regression coefficients of log STCC between age groupings (Paternoster et al., 1998; Clogg, Petkova & Haritou, 1995; see Salvador & Villena, 2013 and Lawrence, Slaon & Sun, 2018 for similar examples). The group comparisons showed that the log STCC coefficients are generally significantly larger in older groupings relative to younger ones (see Table S4; for detail on maximum reductions in hazard for each grouping see Table 2 in the main body). There were no significant differences in comparisons between the youngest groupings (3-7 years vs. 8-12 years) and the oldest groupings (13-17 years vs. 18-22 years, and any combination of 18-22 years, 23-27 years and 28 years or more). The comparisons of the log STCC squared term coefficients showed a similar pattern (Table S4). We also stratify our short-term robustness check models by age categories to account for the potential influence of non-proportional hazards.

In Model 5 (Table S3 for full results; see also Table 1, Table 2 and Fig. 2), the polynomial effects of log STCC on hazard are grouped by organizational size (<10 workers, 10-30 workers, 30-100 workers, 100 workers or more). This was done because large organizations have more claims and are more likely to survive (e.g. Evans, 1987). For organizations with <10 employees, no significant effect exists at the p<.001 level. As before, we used z tests to compare group coefficients. The group comparisons showed that the log STCC coefficients are significantly larger in larger groupings relative to smaller ones (see Table S4). The comparisons of the log STCC squared term coefficients showed a similar pattern.

In Model 6 (Table S3 for full results; see also Table 1, Table 2, and Fig. 2), a model was constructed which grouped the effects of log STCC by growth. To further investigate a potential interaction between short-term growth and STCC, we grouped the effects of log STCC on hazard by short-term growth quartiles. Quartile cutoffs expressed as percent change in employment per quarter were: -51% to -2.25%; -2.25% to 0%; 0% to 2.82%; and 2.82% to 69.35%.

In Model 6 (Table S3; also Table 1, Table 2, and Fig. 2), the polynomial effects of log STCC on hazard are grouped by organizational growth quartiles. This was done because growing organizations have been shown to have more claims and are more likely to survive (e.g. Phillips and Kirchloff, 1989; Fernández-Muñiz et al., 2018). The effect of log STCC on hazard was not significant for organizations with the lowest growth (quartile 1). Again, we used z tests to compare group coefficients (see Table S4 also see Table 2 and Fig. 2). The group comparisons showed that the log STCC coefficients are significantly larger in quartile 3 than all other quartiles. Quartiles 2 and 4 did not differ (p>.05), and quartiles 2, 3, and 4 showed larger effects of log STCC than quartile 1. The comparisons of the log STCC squared term coefficients showed a similar pattern.

Three supplemental tests were also performed, examining the effects of industry groupings, turnover, and output-per-worker on the magnitude of the effect of log STCC on hazard. First, the polynomial effects of log STCC on hazard are grouped by industry. We focus on seven industries because of both the large total number of industries and the fact that many industries lack enough organizations to derive meaningful conclusions. The industries examined were selected to create a quasi-experimental design based on industry-average wages and industry-average STCC. The managerial literature, which predicts that harming workers also will harm the organization, is based on theories of human capital (e.g., Becker, 1993). Wages are a proxy for how productive the human capital in an industry is, hence the first selection criteria for industry was (high or low) wages for the industry. Institutional effects may exist, however, that make accidents accepted in industries where claims are more common. Otherwise stated, in industries where accidents are the norm, harming the workforce might be accepted and not impact survival. In industries with relatively low levels of accidents, harming the workforce may not be seen as acceptable or normal, posing the risk of harm to organizational survival. Therefore, the second selection criteria was industry-average STCC (low, medium, and high).

The seven industries captured in this design were ; low wages and low claims (Retail; NAICS 44-45); low wages and medium claims (Administration; NAICS 56); low wages and high claims (Agriculture; NAICS 11); high wages and low claims (Professional Services; NAICS 54); high wages and medium claims (Manufacturing; NAICS 31-33); high wages and high claims (Construction; NAICS 23). We also examined Accommodation and Food (NAICS 72), a very low-wage, low-claim industry that is large and has a prevalence of precarious workers. However, because wages are so much lower in this industry than any other, we could not create a match. We follow the U.S. Bureau of Labor Statistics by combining NAICS 44-45 into a single retail industry and 31-33 into a single manufacturing industry. As a robustness check, we also decomposed these industries, with the results unchanged. Finally, we also examined the industry's average time to failure because organizations in industries with a relatively low likelihood of failure will be better able to survive in general. Full results are available on request from the authors.

We used z tests to compare group coefficients (see Table S5). The log STCC coefficients are significantly larger for agriculture (high claims) than any of the low claims industries (Retail, and Professional and technical services, and Accommodation and food services), and another high claims industry (Construction). There were no other significant effects. The comparisons of the log STCC squared term coefficients showed a similar pattern.

We also wished to further investigate potential interactions between short-term employee turnover and STCC, so we grouped the effects of log STCC on hazard by short-term turnover quartiles. Quartile cutoffs expressed as the standard deviation of employment per quarter were: 0 to .65; .65 to 1.18, 1.18 to 2.44 and 2.44 to 38.44.

We performed a conditional Cox proportional hazards model to test for polynomial effects of log STCC on hazard grouped by organizational turnover quartiles. This was done because organizations with high turnover may have increased harm to workers (Khanzode et al., 2012; Burt, 2016) and poorer organizational performance (Koys, 2001).The protective effect of increasing log STCC is present only for organizations with higher turnover (quartiles 3 and 4; full results are available on request from the authors). Again, we used z tests to compare group coefficients (see Table S6). The group comparisons showed that the log STCC coefficients did not differ significantly between quartiles 3 and 4. The comparisons of the log STCC squared term coefficients showed a similar pattern.

We also investigated potential interactions between output-per-worker and STCC, so we grouped the effects of log STCC on hazard by output-per-worker quartiles. Quartile cutoffs expressed as industry standardized wages per 100 workers per quarter were: -2.51 to -.55; -.55 to -.19; -.19 to .31 and .31 to 50.99.

We grouped the polynomial effects of log STCC on hazard by organizational output-per-worker quartiles in a conditional cox proportional hazards model (full results available on request from authors). This was done because organizations with higher output-per-worker may expose their workers to greater hazard (Zohar, 2008), but also be more likely to survive (Jovanovic, 1982). Again, we used z tests to compare group coefficients (see Table S6). The group comparisons showed that the log STCC coefficients are significantly larger in quartiles 3 and 4 than quartiles 1 and 2. Quartiles 3 and 4 did not differ significantly, nor did quartiles 1 and 2. The comparisons of the log STCC squared term coefficients showed a similar pattern.

The short-term models indicate that increased STCC predicts increased survival in the current quarter; this effect is curvilinear (u-shaped) and increased STCC eventually harms survival. This pattern is consistent but strongest for older and larger organizations, as well as those with zero to moderate levels of growth and higher output-per-worker. There were no clear pattern across industry or turnover.

Long-term analysis and results

We performed the long-term analysis because the short-term impact of not providing a safe workplace might be to reduce costs, increasing survival. In the long-term, the effects might be different.

Specifically, we ran a set of linear regression analyses with the organization's time to failure in quarters as the dependent variable, and the logged average quarterly claims cost over its lifetime was the key explanatory variable. Control variables were as in the ST analysis, but year and quarter was not included (as the analysis is not carried out at the quarterly level). Each observation in this analysis was an organization; the analysis was performed on 122,570 organizations. Table S7 shows the distribution of the LT sample by industry. The mean log(LTCC) was 3.16 (SD=4.13), ranging from 0 to 11.42.

Multiple linear regression analyses were performed with time to failure in quarters as the dependent variable. First, a model containing only the control variables as independent variables was performed (full results available on request from the authors). Second, a model containing control variables and log LTCC as independent variables was performed. Including log LTCC in the second model explained an additional 5.44% of the variance in survival (33.1% of variance vs. 27.66% of the variance accounted for by control variables; full results available on request from the authors). Increasing log LTCC by 1 is associated with a 1.99 (2.18, 2.27) quarter increase in survival.

A third model was performed (Main effect: Table 3) which contains the control variables, log LTCC, and a log LTCC squared term to test for a non-linear relationship. As with STCC, the third-order polynomial term was non-significant, so no polynomial terms beyond the squared term were included. The formula is as follows:

$$\textit{Time to failure} = \textit{mean employment per quarter} + \textit{industry dummy variables} + \textit{age at entry} + \textit{entry year and quarter} + \textit{output-per-worker} + \textit{turnover} + \textit{growth} + \textit{growth}^2 + \textit{Log LTCC} + (\textit{Log LTCC})^2$$

The relationship between LTCC and time to failure has an upside-down U-shape, as indicated by the negative coefficient for the log LTCC squared term (see also Fig. 3 in the main body). Including this term improved model fit, $\chi 2(1)$ =3215.6. The maximum of this curve does occur within the range of LTCC. At the curve's maximum, organizations increase their time to failure by 22.05 (20.19, 23.92) quarters (see also Table 4 in the main body). This occurs at LTCC= 6.33 (5.97, 6.72) which is above the 65th percentile. From here, the time to failure benefits of LTCC diminish. LTCC levels above 12.67 (11.94, 13.45), which is above the 90th percentile, relate to a shorter time to failure than organizations with no claims.

In a fourth model (Size; Table 3), the polynomial effects of log LTCC are stratified by organizational size, consistent with the short-term models. Again, we used z tests to compare coefficients on LTCC for the separate regressions run with the different groups (Table S8). The results suggest that the effect of log LTCC on time to failure is larger for larger organizations relative to smaller ones (see also Size, Fig. 3 and Table 4).The group comparisons showed that the log LTCC coefficients are significantly bigger in the larger organizations (30-100 workers, and 100+ workers)than the smaller ones (<10 and 10-30 workers). The comparisons of the log LTCC squared term coefficients showed a similar pattern.

In a fifth model (Growth, Table 3, Fig., 3; also see Table 4) the effects of log LTCC were grouped by growth quartiles. To investigate a potential interaction between long-term growth and LTCC, we grouped the effects of log LTCC on survival by long-term growth quartiles, consistent with the short-term models. Quartile cutoffs expressed as percent change in employment per quarter were: -75.26% to -5.2%; -5.2% to 0%; 0% to 3.37%; 3.37% to 113.65%. Again, we used z tests to compare group coefficients (Table S8). The group comparisons showed that the largest effects were associated with zero to moderate levels of growth. Quartile 3 shows larger effects than any other quartile. The comparisons of the log LTCC squared term coefficients showed a similar pattern.

Consistent with the short-term analyses, three additional models were performed to test whether the effects of log LTTC differ across groupings of industry, turnover, and output-per-worker. First, organizations were stratified by industry categories according to their average quarterly wage and log LTCC (as in the short-term models). Full results are available on request from the authors. Increases in log LTCC are associated with longer survival for all industry groups examined. Z tests were again performed but there were no clear patterns (see Table S9).

To further investigate a potential interaction between long-term turnover and LTCC, we grouped the effects of log LTCC on survival by long-term turnover quartiles, consistent with the short-term models. Quartile cutoffs expressed as standard deviation of employment per quarter were: 0 to 1.6; 1.6 to 2.54; 2.54 to 4.91; 4.91 to 5913.87. Full results are available on request from the authors. Again, we used z tests to compare group coefficients (see Table S10). The log LTCC coefficient was significantly larger for quartile 2 than quartile 1, and quartile 4 than quartile 2. There are no other significant differences between quartiles. The comparisons of the log STCC squared term coefficients showed a similar pattern.

To further investigate a potential interaction between long-term output-per-worker and LTCC, we grouped the effects of log LTCC on survival by long-term output-per-worker quartiles, consistent with the short-term models. Quartile cutoffs expressed as industry standardized output-per-worker per 100 workers per quarter, were: -1.92 to -.51; -.53 to -.23; -.23 to .16; .16 to 35.65. Full results are available on request from the authors. Again, we used z tests to compare group coefficients (see Table S10). The log LTCC coefficient was significantly larger for quartiles 2, 3 and 4 than quartile 1. There are no other significant differences between quartiles. The comparisons of the log STCC squared term coefficients showed a similar pattern, with an additional significant comparison between quartiles 2 and 4.

The results of the long-term models indicate that increased LTCC predicts longer organizational survival; this effect is curvilinear (inverse u-shaped) and eventually turns negative. This pattern is consistent but strongest for the largest organizations, and those with zero to moderate levels of growth.

Alternative operationalizations of providing a safe workplace - count of claims

The primary measures of providing a safe workplace are STCC and LTCC, because all things being equal higher claims costs indicate either more claims or more severe claims. However, workers who are unaware of the costs of claims, will be aware of the frequency of claims, and may respond to frequency more than severity. Therefore, we replaced cost of claims with count of claims as a robustness check.

To assess the effect of short-term claims count (STcount) on risk of failure**,** STcounts were captured at each time point (quarter) as a time-varying covariate (Fisher and Lin, 1999). Like STCC, STcount was defined as the mean claims count per 100 workers per quarter per organization in the past two years. As with STCC, STcount was log transformed due to extreme positive skew. To avoid losing 0 values in the transformation, 1 was added prior to log transformation. STcount was top coded at the 99^{th} percentile to reduce the influence of having a very large number of claims. Mean log STcount after top coding was.17 (SD= .38) or .31 (SD=.79) claims per 100 workers per quarter.

To examine the effects of log STcount on risk of failure, a series of conditional cox proportional hazards models were performed on the ST sample (103,906 organizations).

As shown in Table S11, four conditional cox proportional hazards models were constructed. Model 1 (Table S11) includes only the control variables as independent variables. Model 2 (Table S11) includes control variables and log STcount as independent variables. Increases in log STcount did not improve model fit over the control variables alone ($\chi2(1)$ =.06).

Model 3 (Table S11) tests whether there is a substantial non-linear component by including a polynomial term (log $STcount^2$) as an independent variable. There is a protective effect of STcount which appears to have an upper limit, as indicated by the positive coefficient for the log STcount squared term. Including this term improved model fit, $\chi2(1) = 116.65$. Having claims is associated with up to a 12.23 % (5.55 %, 18.43 %) lower risk of failure relative to organizations with zero STcount. Diminishing returns exist beyond this vertex, and when STcounts are very high, they are associated with an increased risk of failure. Risk of failure relative to organizations with no claims, holding all other covariates constant, may be calculated as exp (-0.3858 *log STcount + 0.2852 *(log STcount)^2).

The polynomial effects of log STcount on hazard in Model 4 are grouped by organizational age (3-7 years, 8-12 years, 13-17 years, 18-22 years, 23-27 years, 28 years or more) when examining the effect of log STcount on risk of failure. There was no significant effect for the youngest organizations (3-7 years), but there were significant curvilinear effects for all other groupings, consistent with the results for log STCC.

The short-term models indicate that increased STcount predicts increased survival in the current quarter in the same way as STCC; this effect is curvilinear (U shaped) and increased STcount eventually harms survival.

Long-term claims count

We tested whether the long-term results are robust using a different operationalization of protecting the workforce - claims counts. To test the effect of long-term claims count (LTcount) on time to failure, LTcount was calculated as mean claims counts per 100 workers per quarter per organization, calculated across the lifetime of each organization. Long-term claims count was log transformed due to extreme positive skew. To avoid losing 0 values in the transformation, 1 was added prior to transformation, in a similar fashion to the short-term claims count. LTcount was top coded at the 99th percentile to reduce the influence of having a very large number of claims. Mean LTcount was .20 (SD=.34), or .32 (SD=.66) claims per 100 workers per quarter.

To examine the effects of log LTcount on survival, multiple linear regression analyses were performed on the LT sample (122,570 organizations). Several multiple linear regression analyses were performed with time to failure in quarters as the dependent variable (full results are available on request from authors). First, we included only the control variables as independent variables. Second, we included control variables and log LTcount as independent variables. Including log LTcount in the second model we performed explained an additional .07% of the variance in survival (27.73% of variance vs. 27.66% of the variance accounted for by control variables). Increases in log LTcount improved model fit over the control variables alone ($\chi 2(1)$ =179.79). Increasing log LTcount by 1 is associated with a 2.58 (2.11, 3.05) quarter increase in time to failure.

A third model contained the control variables, log LTcount, and a log LTcount squared term to test for a non-linear relationship. Full results are available on request from the authors. The predicted protective effect of log LTcount has an upper limit, as indicated by the negative coefficient for the log LTcount squared term. Including this term improved model fit, explaining an additional 4.97% of the variance in survival (32.7% of variance vs. 27.73% of the variance accounted for by control variables and LTcount alone). Organizations may increase their time to failure by up to 16.45 (15.41, 17.49) quarters. Diminishing returns exist beyond this vertex, and at very high levels of claims there is an increased risk of failure.

The results of the long-term models indicate that increased LTcount predicts longer organizational time to failure in the same manner as LTCC; this effect is curvilinear (inverse u-shaped) and eventually turns negative.

This robustness check suggests that our results are not sensitive to changing the operationalization of providing a safe workplace from cost of claims to a count of claims, providing additional confidence in the results.

Alternative operationalizations of providing a safe workplace – claims as a binary

Both the claims cost and claims count measures remain skewed even after log transformation. Plus it is possible that there is a fundamental difference between organizations that have no claims (either in the short or long-term). Therefore, as another robustness check we operationalized providing a safe workplace as a binary claims / no claims variable. Providing a safe workplace was dummy coded to test the effects of having one or more claims on the risk of failure - where organizations with one or more claims were coded as 1 and organizations with 0 claims were coded as zero. In the short-term, this was calculated over the previous two years (STdummy). In the short-term 77.48% of observations have 0 claims.

As shown in Table S12, 3 conditional cox proportional hazards models were constructed. Model 1 contains only control variables. Model 2 (Table S12) includes only the control variables and the STdummy as independent variables. Model 2 predicts that organizations with claims have a 10.57 % (8.45 %, 12.65 %) lower failure risk in the current quarter relative to organizations with no short-term claims. Due to the binary measure, there is no polynomial model.

The effect of the STdummy on hazard in Model 3 (Table S12) is grouped by organizational age when examining the effect of the STdummy on risk of failure. The effect is not significant for the youngest organizations.

The short-term models indicate that having claims predicts increased survival in the current quarter, consistent with the results for STCC.

Long-term claims dummy

Providing a safe workplace was also dummy coded for the long-term. In the long-term, this was calculated over the organization's lifetime (LTdummy). 61.26% of organizations never have a claim in their lifetime.

Two multiple linear regression analyses were performed with survival in quarters as the dependent variable. Full results are available from the authors on request. The first model contained only the control variables as independent variables. The second model contained control variables and LTdummy as independent variables. Including LTdummy in Model 2 explained an additional 6.73% of the variance in survival (34.39% of variance vs. 27.66% of the variance accounted for by control variables). Having claims is associated with an 18.62 (18.29, 18.94) quarter increase in survival relative to not having claims.

The results of the long-term models indicate that having claims predicts longer organizational time to failure, in a similar manner as LTCC.

This robustness check suggests that our results are not sensitive to changing the operationalization of providing a safe workplace from cost of claims to a binary claims/no-claims variable, providing additional confidence in the results.

Discrete time hazard models

Our quarterly timescale is coarse and results in a lot of "ties" in the data (Allison, 1982; Singer and Willett 2003). Therefore, we also ran a set of discrete-time hazards models to ensure that our short-term results are robust. We chose the Cox model for our main analysis due its key benefit—not needing to specify the baseline hazard function (Singer and Willett, p. 520; Allison 2014; p. 33-4). Box-Steffensmeier and Jones (2011, 7th edition) noted: "The principal argument we have made is that in most social science settings, the Cox model should generally be preferred over its alternatives, for example the parametric models or some of the discrete models discussed in the last chapter." (p. 85); and further "if interest centers primarily on the relationship between covariates and the hazard rate, then it is difficult to find settings where a parametric model would be preferred over a Cox model." (p.86-7). As our focus is on the relationship between covariates (specifically, claims costs) and the hazard rate; and not the baseline hazard rate, we chose the Cox regression for our main analysis and report the discrete time hazard as a robustness check.

Four conditional discrete time hazard models were constructed for STCC. Full results for these models are available on request from the authors. The first model included only the control variables as independent variables. The second model included control variables and log STCC as independent variables. Increases in log STCC are associated with a lower risk of failure, as indicated by the negative coefficient for log STCC, improving model fit substantially over the control variables alone (AIC=518958 vs. AIC =519010 for control variables alone). The second model predicts that a one-unit increase in log STCC is associated with odds of failure .99 lower relative to organizations with no short-term claims. The odds ratio of failure relative to organizations with no claims, holding all other covariates constant, may be calculated as exp(-0.0096 *log STCC).

The third model tests whether there is a substantial non-linear component by including a polynomial term ($(\log \text{STCC})^2$) as an independent variable. Consistent with the conditional cox proportional hazards models, the protective effect of STCC appears to have an upper limit, as indicated by the positive coefficient for the log STCC squared term. Including this term improved model fit substantially, (AIC= 518835 vs. AIC= 518958 without the squared STCC term). Having claims is associated with an odds ratio as low as 0.79 (0.71, 0.89) relative to organizations with zero STCC. Diminishing returns exist beyond this vertex, and when STCCs are very high, they are associated with an increased risk of failure. The odds ratio of failure relative to organizations with no claims, holding all other covariates constant, may be calculated as exp (-0.0865*log STCC + 0.008*$(\log \text{STCC})^2$.

Finally, the polynomial effects of log STCC on the log odds of failure were grouped by organizational age (3-7 years, 8-12 years, 13-17 years, 18-22 years, 23-27 years, 28 years or more), consistent with the Cox models. There were significant curvilinear effects for all age groupings, consistent with the Cox model results.

The results of the short-term conditional discrete hazard models are consistent with those for the short-term conditional cox proportional hazard models. The results indicate that increased STCC predicts increased survival in the current quarter; this effect is curvilinear (u-shaped) and increased STCC eventually harms survival.

This robustness check suggests that our results are not sensitive to changing from cox proportional hazard models to conditional discrete hazard models, providing additional confidence in the results.

Medium-term analysis

The short-term analysis explores the immediate risk of failure, with STCC being used to predict the risk of failure in the current quarter. Organizations facing existential crises, such as the threat of bankruptcy, could reduce their focus on safety and hence have more claims shortly prior to failure. The short-term results suggest the opposite. However, as a robustness check we explore this possibility by adding a longer lag between STCC and risk of failure. In the primary short-term models, failure was assessed in the current quarter (based on STCC in the prior 8 quarters). In the medium-term analysis, failure is assessed with a one-year lag. Specifically, the lag between STCC and our assessment of failure was 1 quarter in the short-term analysis; in this robustness check we increase this lag to 4 quarters. For ease of reference, we name this new variable medium-term claims costs (MTCC). To examine the effect of MTCC on risk of organizational failure, organizations with fewer than three years of records in the QCEW (2.72% of original population) were eliminated to construct a sample of 93,415 organizations, with a total of 3,645,774 observations, 280,6503 of which do not have claims (76.98%) (MT sample). Mean employment per organization, growth, output-per-worker and turnover were also lagged by one year and included as control variables. All other control variables were as in the short-term analysis.

To examine the effects of log MTCC on risk of failure, a series of conditional cox proportional hazards models were performed on the MT sample (93,415 organizations) similar to what was done with the short-term models. Four conditional cox proportional hazards models were constructed- full results are available from authors on request.

The third model tested whether there is a substantial non-linear component by including a polynomial term (log $MTCC^2$) as an independent variable. The protective effect of MTCC appears to have an upper limit, as indicated by the positive coefficient for the log MTCC squared term. Including this term improved model fit, $\chi2(1) = 237.13$. Full results are available from authors on request. Having claims is associated with up to a 28.21 % (19.05 %, 36.37 %) lower risk of failure relative to organizations with zero MTCC. Diminishing returns exist beyond this vertex, and when MTCCs are very high, they are associated with an increased risk of failure. Risk of failure relative to organizations with no claims, holding all other covariates constant, may be calculated as $\exp(-0.124 * \log MTCC + 0.0116 * (\log MTCC)^2$.

The polynomial effects of log MTCC on hazard in in the final model were grouped by organizational age (3-7 years, 8-12 years, 13-17 years, 18-22 years, 23-27 years, 28 years or more) when examining the effect of log MTCC on risk of failure, consistent with the short-term models. There were significant curvilinear effects for all age groupings- consistent with the log STCC Cox model. Full results are available on request from the authors.

The medium-term models indicate that increased MTCC predicts increased survival in the current quarter; this effect is curvilinear (u-shaped) and increased MTCC eventually harms survival, consistent with the short-term models.

This analysis suggests that the results are not unique to our operationalization of short-term and provides additional confidence in the overall results.

Predicting failure instead of time to failure

Organizations coded as "ongoing" still exit the dataset in 2014. When controlling for both organizational failure and entry year/quarter, no variance in survival exists for ongoing organizations because both entry and exit times are controlled. This lack of variance effectively excludes the longest surviving organizations from the long-term analysis. Therefore, instead of including failure as a covariate, we predict it separately as a robustness check. Specifically, logistic regression analyses were performed with organizational failure as the dependent variable (coded with 1= failure before quarter 4 of 2014, 0= ongoing at the end of the panel). Full results are available on request from the authors.

The first model includes only control variables. The second model includes control variables and log LTCC. This model shows that increasing log LTCC by 1 results in a .022 (.021, .022) decrease in log odds of failure. The reduction in log odds of failure relative to an organization with no LTCC may be calculated as: -0.0216 (3e-04) *log LTCC; (standard errors in brackets).

The third model indicates that the relationship between claims costs and log odds of failure is curvilinear (inverse u), as indicated by the negative coefficient for the squared term. Including the squared term explained an additional 1.08% of the variance in log odds of failure, and improved model fit $\chi 2(1) = 4343.7$. An organization with claims costs may have up to a 0.25 (0.22, 0.28) decrease in log odds of failure. Average log odds of failure was 0.42. The reduction in log odds of failure relative to an organization with no LTCC may be calculated as: -0.081* log long-term claims costs + 0.0066* (log long-term claims costs)^2.

The results of the long-term models predicting failure indicate that increased LTCC predicts a lower odds of failure; this effect is curvilinear (inverse-u) and eventually turns negative.

The robustness check using failure instead of time to failure reaches the same conclusion, adding confidence to the long-term findings.

Alternative functional forms- short-term

The main short-term analyses adopt a quadratic functional form. To test whether the results are robust to the functional form, we modelled log STCC non-parametrically by grouping it into quartiles and deciles.

All values of 0 log STCC were grouped together, and coded as 0. All remaining non-zero values were grouped into quartiles (coded as 1, 2, 3 and 4 respectively). Zero values were grouped together first because 77.47% of the log STCC observations are zero, and therefore breaking the sample directly into quartiles would involve assigning the 0 STCC values into separate groups. The log STCC cutoffs for non-zero values were as follows: quartile 1, 0.65-7.48; quartile 2, 7.48- 8.76; quartile 3, 8.76-9.94; quartile 4, 9.94-11.66. Hereafter, the zero groupings plus the non-zero log STCC quartile groupings are referred to as log STCC quartiles. To examine the effects of log STCC quartiles on risk of failure, a conditional cox proportional hazards model was performed on the ST sample (103, 906 organizations). Control variables were as in the short-term models (Table S3).

First, we tested whether there is a substantial non-linear component by including log STCC quartiles as an independent variable. There is a protective effect of log STCC quartiles which appears to have an upper limit, as indicated by the non-significant effect for the fourth quartile. Including this term improved model fit, $\chi2(4) = 166.9$. Full results are available from the authors on request. Having claims is associated with a 17.75 % (14.16 %, 21.2 %) lower risk of failure for organizations in the first quartile, an 18.01 % (14.32 %, 21.53 %) lower risk of failure for organizations in the second quartile, a 10.58 % (6.71 %, 14.3 %) lower risk of failure for organizations in the third quartile, and no significant effect in the fourth quartile relative to organizations with zero log STCC.

Next, we grouped all the non-zero values of log STCC into deciles, to further explore a non-parametric functional form. Hereafter, the zero STCC group plus the non-zero log STCC decile groupings are referred to as log STCC deciles. To examine the effects of log STCC decile on risk of failure, a conditional cox proportional hazards models were performed on the ST sample (103,906 organizations). Control variables were as before.

We tested whether there is a substantial non-linear component by including log STCC deciles as an independent variable (see Table S13). Full results are available on request from the authors. The results show an effect of claims which is relatively steady, and increases up to the fifth decile, then diminishes, becoming non-significant in the 7th decile, and eventually becomes negative in the tenth decile (see Table S13).

The short-term quartile and decile models indicate that increased log STCC predicts increased survival in the current quarter in a fashion consistent with a curvilinear (U shaped) quadratic functional form.

Alternative functional forms- long-term

To test whether the long-term results are robust to functional form, we modelled log LTCC non-parametrically by grouping it into quartiles and deciles.

First, all values of 0 log LTCC were grouped together, and coded as 0. All remaining non-zero values were grouped into quartiles (coded as 1, 2, 3 and 4 respectively). Zero values were grouped together first because 61.36% of the log LTCC observations are zero, and therefore breaking the sample directly into quartiles would involve assigning the 0 LTCC values into separate groups. The log LTCC cutoffs for non-zero values were as follows: quartile 1, 0.67-7.03; quartile 2, 7.03-8.34; quartile 3, 8.34-9.47; quartile 4, 9.47-11.42. Hereafter, the zero group plus the non-zero log LTCC quartile groupings are referred to as log LTCC quartiles.

To examine the effects of log LTCC quartiles on time to failure, a linear regression analysis was performed on the LT sample (122,570 organizations). Time to failure was the dependent variable.

The first model contained the control variables, and log LTCC quartiles to test for a non-linear relationship. Full results are available on request from the authors. There is a protective effect of log LTCC quartiles which appears to have an upper limit, as indicated by the non-significant effect for the fourth quartile. Including this term improved model fit, $\chi2(4) = 12611$ relative to control variables alone. Having claims is associated with a 19.77 (19.25, 20.29) quarters increase in time to failure for organizations in the first quartile, a 20.43 (19.91, 20.94) quarters increase in time to failure for organizations in the second quartile, a 20.82 (20.29, 21.34) quarters increase in time to failure for organizations in the third quartile, and a 12.83 (12.3, 13.37) quarters increase in time to failure for organizations in the fourth quartile relative to organizations with zero log LTCC.

Next, we grouped all the non-zero values of log LTCC into deciles, to further explore a non-parametric functional form. 61.36% of the observations were 0 log LTCC, the remainder were divided into deciles of non-zero values of log LTCC. Hereafter, the zero groupings plus the non-zero log LTCC decile groupings are referred to as log LTCC deciles. To examine the effects of log LTCC deciles on time to failure, a linear regression analysis was performed on the LT sample (122,570 organizations). Time to failure was the dependent variable.

There is a protective effect of log LTCC quartiles which appears to have an upper limit, as indicated by the decreasing effects from the 6th decile (see Table S13). Including this term improved model fit, $\chi2(10) = 13172$. Full results are available on request from the authors.

The long-term quartile and decile models indicate that increased log LTCC predicts increased survival in the current quarter in a fashion consistent with a curvilinear (U shaped) quadratic functional form.

Removing small organizations- short-term

The samples used in the main analyses excluded organizations that were always very small (never exceeded 5 employees) while maintaining organizations that grew from very small to larger. It is possible that the exclusion criterion drove the results. Hence. we created additional short and long-term samples where we excluded organizations that never exceeded 10 employees.

The new short-term sample consisted of 61,054 organizations, with a total of 2,634,907 observations, 1,821,352 of which do not have claims (69.12%). Full results for these models are available on request from the authors.

Three conditional cox proportional hazards models were constructed. The first model included only the control variables as independent variables. The second model included control variables and log STCC as independent variables. Increases in log STCC are associated with a lower risk of failure, as indicated by the negative coefficient for log STCC, improving model fit over the control variables alone ($\chi2(1) = 16.96$). The second model predicts that a one-unit increase in log STCC is associated with a 0.65 % (0.34 %, 0.95 %) lower failure risk in the current quarter relative to organizations with no short-term claims. Risk of failure relative to organizations with no claims, holding all other covariates constant, may be calculated as exp (-0.006*log STCC).

The third model tested whether there is a substantial non-linear component by including a polynomial term ((log STCC)^2) as an independent variable. These models were performed separately to assess the impact of STCC on model fit, relative to the control variables. The protective effect of STCC appears to have an upper limit, as indicated by the positive coefficient for the log STCC squared term. Including this term improved model fit, $\chi2(1) = 63.94$. Having claims is associated with up to a 16.49 % (5.24 %, 26.4 %) lower risk of failure relative to organizations with zero STCC. Diminishing returns exist beyond this vertex, and when STCCs are very high, they are associated with an increased risk of failure. Risk of failure relative to organizations with no claims, holding all other covariates constant, may be calculated as exp (-0.0687 *log STCC + 0.0065*(log STCC)^2.

This analysis suggests that the results are robust when the smallest organizations are excluded in the short-term analysis and provides additional confidence in the overall results.

Removing small organizations – long-term

To examine the effects of log LTCC on time to failure, a set of linear regression analyses were performed on the LT sample, with organizations that never exceed 10 employees removed. The sample consisted of 68,717 organizations, 32,178 of which do not have claims (46.82%). Full results for these models are available on request from the authors.

Three multiple linear regression analyses were performed with time to failure in quarters as the dependent variable. The first model contained only the control variables as independent variables. Model 2 contains control variables and log LTCC as independent variables. Including log LTCC in the second model explained an additional 5.36% of the variance in survival (37.33% of variance vs. 29.52% of the variance accounted for by control variables). Increasing log LTCC by 1 is associated with a 2.63 (2.56, 2.7) quarter increase in survival.

A third model contains the control variables, log LTCC, and a log LTCC squared term to test for a non-linear relationship. A stopping rule was implemented, such that non-significant polynomial terms would not be included in the final model. Due to the third-order polynomial term being non-significant, no polynomial terms beyond the squared term were included. The predicted protective effect of log LTCC has an upper limit, as indicated by the negative coefficient for the log LTCC squared term (see also Fig. S8). Including this term improved model fit, $\chi2(1) = 1702.2$. Organizations may increase their time to failure by up to 21.23 (18.81, 23.65) quarters. Diminishing returns exist beyond this vertex, and the effect eventually turns negative.

This analysis suggests that the results are robust when the smallest organizations are excluded from the long-term analysis and provides additional confidence in the overall results.

Alternative operationalizations of industry

In the main analysis we control for potential differences between industries using two-digit NAICS codes. This is done using a series of dummy variables. However this is a broad categorization which may miss more fine grained differences in professional riskiness between industries, which could result in differing risks of claims and organizational failure.

To address this, we performed two robustness checks. We performed each robustness check for both the short-term model and the long-term model; thus a total of four analyses were performed.

In the short term, we first replaced the industry dummies with the professional riskiness of each industry; at the four-digit NAICS level. To examine the effects of log STCC on risk of failure, when controlling for professional riskiness, a series of conditional cox proportional hazards models were performed on the Professional Riskiness sample (84,190 organizations), similar to what was done with the short-term models. Four conditional cox proportional hazards models were constructed- full results for these models are available from the authors on request.

The BLS accident rate data extend from 1994 to 2014 (BLS, 2019b). Professional riskiness was defined as the incidence rate of nonfatal occupational injuries and illnesses per 100 full time workers, per four-digit NAICS group, per year. The same value was used in all four quarters for a given year. Data which were reported with NAICS 2002, 2007, or Standard Industrial Classification 1987 systems were converted into NAICS 2012. The sample for these analyses, consisted of 84,190 organizations, and 2,563,464 observations (as the data only extends back to 1994, and requires a four-digit NAICS code).

The first model includes only control variables. The second model tested for effects of professional riskiness on likelihood of failure, by including professional riskiness as a control variable. Professional riskiness is associated with an increased likelihood of failure, as indicated by the positive coefficient for the professional riskiness term. Including this term improved model fit relative to controls alone, $\chi2(1) = 208.93$ (see Table S14). Full results are available from the authors on request.

The third model tests for the non-linear effects of log STCC, when including professional riskiness as a control variable. Consistent with the main analysis, there is a protective effect of log STCC which appears to have an upper limit as indicated by the negative coefficient for the log STCC term and the positive coefficient for the (log STCC)^2 term (both significant at $p<.001$). Including the log STCC + (log STCC)^2 terms improved model fit relative to controls and professional riskiness alone (Model 2), $\chi2(2) = 156.99$, (see Table S14 and S16). Having claims is associated with up to a 23.13 % (9.48 %, 34.72 %) lower risk of failure relative to organizations with zero STCC. Diminishing returns exist beyond this vertex, and when STCC is very high, it is associated with an increased risk of failure. Risk of failure relative to organizations with no claims, holding all other covariates constant, may be calculated as exp (-0.0906*log STCC + 0.0078*(log STCC)^2).

The second short-term robustness check addressed the issue that there might be industry heterogeneity not captured by professional riskiness or two-digit NAICS categorizations. Therefore, we also performed an analysis where we used four-digit NAICS dummy variables to replace the two-digit NAICS dummy controls using the same sample as above (Model 4, Table S15; also see Table S16). Including four digit NAICS controls improves model fit relative to control variables alone $\chi2(291) = 4095.8$. The results for log STCC remain highly consistent. Including the log STCC + (log STCC)^2 terms improved model fit relative to controls and four-digit NAICS dummy variables alone $\chi2(2) = 143.26$. Having claims is associated with up to a 23.5 % (10.55 %, 34.57 %) lower risk of failure relative to organizations with zero STCC. Diminishing returns exist beyond this vertex, and when STCC is very high, it is associated with an increased risk of failure. Risk of failure relative to organizations with no claims, holding all other covariates constant, may be calculated as exp (-0.0958*log STCC + 0.009*(log STCC)^2).

The two short-term models indicate that replacing the two-digit industry dummies with four-digit industry accident rates to account for professional riskiness, does not materially change the short-term results. As with the main analysis, STCC predicts increased survival in the current quarter; this effect is curvilinear (U shaped) and increased STCC eventually harms survival, for all levels of professional riskiness. Further, the results are consistent when we replace the two-digit industry dummies with four-digit industry dummies.

Long-term industry

We first tested whether the long-term results were robust to replacing the two-digit industry dummies with a four-digit measure of professional riskiness. Professional riskiness was defined as the incidence rate of nonfatal occupational injuries and illnesses per 100 full time workers, per four-digit NAICS group per year, calculated across the lifetime of each organization.

Multiple linear regression analyses were performed with time to failure in quarters as the dependent variable. First, a model containing only the control variables as independent variables was performed - full results available on request from the authors. Second, a model containing control variables, with professional riskiness (aggregated across the dataset) was performed. Including professional riskiness in the second model explained an additional .08% of the variance in survival (25.24% of variance vs. 25.16% of the variance accounted for by control variables (see Table S17 and S19); full results available on request from the authors).

A third model was performed which contains the control variables, professional riskiness, log LTCC, and a log LTCC squared term to test for a non-linear relationship between log LTCC and time to failure. The non-linear effects of log LTCC were consistent with the main results, controlling for professional riskiness. Including log LTCC + $(\log \text{LTCC})^2$ improved model fit, $\chi2(2) = 10255$. At the curve's maximum, organizations increase their time to failure by 20.62 (18.73, 22.51) quarters. From here, the time to failure benefits of LTCC diminish, eventually becoming negative. See Table S17 and S19. Full results are available on request from the authors.

The second long-term robustness check addressed the issue that there might be industry heterogeneity not captured by professional riskiness, or two-digit NAICS categorizations. Therefore, we also performed an analysis where we used four-digit NAICS dummy control variables to replace the two-digit NAICS dummy controls using the same sample as above (see Table S19). Including four-digit NAICS controls improves model fit relative to control variables alone $\chi2(304) = 20228$ (see Model 2, Table S18). The results for log LTCC remain consistent. Including the log LTCC + $(\log \text{LTCC})^2$ terms improved model fit relative to controls and four-digit NAICS dummy variables alone (Model 3), $\chi2(2) = 11911$. Having claims is associated with up to a 20.79 (18.88, 22.7) quarters increase in time to failure relative to organizations with zero LTCC (see Table S18 and S19). Diminishing returns exist beyond this vertex, and when LTCC is very high, it is associated with a reduced time to failure. Risk of failure relative to organizations with no claims, holding all other covariates constant, may be calculated as $\exp(6.4226 * \log \text{STCC} - 0.4961 * (\log \text{STCC})^2)$.

The two long-term models indicate that replacing the two-digit industry dummies with four-digit industry accident rates to account for professional riskiness, does not change the primary long-term results. Increased LTCC predicts increased survival; this effect is curvilinear (U shaped) and increased LTCC eventually harms survival. Further, the results are consistent when we replace the two-digit industry dummies with four-digit industry dummies.

Exhibits short-term analysis

Tables S1 to S6

Table S1. Industry distribution of ST sample (short-term analysis).

Two digit NAICS code and description		*Total Organizations*		*Total Observations*	
		N	**% of total**	**N**	**% of total**
11	*Agriculture, Forestry, Fishing and Hunting*	4708	4.53	197293	4.88
21	*Mining, Quarrying, and Oil and Gas Extraction*	189	0.18	8538	0.21
22	*Utilities*	92	0.09	5520	0.14
23	*Construction*	12473	12	470896	11.64
31	*Manufacturing (A; Food and Textiles)*	1390	1.34	55521	1.37
32	*Manufacturing (B; Chemical, Minerals, Plastics, Paper)*	2398	2.31	106085	2.62
33	*Manufacturing (C; Aerospace, Computer, Metals, Ships)*	3806	3.66	179530	4.44
42	*Wholesale Trade*	6340	6.1	270977	6.7
44	*Retail (A; Motor, Furniture, Health,Electronic)*	10122	9.74	384867	9.51
45	*Retail (B; Sporting Goods, General, Miscellaneous)*	3689	3.55	136023	3.36
48	*Transportation and Warehousing (A; Air, Rail,Deep Sea etc.)*	2370	2.28	93823	2.32
49	*Transportation and Warehousing (B; Postal Services, Couriers etc.)*	278	0.27	9487	0.23
51	*Information*	1845	1.78	67010	1.66
52	*Finance and Insurance*	2780	2.68	119977	2.97
53	*Real Estate and Rental and Leasing*	2964	2.85	121966	3.01
54	*Professional, Scientific, and Technical Services*	7563	7.28	314640	7.78
55	*Management of Companies and Enterprises*	174	0.17	6049	0.15
56	*Administration*	5698	5.48	197091	4.87
61	*Educational Services*	1299	1.25	51362	1.27
62	*Health Care and Social Assistance*	9445	9.09	405291	10.02
71	*Arts, entertainment and recreation*	1839	1.77	69898	1.73
72	*Accommodation and Food*	14771	14.22	414563	10.25
81	*Other Services (except Public Administration)*	7673	7.38	359905	8.89

Table S2. Yearly short-term claims cost (log STCC) descriptive statistics. Max was 11.66 in all years due to top-coding. Min was 0 in all years (no claims).

		Log STCC	
Year	**Mean**	**SD**	**N observations**
1991	2.43	3.95	128697
1992	2.28	3.86	135541
1993	2.27	3.87	140377
1994	2.3	3.89	144698
1995	2.31	3.9	148840
1996	2.22	3.84	152912
1997	2.14	3.79	158313
1998	2.13	3.79	162414
1999	2.08	3.76	165219
2000	2.05	3.75	167556
2001	2.01	3.73	170712
2002	1.93	3.69	173842
2003	1.89	3.67	175902
2004	1.89	3.7	177616
2005	1.9	3.71	179096
2006	1.89	3.7	181716
2007	1.9	3.71	185212
2008	1.89	3.7	187858
2009	1.79	3.63	186979
2010	1.66	3.54	186152
2011	1.62	3.51	184885
2012	1.61	3.5	184360

Table S3. Conditional proportional hazards models, full results. Conditional cox proportional hazards models show that increasing STCC reduces hazard but the effect is non-linear. The dependent variable for all models was risk of failure at time t (hazard). Model 1 includes only control variables. Model 2 tests the linear effect of STCC. Model 3 tests for polynomial effects of STCC. Model 4 examines the polynomial effects of STCC grouped by organization age. Model 5 examines the polynomial effects of STCC grouped by organization size. Model 6 examines the polynomial effects of STCC grouped by growth quartiles.

Coefficients are rounded to 4 digits, standard errors are in brackets

p<.001 unless otherwise specified

Independent Variable Specification	**Model 1** **Controls**	**Model 2** **Linear effect**	**Model 3** **Main Effect**	**Model 4** **Age**	**Model 5** **Size**	**Model 6** **Growth**	**% of total obs.**
Entry year and quarter	-0.0029 (0.0017) *p= 0.0848*	-0.0027 (0.0017) *p= 0.1121*	-0.0025 (0.0017) *p= 0.1359*	0 (0.0017) *p= 0.9986*	3e-04 (0.0017) *p= 0.8659*	0 (0.0017) *p= 0.9952*	
Mean employment per quarter in the past 2 years	-0.0025 (2e-04)	-0.0023 (2e-04)	-0.0021 (2e-04)	-0.0018 (1e-04)	-4e-04 (1e-04)	-4e-04 (1e-04)	
Year Quarter dummies	Included	Included	Included	Included	Included	Included	
Industry dummies	Included	Included	Included	Included	Included	Included	
Quarterly growth	-7.1658 (0.0504)	-7.1444 (0.0504)	-7.1237 (0.0504)	-7.1308 (0.0504)	-7.0521 (0.0506)	-4.1466 (0.0621)	
Quarterly growth^2	-3.9668 (0.0608)	-3.9479 (0.0608)	-3.9312 (0.0608)	-3.9397 (0.0607)	-3.9116 (0.0606)	-1.2026 (0.0674)	
Output-per-worker	-0.2147 (0.0056)	-0.2124 (0.0056)	-0.2127 (0.0056)	-0.212 (0.0056)	-0.2016 (0.0055)	-0.1991 (0.0056)	
Turnover	0.0136 (0.001)	0.0144 (0.001)	0.015 (0.001)	0.0146 (0.001)	0.0217 (0.001)	-0.0036 (0.001)	
Log STCC		-0.0094 (0.0013)	-0.0852 (0.0071)				
(log STCC)2			0.0079 (7e-04)				
Log STCC: 3-7 years				-0.0417 (0.0099)			34.46
Log STCC: 8-12 years				-0.0616 (0.0149)			20.89
Log STCC: 13-17 years				-0.111 (0.0192)			15.42
Log STCC: 18-22 years				-0.168 (0.0256)			10.6
Log STCC: 23-27 years				-0.1927 (0.0325)			6.91
Log STCC: 28+ years				-0.2214 (0.0246)			11.72
(log STCC)^2: 3-7 years				0.0047 (0.001)			
(log STCC)^2: 8-12 years				0.0056 (0.0015)			
(log STCC)^2: 13-17 years				0.0094 (0.002)			
(log STCC)^2: 18-22 years				0.0139 (0.0026)			

(log STCC)²: 23-27 years				0.0161 (0.0033)			
(log STCC)²: 28+ years				0.0191 (0.0025)			
Log STCC: < 10 workers					0.0088 (0.0109), p= 0.4191		60.8
Log STCC: 10-30 workers					-0.0388 (0.0116)		25.68
Log STCC: 30-100 workers					-0.1597 (0.018)		9.74
Log STCC: 100+ workers					-0.2755 (0.0355)		3.78
(log STCC)²: < 10 workers					-4e-04 (0.0011), p= 0.6954		
(log STCC)²: 10-30 workers					0.0046 (0.0012)		
(log STCC)²: 30-100 workers					0.0143 (0.0019)		
(log STCC)²: 100+ workers					0.0172 (0.0038)		
Log STCC: growth quartile 1						0.0036 (0.0084), p= 0.6712	24.85
Log STCC: growth quartile 2						-0.1388 (0.0228)	17.19
Log STCC: growth quartile 3						-0.236 (0.0207)	32.93
Log STCC: growth quartile 4						-0.1664 (0.0207)	25.02
(log STCC)²: growth quartile 1						-3e-04 (8e-04), p= 0.679	
(log STCC)²: growth quartile 2						0.0129 (0.0024)	
(log STCC)²: growth quartile 3						0.0207 (0.0021)	
(log STCC)²: growth quartile 4						0.017 (0.0021)	
Likelihood Ratio test	$\chi^2(123)= 84734$	$\chi^2(124)= 84785$	$\chi^2(125)= 84907$	$\chi^2(135)= 85122$	$\chi^2(131)= 82956$	$\chi^2(131)= 45286$	
Summary Findings	Controls predict hazard.	A one unit increase in log STCC results in a .94% reduction in risk of failure.	The relationship between log STCC and risk of failure is curvilinear.	The protective effect of recent claims costs is larger for older organizations than younger ones.	The protective effect of log recent claims costs is present only for organizations with >10 workers, and is greater for larger organizations than smaller ones.	The protective effect of recent claims costs is larger for organizations with moderate growth than low growth.	

Table S4. Z tests comparing the model coefficients for Log STCC and (log STCC)^2 between age, size and growth groupings.

Z coefficients are rounded to 2 digits, and *= p<.05, **=p<.01, ***=p<.001.

Age Groups						
		Log STCC				
		3-7 years	**8-12 years**	**13-17 years**	**18-22 years**	**23-27 years**
Log STCC	*8-12 years*	-1.11				
	13-17 years	-3.21 **	-2.03 *			
	18-22 years	-4.6 ***	-3.59 ***	-1.78		
	23-27 years	-4.44 ***	-3.67 ***	-2.16 *	-0.6	
	28 years or more	-6.78 ***	-5.56 ***	-3.54 ***	-1.5	-0.7
		(Log STCC)^2				
(Log STCC)^2	*8-12 years*	0.5				
	13-17 years	2.1 *	1.52			
	18-22 years	3.3 ***	2.77 **	1.37		
	23-27 years	3.31 ***	2.9 **	1.74	0.52	
	28 years or more	5.35 ***	4.63 ***	3.03 **	1.44	0.72

Size Groups				
		Log STCC		
		< 10 workers	***10-30 workers***	***30-100 workers***
Log STCC	*10-30 workers*	-2.99 **		
	30-100 workers	-8.01 ***	-5.65 ***	
	100 + workers	-7.66 ***	-6.34 ***	-2.91 **
		(Log STCC)^2		
(Log STCC)^2	*10-30 workers*	3.07 **		
	30-100 workers	6.7 ***	4.32 ***	
	100 + workers	4.45 ***	3.16 **	0.68

Growth Groups				
		Log STCC		
		quartile 1	**quartile 2**	**quartile 3**
Log STCC	*quartile 2*	-5.86 ***		
	quartile 3	-10.73 ***	-3.16 **	
	quartile 4	-7.61 ***	-0.9	2.38 *
		(Log STCC)^2		
(Log STCC)^2	*quartile 2*	5.22 ***		
	quartile 3	9.34 ***	2.45 *	
	quartile 4	7.7 ***	1.29	-1.25

Table S5. Z tests comparing the model coefficients for Log STCC and (log STCC)^2 between industry groupings. Z coefficients are rounded to 2 digits, and *= p<.05, **=p<.01, ***=p<.001.

		Industry Group						
			Log STCC					
		Industry Group	**[1]**	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**
Log STCC	*[1]*	*Accommodation & Food: Very low wage, low claims*						
	[2]	*Administrative & Support and Waste Manindustryment & Remediation low wage, medium claims*	-0.77					
	[3]	*Agriculture and Forestry low wage, high claims*	-2.97 **	-1.82				
	[4]	*Construction high wage, high claims*	-0.63	0.3	2.49 *			
	[5]	*Manufacturing high wage, medium claims*	-1.59	-0.53	1.49	-1.03		
	[6]	*Professional & Technical Services High wage, low claims*	0.63	1.04	2.38 *	0.94	1.47	
	[7]	*Retail Trade low wage, low claims*	-0.31	0.51	2.65 **	0.29	1.25	0.78
			(Log STCC)^2					
			[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**
(Log STCC)^2	*[1]*	*Accommodation & Food: Very low wage, low claims*						
	[2]	*Administrative & Support and Waste Management & Remediation: low wage, medium claims*	0.65					
	[3]	*Agriculture and Forestry: low wage, high claims*	2.51 *	1.57				
	[4]	*Construction: high wage, high claims*	0.63	-0.18	-2.1 *			
	[5]	*Manufacturing: high wage, medium claims*	1.2	0.37	-1.38	0.68		
	[6]	*Professional & Technical Services: High wage, low claims*	-0.46	-0.82	-1.91	-0.77	-1.1	
	[7]	*Retail Trade : low wage, low claims*	0.04	-0.61	-2.44 *	-0.57	-1.14	-0.47

Table S6. Z tests comparing Log STCC coefficients, and (log STCC)^2 coefficients between quartile groupings for output per worker, and turnover. Z coefficients are rounded to 2 digits, and *= p<.05, **=p<.01, ***=p<.001.

Output per Worker Groups					
			Log STCC		
			[1]	**[2]**	**[3]**
	[1]	*quartile 1*			
Log STCC	*[2]*	*quartile 2*	1.32		
	[3]	*quartile 3*	-2.1 *	-3.32 ***	
	[4]	*quartile 4*	-2.01 *	-3.15 **	-0.04
			(Log STCC)^2		
(Log STCC)^2	*[1]*	*quartile 1*			
	[2]	*quartile 2*	-1.41		
	[3]	*quartile 3*	1.52	2.88 **	
	[4]	*quartile 4*	1.07	2.33 *	-0.33

Turnover Groups					
			Log STCC		
			[1]	**[2]**	**[3]**
Log STCC	*[1]*	*quartile 1*			
	[2]	*quartile 2*	1.2		
	[3]	*quartile 3*	-1.6	-4.06 ***	
	[4]	*quartile 4*	-1.76	-4.57 ***	-0.16
			(Log STCC)^2		
(Log STCC)^2	*[1]*	*quartile 1*			
	[2]	*quartile 2*	-1.11		
	[3]	*quartile 3*	1.62	3.92 ***	
	[4]	*quartile 4*	1.82	4.42 ***	0.24

Exhibits long-term analysis

Tables S7 to S10

Table S7. Industry distribution of LT sample (long-term analysis).

Two digit NAICS code and description		N	% of total
11	*Agriculture, Forestry, Fishing and Hunting*	5484	4.47
21	*Mining, Quarrying, and Oil and Gas Extraction*	222	0.18
22	*Utilities*	99	0.08
23	*Construction*	14738	12.02
31	*Manufacturing (A; Food and Textiles)*	1638	1.34
32	*Manufacturing (B; Chemical, Minerals, Plastics, Paper)*	2817	2.3
33	*Manufacturing (C; Aerospace, Computer, Metals, Ships)*	4277	3.49
42	*Wholesale Trade*	7226	5.9
44	*Retail (A; Motor, Furniture, Health,Electronic)*	11856	9.67
45	*Retail (B; Sporting Goods, General, Miscellaneous)*	4250	3.47
48	*Transportation and Warehousing (A; Air, Rail,Deep Sea etc.)*	2789	2.28
49	*Transportation and Warehousing (B; Postal Services, Couriers etc.)*	335	0.27
51	*Information*	2192	1.79
52	*Finance and Insurance*	3087	2.52
53	*Real Estate and Rental and Leasing*	3280	2.68
54	*Professional, Scientific, and Technical Services*	8484	6.92
55	*Management of Companies and Enterprises*	210	0.17
56	*Administration*	6865	5.6
61	*Educational Services*	1467	1.2
62	*Health Care and Social Assistance*	10569	8.62
71	*Arts, entertainment and recreation*	2236	1.82
72	*Accommodation and Food*	19648	16.03
81	*Other Services (except Public Administration)*	8801	7.18

Table S8. Z tests comparing the model coefficients for Log LTCC and (Log LTCC)^2 between size and growth groupings. Z coefficients are rounded to 2 digits, and *= p<.05, **=p<.01, ***=p<.001.

			Size Groups		
			Log LTCC		
			[1]	**[2]**	**[3]**
Log LTCC	*[1]*	*< 10 workers*			
	[2]	*10-30 workers*	0.81		
	[3]	*30-100 workers*	-3.67 ***	-4.04 ***	
	[4]	*100+ workers*	-2.67 **	-2.95 **	-0.5
(Log LTCC)^2			***(Log LTCC)^2***		
			[1]	**[2]**	**[3]**
	[1]	*< 10 workers*			
	[2]	*10-30 workers*	0.53		
	[3]	*30-100 workers*	5.53 ***	4.9 ***	
	[4]	*100+ workers*	5.12 ***	4.82 ***	1.78
			Growth Groups		
			Log LTCC		
			[1]	**[2]**	**[3]**
Log LTCC	*[1]*	*quartile 1*			
	[2]	*quartile 2*	24.22 ***		
	[3]	*quartile 3*	37.25 ***	12.13 ***	
	[4]	*quartile 4*	13.38 ***	-9.8 ***	-21.65 ***
(Log LTCC)^2			**(Log LTCC)^2**		
	[1]	*quartile 1*			
	[2]	*quartile 2*	-13.64 ***		
	[3]	*quartile 3*	-22.32 ***	-7.99 ***	
	[4]	*quartile 4*	-10.17 ***	2.85 **	10.57 ***

Table S9. Z tests comparing the model coefficients for Log LTCC and (Log LTCC)^2 between industry groupings. Z coefficients are rounded to 2 digits, and *= p<.05, **=p<.01, ***=p<.001.

		Industry Group						
			Log LTCC					
		Industry Group	**[1]**	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**
	[1]	Accommodation & Food: Very low wage, low claims						
Log LTCC	*[2]*	Administrative & Support and Waste Management & Remediation low wage, medium claims	1.98 *					
	[3]	Agriculture and Forestry low wage, high claims	5.46 ***	2.77 **				
	[4]	Construction high wage, high claims	1.07	-1.17	-4.62 ***			
	[5]	Manufacturing high wage, medium claims	5.04 ***	2.27 *	-0.64	4.15 ***		
	[6]	Professional & Technical Services High wage, low claims	11.99 ***	9.11 ***	7 ***	11.35 ***	7.73 ***	
	[7]	Retail Trade low wage, low claims	3.73 ***	0.98	-2.21 *	2.73 **	-1.61	9.31 ***
			(Log LTCC)^2					
	[1]	Accommodation & Food: Very low wage, low claims						
(Log LTCC)^2	*[2]*	Administrative & Support and Waste Management & Remediation: low wage, medium claims	0.94					
	[3]	Agriculture and Forestry: low wage, high claims	-1.23	-1.91				
	[4]	Construction: high wage, high claims	3 **	1.4	3.9 ***			
	[5]	Manufacturing: high wage, medium claims	-0.65	-1.42	0.56	-3.37 ***		
	[6]	Professional & Technical Services: High wage, low claims	-7.93 ***	-7.91 ***	-6.66 ***	-9.99 ***	-7.17 ***	
	[7]	Retail Trade : low wage, low claims	-0.17	-1.07	1.06	-3.11 **	0.48	-7.75 ***

Table S10. Z tests comparing Log LTCC coefficients, and (Log LTCC)^2 coefficients between quartile groupings for output per worker, and turnover. Z coefficients are rounded to 2 digits, and *= p<.05, **=p<.01, ***=p<.001.

Output per Worker Groups

			Log LTCC [1]	[2]	[3]
Log LTCC	*[1]*	*quartile 1*			
	[2]	*quartile 2*	2.86 **		
	[3]	*quartile 3*	1.87	-1.27	
	[4]	*quartile 4*	0.86	-2.55 *	-1.32
				(Log LTCC)^2	
(Log LTCC)^2	*[1]*	*quartile 1*			
	[2]	*quartile 2*	-2.59 **		
	[3]	*quartile 3*	-1.35	1.51	
	[4]	*quartile 4*	1.05	4.3 ***	2.94 **

Turnover Groups

			Log LTCC [1]	[2]	[3]
Log LTCC	*[1]*	*quartile 1*			
	[2]	*quartile 2*	4.68 ***		
	[3]	*quartile 3*	4.84 ***	0.05	
	[4]	*quartile 4*	5.47 ***	0.76	0.73
				(Log LTCC)^2	
(Log LTCC)^2	*[1]*	*quartile 1*			
	[2]	*quartile 2*	-2.89 **		
	[3]	*quartile 3*	-1.27	1.83	
	[4]	*quartile 4*	-0.57	2.58 **	0.78

Exhibits count of claims robustness check

Table S11

Table S11. Conditional proportional hazards models, full results using STcount. Conditional cox proportional hazards models show that increasing STcount reduces hazard but the effect is non-linear. The dependent variable for all models was risk of failure at time t (hazard). Model 1 tests the effects of control variables on hazard (risk of failure at time t). Model 2 tests the effect of STcount. Model 3 tests for polynomial effects of STcount. Model 4 examines the polynomial effects of STcount grouped by organization age.

Coefficients are rounded to 4 digits, standard errors are in brackets, and p<.001 unless otherwise specified.

Independent Variable Specification	**Model 1 Controls**	**Model 2 Linear effect**	**Model 3 Main Effect**	**Model 4 Age**	**% of total obs.**
Entry year and quarter	-0.0029 (0.0017), p= 0.0848	-0.0029 (0.0017), p= 0.0857	-0.0026 (0.0017), p= 0.1294	-5e-04 (0.0017), p= 0.7699	
Year /quarter dummies	Included	Included	Included	Included	
Mean employment per quarter in the past 2 years	-0.0025 (2e-04)	-0.0025 (2e-04)	-0.0023 (2e-04)	-0.0021 (2e-04)	
Industry dummies	Included	Included	Included	Included	
Quarterly growth	-7.1658 (0.0504)	-7.1653 (0.0504)	-7.1211 (0.0505)	-7.1263 (0.0505)	
Quarterly growth^2	-3.9668 (0.0608)	-3.9663 (0.0608)	-3.9262 (0.0608)	-3.9328 (0.0608)	
Output-per-worker	-0.2147 (0.0056)	-0.2146 (0.0056)	-0.2125 (0.0056)	-0.2118 (0.0056)	
Turnover	0.0136 (0.001)	0.0136 (0.001)	0.0145 (0.001)	0.0141 (0.001)	
Log STcount		-0.0028 (0.0112), p= 0.8021	-0.3858 (0.0375)		
(Log STcoun)t^2			0.2852 (0.0263)		
Log STcount: 3-7 years				0.0214 (0.0524), p= 0.6822	34.46
Log STcount: 8-12 years				-0.3083 (0.0791)	20.89
Log STcount: 13-17 years				-0.7415 (0.1024)	15.42
Log STcount: 18-22 years				-1.034 (0.134)	10.6
Log STcount: 23-27 years				-1.2396 (0.1662)	6.91
Log STcount: 28+ years				-1.2261 (0.1255)	11.72
Log STcount^2: 3-7 years				0.0376 (0.0369), p= 0.3079	
(Log STcount)^2: 8-12 years				0.2231 (0.0564)	
(Log STcount)^2: 13-17 years				0.5013 (0.0729)	
(Log STcount)^2: 18-22 years				0.6571 (0.0957)	
(Log STcount)^2: 23-27 years				0.8271 (0.1178)	
(Log STcount)^2: 28+ years				0.8199 (0.0899)	
(Log STcount)^2: 100+ workers					
Likelihood Ratio test	$\chi^2(123)= 84734$	$\chi^2 (124)= 84734$	$\chi^2 (125)= 84850$	$\chi^2 (135)= 85040$	
Summary Findings	Controls predict hazard.	Log STcount does not significantly predict risk of failure.	The relationship between log STcount and risk of failure is curvilinear.	The protective effect of log STcount is larger for older organizations than younger ones.	

Exhibits claims as a binary robustness check

Table S12

Table S12. Conditional proportional hazards models, full results using STdummy. Conditional cox proportional hazards models show that increasing STdummy reduces hazard. The dependent variable for all models was risk of failure at time t (hazard). Model 1 tests the effects of control variables on hazard (risk of failure at time t). Model 2 tests the effect of STdummy. Model 3 examines the effects of STdummy grouped by organization age.

Coefficients are rounded to 4 digits, standard errors are in brackets, and p<.001 unless otherwise specified.

Independent Variable Specification	**Model 1 Controls**	**Model 2 STdummy**	**Model 3 Age**	**% of total obs.**
Entry year and quarter	-0.0056 (0.0017)	-0.0026 (0.0017), p= 0.1248	-2e-04 (0.0017), p= 0.8971	
Year /quarter dummies	Included	Included	Included	
Mean employment per quarter in the past 2 years	0 (1e-04), p= 0.4477	-0.0022 (2e-04)	-0.002 (2e-04)	
Industry dummies	Included	Included	Included	
Quarterly growth	-6.0488 (0.0862)	-7.1347 (0.0504)	-7.1408 (0.0504)	
Quarterly growth^2	-0.6571 (0.0153)	-3.9397 (0.0608)	-3.9475 (0.0608)	
Output-per-worker	-0.2092 (0.0056)	-0.2118 (0.0056)	-0.211 (0.0056)	
Turnover	-0.0378 (0.001)	0.0147 (0.001)	0.0143 (0.001)	
STdummy		-0.1117 (0.012)		
STdummy: 3-7 years			0.0197 (0.0165), p= 0.2305	34.46
STdummy: 8-12 years			-0.0896 (0.0246)	20.89
STdummy: 13-17 years			-0.2131 (0.0315)	15.42
STdummy: 18-22 years			-0.3478 (0.0414)	10.6
STdummy: 23-27 years			-0.3884 (0.0515)	6.91
STdummy: 28+ years			-0.4012 (0.0393)	11.72
Likelihood Ratio test	$\chi^2(123)=$ 84734	χ^2 (124)= 84822	χ^2 (129)= 85020	

Exhibits alternative functional forms robustness check

Table S13

Table S13. Values of log STCC/ log LTCC and associated with maximum hazard reduction relative to organizations with zero STCC/ LTCC, grouped by log STCC/LTCC deciles. Columns 1 and 2 refer to the percentage reduction in hazard is calculated as the difference in hazard at t between organizations with zero STCC/LTCC.

		Log STCC			*Log LTCC*		
Groupings		**Lower limit**	**Upper limit**	**Maximum hazard reduction (%) (95% CI)**	**Lower limit**	**Upper limit**	**Maximum hazard reduction (%) (95% CI)**
	1	0.65	6.28	17.98 % (12.48 %, 23.13 %)	0.67	5.75	20.66 (19.89, 21.44)
	2	6.28	7.15	19.62 % (14.14 %, 24.75 %)	5.75	6.69	19.01 (18.24, 19.78)
	3	7.15	7.78	15.14 % (9.45 %, 20.47 %)	6.69	7.34	19.6 (18.83, 20.37)
	4	7.78	8.29	16.04 % (10.29 %, 21.43 %)	7.34	7.88	20.49 (19.72, 21.26)
	5	8.29	8.76	21.15 % (15.51 %, 26.43 %)	7.88	8.34	20.96 (20.19, 21.73)
Deciles	*6*	8.76	9.20	14.69 % (8.83 %, 20.18 %)	8.34	8.79	21.27 (20.49, 22.04)
	7	9.20	9.68	-1.35 % (-5.18 %, 2.34 %)	8.79	9.23	21.03 (20.25, 21.81)
	8	9.68	10.22	9.44 % (3.43 %, 15.08 %)	9.23	9.73	19.54 (18.75, 20.32)
	9	10.22	10.97	5.45 % (-0.49 %, 11.03 %)	9.73	10.37	16.2 (15.41, 16.98)
	10	10.97	11.66	-8.5 % (-14.28 %, -3.01 %)	10.37	11.42	6.12 (5.33, 6.9)

Exhibits alternative operationalizations of industry

Table S14

Table S14. Conditional proportional hazards models with professional riskiness industry controls, full results. Conditional cox proportional hazards models show that increasing STCC reduces hazard but the effect is non-linear, when accounting for professional riskiness. The dependent variable for all models was risk of failure at time t (hazard). Model 1 includes only control variables. Model 2 tests the effect of professional riskiness. Model 3 tests for polynomial effects of STCC, with professional riskiness as the control for industry. Industry dummies were not included in models the models, due to the expectation of a high level of multi-collinearity with professional riskiness.

Coefficients are rounded to 4 digits, standard errors are in brackets

p<.001 unless otherwise specified

Independent Variable Specification	**Model 1** **Controls**	**Model 2** **Industry = Prof. Risk**	**Model 3** **Main Effect: Prof. Risk**
Entry year and quarter	-7e-04 (0.0023) , p= 0.7522	-0.0014 (0.0023) , p= 0.5483	-8e-04 (0.0023) , p= 0.7215
Mean employment per quarter in the past 2 years	-0.0017 (2e-04)	-0.0017 (2e-04)	-0.0013 (2e-04)
Year Quarter dummies	Included	Included	Included
Quarterly growth	-6.9276 (0.0625)	-6.9034 (0.0625)	-6.8509 (0.0624)
Quarterly growth^2	-3.6964 (0.0762)	-3.6785 (0.0762)	-3.6366 (0.076)
Output-per-worker	-0.2092 (0.007)	-0.2047 (0.007)	-0.2023 (0.007)
Turnover	0.0053 (0.0012)	0.0054 (0.0012)	0.0077 (0.0012)
Professional Riskiness	Not included	0.0025 (2e-04)	0.0026 (2e-04)
Log STCC			-0.0906 (0.0091)
(log STCC)2			0.0078 (9e-04)
Likelihood Ratio test	$\chi^2(89)= 52960$	$\chi^2 (90)= 53168$	$\chi^2 (92)= 53325$
Summary Findings	Controls predict hazard.	Increase in professional riskiness is associated with an increase in risk of failure.	The relationship between log STCC and risk of failure is curvilinear, controlling for professional riskiness.

Table S15

Table S15. Conditional proportional hazards models with NAICS four digit industry controls, full results. Conditional cox proportional hazards models show that increasing STCC reduces hazard but the effect is non-linear, when accounting for four digit NAICS coddes. The dependent variable for both models was risk of failure at time t (hazard). Model 1 includes only control variables. Model 2 tests the effects of four-digit NAICS codes. Model 3 examines the polynomial effects of STCC with four-digit NAICS codes as the control for industry.

Coefficients are rounded to 4 digits, standard errors are in brackets

p<.001 unless otherwise specified

Independent Variable Specification	**Model 1** **Controls**	**Model 1** **Industry = NAICS 4 Digit**	**Model 3** **Main Effect NAICS 4-Digit**
Entry year and quarter	-7e-04 (0.0023) , p= 0.7522	-0.0058 (0.0023) , p= 0.0127	-0.0053 (0.0023) , p= 0.0233
Mean employment per quarter in the past 2 years	-0.0017 (2e-04)	-0.0023 (2e-04)	-0.0019 (2e-04)
Year Quarter dummies	Included	Included	Included
Quarterly growth	-6.9276 (0.0625)	-6.8527 (0.0636)	-6.8014 (0.0636)
Quarterly growth^2	-3.6964 (0.0762)	-3.6922 (0.0765)	-3.6506 (0.0764)
Output-per-worker	-0.2092 (0.007)	-0.2305 (0.0076)	-0.2272 (0.0076)
Turnover	0.0053 (0.0012)	0.0118 (0.0012)	0.0138 (0.0012)
Four digit NAICS codes	Not included	Included	Included
Log STCC			-0.0958 (0.0091)
(log STCC)2			0.0086 (9e-04)
Likelihood Ratio test	$\chi^2(89)= 52960$	$\chi^2\ (380)= 57055$	$\chi^2\ (382)= 57199$
Summary Findings	Controls predict hazard.	Four digit NAICS codes improve model fit relative to the other controls alone.	The protective effect of log STCC is consistent, controlling for four-digit NAICS codes.

Table S16

Table S16. Values of log STCC and associated with maximum hazard reduction, and increased hazard relative to organizations with zero STCC, controlling for industry using professional riskiness and four digit NAICS codes.

Column (1) Maximum Reduction in Hazard, %: Column 1 refers to the percentage reduction in hazard between an organization with zero claims and one at the vertex (minimum) of the polynomial relationship between STCC and hazard of failure. Columns (2) and (3) provide the log(STCC) and the STCC at which this vertex occurs: This refers to the values of log(STCC) [col 2] and STCC [col 3] at which employers reduce their likelihood of failure the most by having claims, relative to an organization with no claims.

Columns (4) and (5) refer to values of log(STCC) [col 4] and STCC [col 5] above which hazard of failure is predicted to be greater than that of organizations with zero STCC. This refers to the point at which employers increase their likelihood of failure by having claims. 95% confidence intervals are in brackets.

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Max. reduction in hazard	**Value of STCC/log(STCC) at which this max. reduction occurs**		**Increased hazard**	
All organizations (prof. risk control)	23.13 % (9.48 %, 34.72 %)	5.81 (3.8, 9.01)	332.85 (43.63, 8179.13)	11.62 (7.6, 18.02)	110788.2 (1990.95, 66914604.93)
All organizations (NAICS 4-digit dummy control)	23.5 % (10.55 % , 34.57 %)	5.59 (3.76 , 8.4)	268.84 (41.94 , 4452.04)	11.19 (7.52 , 16.8)	72274.37 (1842.8 , 19829585.96)

Table S17

Table S17. Linear regression models show that increasing LTCC increases survival, but the effect is non-linear. The dependent variable for all models was survival, in quarters. Model 1 includes only control variables. Model 2 tests for the effects of professional riskiness. Model 3 tests for the polynomial effects of LTCC, controlling for industry using professional riskiness.

The following control variables were included in all models: entry year and quarter, mean employment per quarter, age at entry, growth, turnover, and output-per-worker. Industry dummy variables were not included in the models.

Coefficients are rounded to four digits and p<.001 unless otherwise specified. Standard errors are in brackets.

Independent Variable Specification	Model 1 Controls	Model 2 Industry = Prof. Risk	Model 3 Main Effect Prof. Risk
Control variables	Included	Included	Included
Professional Riskiness		-0.095 (0.0039)	-0.1091 (0.0038)
Log LTCC			6.6936 (0.0939)
(log LTCC)2			-0.5432(0.0101)
R^2	$R^2 = .25$, F(7, 116597) = 5601, p < .001.	$R^2 = .25$, $F(8,114982) = 4853$, $p < .001$.	$R^2 = .32$, $F(10, 114980) = 5317$, $p < .001$.

Table S18

Table S18. Linear regression models show that increasing LTCC increases survival, but the effect is non-linear. The dependent variable for all models was survival, in quarters. Model 1 includes only control variables. Model 2 tests for the effects of four digit NAICS codes. Model 3 tests for the polynomial effects of LTCC, controlling for industry using four digit NAICS codes.

The following control variables were included in all models: entry year and quarter, mean employment per quarter, age at entry, growth, turnover, and output-per-worker.

Coefficients are rounded to four digits and p<.001 unless otherwise specified. Standard errors are in brackets.

Independent Variable Specification	Model 1 Controls	Model 2 Industry = NAICS 4- digit	Model 3 Main effect NAICS 4 Digit
Control variables	Included	Included	Included
Four digit NAICS codes	Not included	Included	Included
Log LTCC			6.4226 (0.0884)
(log LTCC)2			-0.4961 (0.0096)
R^2	R^2 = .25, F(7, 116597) = 5601, p < .001.	R^2 = .37, F(311, 122250) = 233 , p < .001.	R^2 = .42, F(308, 116296) = 275.6, p < .001.

Table S19

Table S19. Values of log LTCC associated with the maximum survival, and with reduced survival relative to organizations with 0 LTCC.

Column (1) Maximum Increase in Survival (quarters): Column 1 refers to the increase in survival time (in quarters) between am organization with zero claims and one at the vertex (maximum) of the polynomial relationship between LTCC and survival.

Columns (2) and (3) provide the log(LTCC) and the LTCC at which this vertex occurs: This refers to the values of log(LTCC) [col 2] and LTCC [col 3] at which employers increase their survival time the most by having claims, relative to an organization with no claims.

Columns (4) and (5) refer to values of log(LTCC) [col 4] and LTCC [col 5] above which survival is predicted to be less than that of organizations with zero LTCC. This refers to the point at which employers reduce their survival by having claims. 95% confidence intervals are in brackets.

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Max. Increase in Survival	**Value of LTCC/log(LTCC) at which this max. reduction occurs**		**Survival < 0**	
All organizations (prof. risk control)	20.62 (18.73 , 22.51)	6.16 (5.78 , 6.57)	471.24 (321.11 , 711.25)	12.32 (11.56 , 13.14)	507573.3 (184315.75 , 1546042.73)
All organizations (NAICS 4-digit dummy control)	20.79 (18.88 , 22.7)	6.47 (6.07 , 6.91)	646.32 (430.83 , 1000.79)	12.95 (12.14 , 13.82)	419016.69 (186478.36 , 1003577.05)