Title

Managerial time horizons and the decision to put operational workers at risk: the role of debt

Abstract

Previous research has established a link between the debt component of capital structure and managers making risky decisions. Literature in finance and strategy has explored the role of debt and concluded that increases in debt focus managerial decision making on short-term financial goals, suggesting that increases in debt might also lead to managers making decisions that put operational workers and the firm at long-term risk. Therefore this research explores if the strategic choice of a firm's level of debt predicts the firm's likelihood of breaching safety regulations. Furthermore, this study explores the short and long term financial implications of breaching safety regulations. Secondary safety and financial data collected in the United Kingdom is used to answer the research questions using logistic models and an event study. The results show that decisions on debt are a significant predictor of a firm's likelihood of breaching safety regulation and that breaching safety regulation harms long-term financial performance. Strategic decisions on debt levels lead to further decisions that place the workforce and profitability of the firm at risk.

Keywords: worker safety, secondary data, event studies, finance

INTRODUCTION

Operational workers in the developed world still face a significant risk of getting hurt or killed at work, even in the presence of significant safety regulation and enforcement

(Plambeck & Taylor, 2016). For instance, the United Kingdom (UK) is a small, developed, and highly regulated country where in 2016/17 609,000 people were injured at work (with 137 fatalities), which lead to 31.2 million lost working days (HSE, 2018). Numbers in other developed countries are similar (e.g. BLS, 2018). To start to mitigate this harm, this research explores managerial decision-making time frames and how they impact on the safety of operational workers in the developed world.

The literature indicates that firms with more leveraged capital structures will focus on maximizing profits in the short-term, influencing their decision-making and their likelihood of breaching regulation. This suggests that when managers choose to change their capital structure, they are making a strategic choice that influences future decisions and outcomes of importance to multiple stakeholders, and that certain decisions could create trade-offs between the societal goal of protecting workers and the managerial goal of maximizing profits. Therefore, this research studies whether the strategic choice to change the debt component of a firm's capital structure predicts the likelihood of a firm breaching safety regulations and putting workers in jeopardy.

Breaches of safety regulation are examined from the perspective of two sets of stakeholders: 1) managers and owners who are the stakeholders addressed in most traditional OM research and for whom performance is usually defined in terms of profits; and 2) workers, safety regulators and the communities where firms operate who are often overlooked in OM research and for whom the safety of the workers is a critical outcome. In so doing, we follow other recent research (Levine & Toffel, 2010; Porteous, Rammohan, & Lee, 2015) that simultaneously studied safety outcomes that are important to workers and financial outcomes that are important to managers and owners.

The literature provides conflicting predictions on the relationship between the outcomes that matter to managers and the outcomes that matter to workers.

Occupational safety researchers propose that there is a trade-off between safety and business outcomes at both the operational and organizational level of analysis (e.g. Landsbergis, 2003; Power et al., 2015). Research in operations management finds the opposite; there need not be trade-offs between safety and business outcomes (e.g. Pagell, Johnston, Veltri, Klassen, & Biehl, 2014). However, these studies also provide evidence that in the pursuit of profits many firms continue to make the decision to put workers in jeopardy.

This research explores the conflicting predictions from the safety and operational literatures by examining how changes in the debt component of a firm's capital structure influence their likelihood to breach safety regulation and place workers in jeopardy. Breaches (violations) of safety regulations are the worker outcome examined in this research. For a firm to be deemed in breach means they have failed to comply with safety legislation.

Breaches provide insight into the managerial decision making aspects of safety. Poor safety outcomes can be the result of both worker behaviors and the production system that management's decisions create (Brown, Willis, & Prussia, 2000; Hogan & Foster, 2013). Research suggests that when management creates and maintains a safe production system, accidents are, in general, minimized (Brown et al., 2000). However, no organization can account for all individual behaviors or truly random events. Breaches exclusively capture managerial decision making and behavior. Random events or accidents that are truly caused by reckless worker behavior should not result in being prosecuted or found in breach of regulation.

In addition to focusing exclusively on managerial decisions, breaches are also indicative of management not meeting their minimal responsibilities to workers and of breaking the law. Breaches need not be intentional, but regulation is known and applied to all firms. Hence, being found to have breached safety regulation is indicative of either a decision to be unaware of required behavior or a willingness to chance being found in breach in pursuit of other business goals. Breaches then capture the managerial aspect of putting workers in jeopardy.

A breach is more serious than a regulator fining a firm. A breach means that the regulator submitted the case to prosecutors and that the firm was found guilty of breaking the law in court. Prosecuting a firm for being in breach is one of many tools the UK Health and Safety Executive (HSE) can use to ensure compliance with safety regulation and prevent harm to workers. Prosecutions are very rare, the HSE generally deals with workers who are placed in jeopardy by giving advice, issuing warnings or withdrawing licenses (HSE, 2018).

Breaches are rare because being in breach indicates illegal managerial behavior that put workers in jeopardy and led to injury or even death. For example, only five hundred and nineteen UK manufacturing firms were found to have breached UK safety regulations between 2004 and 2012. Hence, while all accidents have an unacceptable human cost, the vast majority do not result in breaches. This research starts with the knowledge that firms with breaches made decisions that failed their workers and did not meet society's expectations.

The research's primary objective is to determine if the debt component of capital structure predicts breaches leading to the first research question, *when controlling for industry and firm level factors does the debt component of a manufacturing firm's capital structure predict the firm's likelihood to decide to breach safety regulations?* The research's secondary objective is to understand whether breaches are rational from a profit maximizing perspective, with the intent of contributing to the elimination of this behavior. This leads to our second research question, *what are the short and long-term* *financial implications of breaching safety regulations?* The financial outcomes studied are return on assets (ROA), profit margin and sales growth.

The first research question attempts to understand what causes firms to decide to breach regulation, while the second explores why this might be the case. In other words, workers, unions, regulators and society at large can best respond to breaches of regulation by understanding what motivates them. If firms do profit from placing workers in jeopardy, the response would need to be very different than if this behavior had negative consequences for both the workers and the firm.

This research acknowledges that firms can manage operations and safety as simultaneous goals but explores whether strategic decisions related to debt and capital structure explain why many firms do not. In so doing we further develop our understanding of if / when safety and other operational goals are complimentary while also informing debates in HR, strategy and finance on the role of capital structure on managerial behavior and firm outcomes. Finally, we make contributions to all of these literatures by examining the impact of debt on both economic and social performance.

LITERATURE

Researchers have long debated the impact of managerial choices regarding capital structure on decision-making and outcomes (Barton & Gordon, 1988). Capital structure has multiple components, but leverage is often the focus of research (Liu, van Jaarsveld, Batt, & Frost, 2014). Leverage has two primary components, operating and financial leverage (e.g. Saunders, et al., 1990) and a firm's level of leverage is a function of managerial decisions and industry characteristics (Simely & Li, 1999; Kayo & Kimura, 2011). For instance, firms in industries that are capital intensive generally have higher operating leverage (Mandelker & Rhee, 1984). Operating leverage is to a great extent a function of industry characteristics. However, firms in the same industry have much more discretion in their level of financial leverage. Therefore, it is common to decompose operating leverage and financial leverage into separate elements (Garcia-Feijoo & Jorgensen, 2010). This research is interested in managerial decision-making and hence it explores financial but not operating leverage.

Discussions of how decisions about financial leverage effect firm outcomes tend to focus on the right mix of debt and assets (or equity) to maximize returns (e.g., Stenbacka & Tombak, 2002), or how this mix influences managerial decision-making (e.g., Liu et al., 2014). We specifically address the debt component of financial leverage because the value of assets can change without managerial intervention; for instance due to depreciation. Changes in debt levels require a managerial decision.

This research focuses on the links between the strategic decision to change a firm's level of debt and managerial decision-making about putting workers in jeopardy. Researchers from finance (Chen & Steiner, 1999), strategy (O'Brien, David, Yoshikawa, & Delios, 2014) and human resources (Liu et al., 2014) all reach the same conclusion; increased debt can reduce agency problems by focusing managers on short-term financial goals.

The financial implication of this short-term focus is what has historically been debated in the literature. In this research, we examine both the human and financial implications of this short-term focus because it is the short-term emphasis on financial goals that links the research on capital structure and managerial decision making to the research that suggests a trade-off between being safe and other operational outcomes. Liu et al. (2014) explored the impact of capital structure on investments in human capital noting, "*These high debt levels put pressure on managers to cut costs or increase short-term revenues to service the debt and avoid financial distress.*

Obligations to creditors may lead managers to forgo investment in strategic assets that would benefit long-term growth and sustainability" (p. 430). They found that as debt increased, investments in human capital declined, which is in line with research that found that increased leverage leads to a reduction in investments in R&D (e.g., Simerly & Li, 1999). Increased debt is linked to a shorter-term focus, a focus that also leads to a reduction in managerial willingness to invest in R&D or human capital. As debt increases managers place greater emphasis on cutting costs or increasing revenue, especially in the short-term.

Safety researchers have long argued that the same short-term focus to cut costs or increase productivity, places workers in jeopardy (Landsbergis, 2003; Westgaard & Winkel, 2011). A more targeted version of this argument relates to the concept of role overload (McLain, 1995) or safety tipping points (Kuntz, Mennicken, & Scholtes, 2015). Efforts to increase productivity are often focused on removing slack which leaves workers with less time for accomplishing tasks (Pagell et al., 2014). When workers have buffers of slack they have time to be safe and productive, but once the buffers are depleted short cuts will be taken (Kuntz et al., 2015).

The proposition is that deciding to run a production system faster and/or leveraging existing assets to produce more output places workers in jeopardy. Once workers reach the point of role overload, accidents and illness will increase; the pursuit of business goals and the taking of business risks place workers in jeopardy. This literature does not make explicit predictions about risks such as entering new markets or developing new products. Instead the focus is on trying to leverage existing assets to increase production, sales or profits, with managers having to make trade-offs between placing workers in jeopardy and improved operational performance.

Specifically, increases in debt are associated with a decrease in managerial decision time horizons, which could potentially place workers in increased jeopardy (e.g. Westgaard & Winkel, 2011).

> **H1:** As a firm's level of debt increases, their propensity to breach safety regulations will increase.

Research question two addresses the relationship between breaching safety regulations and short and long-term financial performance. The firms with safety breaches are already known to perform poorly when it comes to protecting the workforce, the question is whether these firms are profiting at the expense of their workers and society.

Our primary metric of financial performance is ROA, due to its frequent use as a measure of profits (Levine & Toffel, 2010; Barnett & Salomon, 2012) and because the safety literature on trade-offs is, in essence, arguing that efforts to improve the return on/productivity of assets, also increase the likelihood of putting workers in jeopardy. Our secondary measures of financial performance are profit margin and sales growth. The arguments surrounding profit margin would be similar to those for ROA; efforts to increase sales from the same asset base will increase the likelihood of putting workers in jeopardy. The final metric of financial performance examines sales growth. For sales to grow, requires an increase in output. Increases in output have been posited to also increase the likelihood of accidents (Landsbergis, 2003; Zohar & Luria, 2005).

Combining the findings that increased debt focuses managers on short-term financial returns with the trade-off perspective found in the safety literature, leads to the proposition that putting workers in jeopardy should increase short-term financial performance.

H2: Firms with safety breaches will have positive abnormal ROA, profit margins, and sales growth in the year of the breach.

However, the human capital perspective and recent research in socially sustainable operations, both suggest that putting workers in jeopardy will harm long-term operational and financial performance (Jiang, Lepak, Hu, & Baer, 2012; Pagell et al., 2014). If increased debt does lead to a short-term focus on increasing productivity and a subsequent increase in the likelihood that operational workers are placed in jeopardy, then long-term profits could be harmed. Safety management occurs in the operational sphere with most occupational accidents affecting operational workers and by extension their work. Operational workers play a key role in continuously improving processes and creating competitive advantage (de Menezes, Wood, & Gelade, 2010; Longoni, Pagell, Johnston, & Veltri, 2013; Longoni & Cagliano, 2015). Operational workers who are safe can be fully engaged in creating products and services and continuously improving systems. Operational workers whose jobs place them in jeopardy will distrust management and spend their time engaged in self-protection activities (e.g., Mayer & Gavin, 2005; Wiengarten & Longoni, 2017), rather than fully focusing on doing their jobs or improving the production system. Long-term profitability is harmed due to the costs of accidents and illness, the cost of workers being engaged in self-protection activities, and the lost opportunities for product and process innovation due to depleting rather than investing in human capital. Hence, if there are financial benefits from placing workers in jeopardy they will be short-term.

H3: Firms with safety breaches will have negative abnormal ROA, profit margins, and sales growth in the years after a breach occurs.

DATA

Managers are unlikely to admit to putting workers in jeopardy, making unbiased data a requirement for answering the research questions. Therefore, we compiled data from secondary sources. Safety breach records came from the *UK Health and Safety Executive Register of Prosecutions and Notices.* The Health and Safety Executive (HSE) is an independent regulator, acting in the public interest to reduce work-related deaths and accidents across the United Kingdom's workplaces. Breaches are identified based on an investigation by the HSE (HSE, 2018). The HSE investigates incidents that "indicate a likelihood of a serious breach of health and safety law" including incidents that resulted in death, serious injuries or occupational disease (for full details on enforcement actions please see HSE, 2018). The information in the HSE database is extensive including the details for the breach, location of offence and enforcement division.

We collected data on all breaches that occurred in UK manufacturing firms. We focused on manufacturing both because operational workers in manufacturing are critical to creating competitive advantage (de Menezes et al., 2010; Longoni et al., 2013) and because manufacturing workers suffer a disproportionate number of accidents.

This data was matched to manufacturing firm financial information from the *Bureau Van Dijk Database (FAME)*. We collected data on all active manufacturing firms in FAME that were in the same industries as the firms that had breach records in the HSE database. The FAME database covers all public or private firms regardless of size or industry in the United Kingdom and Ireland, so we limited our data collection to manufacturing firms located in England, Wales and Scotland to align with the HSE database. The data was collected by a research assistant and then verified by two co-authors to ensure the correctness of data and the matching procedure.

There are 4,058 manufacturing firms in the 2-digit SIC codes of interest that were active in the requisite years in the FAME database (UK SIC 10 to 33). Our research design requires two years of financial data prior (for research question one: predicting breaches) and two years subsequent (for research question two: evaluating the impact of the breach) to a breach. Because the data available from FAME is from 2004 to 2014, we investigated breaches that occurred from 2006 to 2012. Complete financial data for 2015 onward was not available at the time of data collection.

Research question one was answered by combining the HSE data with the FAME data, for all manufacturing firms in SIC codes where one or more breaches had occurred between 2006-2012. This provides an initial sample of 4,058 firms, in 24 2-digit SIC codes, with 28,406 observations and 942 breaches. There are 519 manufacturing firms with at least 1 breach of safety regulations and 423 have breaches in multiple years.

Ninety five percent of the firms in the FAME database are privately held and private firms committed over 96% of the breaches. Therefore, the analysis focuses only on private firms. Furthermore, multiple firms had missing information for one or more of the indicators (e.g., leverage, employee wage and productivity) used in the study. Thus, firms that were publicly held or had missing data were excluded from the analysis. The final sample to answer research question one includes 3,398 private firms, in 22 2-digit SIC codes, with 15,324 observations. Two hundred forty two of these private firms committed 355 breaches. The distribution of the 355 breaches by industry is presented in Figure 1. Manufacturers of food products (SIC 10) had the most breaches, followed by fabricated metal products (SIC 25), rubber and plastic products (SIC 22), chemical products (SIC 20) and non-metallic mineral products (SIC 23).

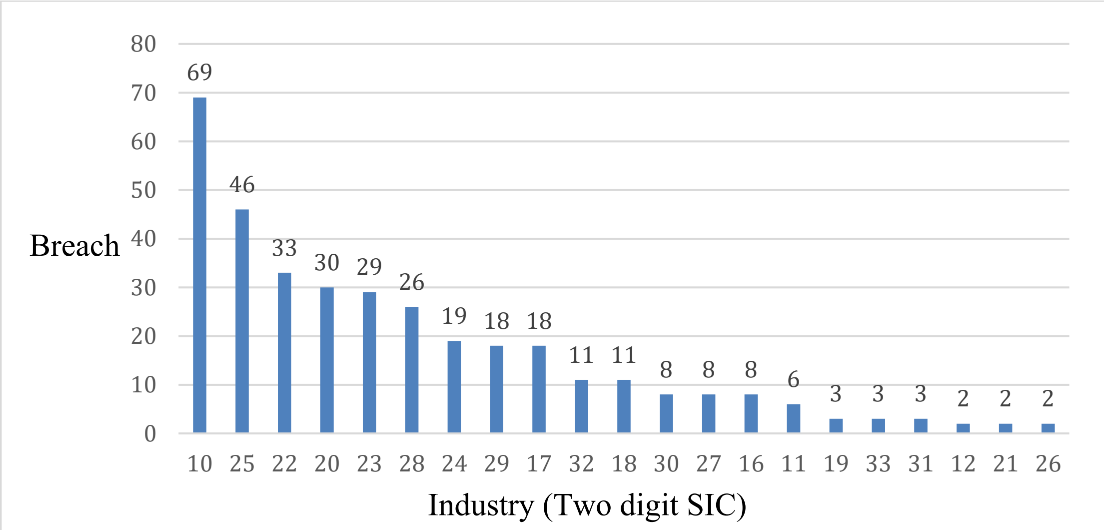

Figure 1: Industry distribution of breaches

Measures

We study breaches of safety regulation because unlike accidents, which may be caused by worker behaviors, a breach indicates that the firm has broken the law and is not meeting minimal regulatory expectations. A breach is evidence of irresponsible managerial decision making behavior that put workers in jeopardy.

For research question one the primary predictor of interest is change in debt. All independent variables from the FAME data, except the fixed-effect dummy variables, were calculated as the two-year average prior to the year of the breach. Change in debt was operationalized as the percentage change in debt compared to 2 years prior to the breach (from year -3 to year -1). Change in debt is a widely adopted indicator of debt issuance used by financial databases such as COMPUSTAT (Standard & Poor's, 2003).

To predict breaches and create propensity scores we also included a number of industry and firm level controls in the models. These indicators could predict the likelihood of a breach, but are not likely to be directly responsible for breaches. We measure these attributes to eliminate alternative explanations for the results.

Three time-variant industry control variables are included in the model; industry accident rate (number of accidents per 100,000 employees), industry median overtime work hours and industry average financial leverage. The likelihood of accidents varies by industry and many breaches are discovered during accident investigations, suggesting that the likelihood of accidents may also be linked to the likelihood of breaches. Therefore, we control for industry using industry accident rate data obtained from the HSE.

Similarly, extensive research has been conducted on the impact of working hours on occupational accidents. Previous literature has identified that overtime can have negative effects on both physical and mental health and is a cause of workplace accidents. (e.g., Trinkoff, Le, Geiger-Brown, Lipscomb, & Lang, 2006). We used industry level data because firm level data on overtime hours is not readily available. We control for the median of industry overtime hours because the propensity for accidents and breaches in industries with long working hours is likely to be higher even if the work itself is not inherently dangerous. This data was also obtained from the HSE.

Finally, firm-specific capital structure decisions may be affected by industry norms. Thus, we control for the industry average level of financial leverage to isolate firm-specific decisions from the industry influence. Industry average financial leverage is measured by debt divided by total assets (from all firms in the industry) using data from FAME.

The literature suggests that there are additional managerial decisions or actions that are predictors of accidents and illness that could also be predictors of breaches. Therefore, we also added firm level control variables to the model.

Safety research finds that the adoption of human resource management systems that emphasize training, empowerment, participation and the like (Barling, Kelloway, & Iverson, 2003), improve safety climates and safety performance. These findings are in line with research in management indicating that investing in human capital improves operational and financial performance (Jiang et al., 2012). Firms that value human capital are less willing to put workers in jeopardy (e.g., Pagell et al., 2014). In some industries, such as mining, all firms pay a premium to their workers because the work is dangerous, limiting the supply of labour. However, at the firm level of analysis wages per employee are a proxy for valuing human capital. Therefore, the decision to pay workers more is an indication of an investment in human capital. Increased wages would be a proxy for a decreased willingness to put workers in jeopardy; hence we control for wage per employee using FAME data.

Managers and economists view increased productivity as a desirable goal. Yet the significant body of research that predicts a trade-off between safety and other operational outcomes often focuses on productivity (e.g., Zohar, 2000). Increased productivity is expected to increase profits, but focusing on higher levels of output (sales) per-employee, has also been predicted to put employees in jeopardy (Zohar, 2000; Westgaard & Winkel, 2011). We control for labor productivity (the ratio of operating income to number of employees) using FAME data.

Larger and/or more profitable firms may have more resources to insure compliance with regulation. Smaller firms may not have the resources to dedicate to compliance, while firms under financial pressure may feel compelled to take shortcuts on safety. Therefore, we control for profit margin (operating income over sales), sales growth (yearly change of sales) and firm size (number of employees).

The influence of changes in a firm's level of debt may be affected by the base debt level or changes in the value of assets (which may be outside the managers control). Thus, we control for the actual debt level and the change in total assets.

Furthermore, we control for the deviation between the target leverage level and actual leverage level because the decision to increase or decrease debt may be a strategic decision by management to optimize the level of leverage (Flannery & Rangan, 2006) that is not linked to time horizons and hence should not predict breaches. To calculate the target leverage level in year t, we regress financial leverage on the one year (t-1) lagged independent variables for financial leverage, earning before interests and tax (EBIT), total assets, industry leverage level and the change of industry leverage (Flannery & Rangan, 2006):

$$\textit{(Target) Financial leverage}_{ijt}\ (\mathrm{y}) = \beta_0 + \beta_1 \textit{Financial leverage}_{ijt-1} + \beta_2 \textit{EBIT ratio}_{ijt-1} + \beta_3 \textit{Total assets}_{ijt-1} + \beta_4 \textit{Industry leverage}_{jt-1} + \beta_5 \textit{Industry Leverage Change}_{jt-1} + u$$

The results of this regression analysis are in Appendix J. The analysis uses the deviation between the target leverage level and actual leverage level, which is the estimated residual (u) in the above regression model.

We also control for the year of a breach because general economic conditions may influence the likelihood and impact of a breach. Finally, we included a dummy variable for industry (based on 2 digit SIC code) to control for time-invariant factors specific to an industry such as production technology and regulation. The variance-inflation factors are low which should minimize concerns about multi-collinearity that could result from including both industry time-variant and invariant variables (Wiengarten, Fan, Lo, & Pagell, 2017).

Research question two requires information on the timing of the breach that comes from the HSE database. The dependent variables for research question two, ROA, profit margin and sales growth, are all taken from the FAME database.

Controlling for the impact of missing data

The sample size reduces from 28,406 to 15,324 observations because of missing data in the FAME database. Using secondary data does not guarantee that the missing data is missing at random. For instance, firms with poor safety records might also be the same firms who are less likely to fulfill their financial reporting duties. Therefore, dropping observations may bias the results. To address this concern a two-stage analysis was conducted (Allison, 2002). We create a binary variable "missing data" to indicate whether the observation has one or more missing values for the independent variables. We then conducted a probit analysis with missing data as the dependent variable and firm sales, number of employees, financial leverage, ROA and the firm's breach history before year -2 as independent variables. We choose these variables to predict missing data because small, poor performing and highly leveraged firms are more likely to have missing data issues (Lavie, 2007). We performed natural logarithm transformations to firm sales and number of employees to correct for skewness. In addition, we included the percentage of firms in the industry with missing data and the number of firms in the industry with a breach in year -2 as independent variables, because firms can learn from competitors' failure to avoid similar mistakes (Yiu, Xu, & Wan, 2014). These two variables are industry-level so they are exogenous variables, which fulfills the exclusion restriction requirement for the first stage model and makes the Inversed Mill's Ratio valid for second stage of the analysis (Leung & Yu, 1996; Puhani, 2000). The independent variables have a one-year lag to the dependent variable. We also include industry and year in this analysis. The results of the logistic analysis (Table 1) indicate that firms with lower sales ($p < .01$), fewer employees ($p < .01$), a poor breach history ($p < .01$) and in industries with less missing data and breaches will systematically have a higher likelihood of missing data ($p < .01$). To control for the missing data the inverse Mill's ratio was generated from the probit analysis and added to the models used to test the hypotheses (Allison, 2002; Lavie, 2007).

[Insert Table 1 about here]

Since number of employees, labor productivity and wages per employee are highly skewed in our sample and control firms, we conducted a natural logarithm transformation of these independent variables for the second stage model. We winsorized profit and change in debt by 1% because outliers were found in these variables. Following previous practices in developing a selection model (e.g., Levine & Toffel, 2010) all independent variables except the inverse Mill's ratio and dummy variables, are the average of the two years prior to the safety breach. When data was only available for one of the two years, we used that value for the analysis (Levine & Toffel, 2010). Table 2 shows the descriptive statistics and correlation matrix while table 3 provides a summary of all measures used in the models.

[Insert Tables 2 & 3 about here]

RESULTS

The analysis was conducted in two steps. First, to answer research question one we used a fixed-effect logistic regression to test the role of changes in the debt component of capital structure in predicting breaches of safety regulation. The model is based on the following formula:

$$\Pr(Breach_{ijt}) = F(Profit_{ijt-1\&t-2}, Sales\ growth_{ijt-1\&t-2}, Employee_{ijt-1\&t-2}, Wage_{ijt-1\&t-2}, Productivity_{ijt-1\&t-2}, Inverse\ Mill's\ Ratio_{ijt-1}, Change\ in\ total\ assets_{ijt-1\&t-2}, Change\ in\ debt_{ijt-1\&t-2}, debt_{ijt-1\&t-2}, Overtime_{jt-1\&t-2}, Accident\ Rate_{jt-1\&t-2}, Year_t, Indusrty_j, u)$$

where F(.) is the logistic function, i represents the i^{th} company in the industry j and t represents the year of observation.

In order to answer research question two, we conducted an event study with the safety breach as the event. The event study was conducted to determine the short and long-term financial impact of a breach.

Logistic regression analysis to answer research question one

Table 4 presents the results of the logistic regression. The control model includes all of the control variables, while change in debt was added to the full model. We used breaches that occurred from 2006 to 2012, so the regression covers that time period. Predictors were the two-year average for the years before the breach year. For example, for firms that had a breach in 2006, data from 2004 and 2005 were used for the predictors. When the data from 2004 (or 2005) were not available, we used only the data from 2005 (or 2004). For the firms that did not have a breach in 2006 the predictors were constructed in the same way. The highest variance-inflation factor (VIF) is 2.8, thus multi-collinearity does not appear to be a serious concern.

The full model in Table 4 indicates that change in debt is a significant positive predictor of breaches of safety regulation (coefficient = 0.895, $p < .05$) and improves the goodness-of-fit of the model (incremental log-likelihood = 2.57, $p < .01$). The R^2 of the model explains 18.59% of the occurrence of safety breaches. Thus, H1 is supported.

Figure 2 presents the post-hoc marginal effect analysis of change in debt on the likelihood of breach. Firms with a 20% increase in debt had a 0.4% higher likelihood of a breach (per year) compared to firms that had no change in debt. Given the average likelihood of having breach per year is 2.3% in our sample, the increased likelihood of 0.4% is substantial (17.39%).

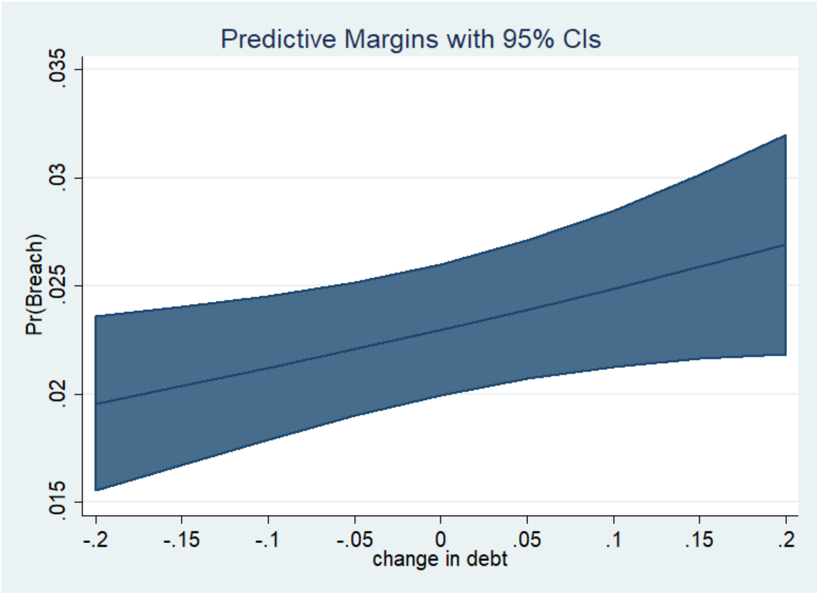

Figure 2: Marginal effect analysis of change in debt

In addition, the coefficient of debt level is also positive and significant (0.376, $p < 0.01$), indicating that firms are more likely to breach when they have a higher level of debt. In addition, firm size and profit level are significant predictors of a firm's propensity to breach safety regulation. The Inverse Mill's ratio is also significant, indicating its inclusion was necessary to correct for bias from missing data.

[Insert Table 4 about here]

Event study to answer research question two

To explore research question two on the financial implications of breaching safety regulations, we tested how the timing and magnitude of a safety breach affects a firm's short and long-term abnormal financial performance. This analysis adopts a long-horizon event study research design. (i.e., Barber & Lyon, 1997; Hendricks & Singhal, 2005)

The data on safety breaches is based on observations and not randomly distributed. Therefore, regressing financial performance on breaches could raise concerns over selection bias. For instance, firms with limited managerial skills could have both poor financial performance and more breaches. Selection bias raises an endogeneity concern due to unobservable confounding events (Ketokivi and McIntosh, 2017). Sample-control matching approaches are widely used to mitigate selection bias concerns (Ho, Lim, Reza & Xia, 2017).

We constructed matches between firms who had a breach (sample) and control firms without a breach to examine the differences between firm financial performance with and without treatment (a breach). The aim is to capture abnormal financial performance by comparing the performance changes for the sample firms before and after a breach, with the performance changes in the same period in the control firms. The goal of the matching process is to find a control firm for each sample firm, with similar observable characteristics before the breach (Caliendo & Kopeinig, 2008). When the observable characteristics have multiple dimensions, the propensity score matching approach is an appropriate solution (Caliendo & Kopeinig, 2008; Corbett, Montes-Sancho & Kirsch, 2005). We matched the firms with breaches to firms without breaches based on a propensity score approach similar to that used in Levine and Toffel (2010).

The propensity scores in these matches are based on all of the significant predictors of breaches identified in Table 4, which are profit, employment, Inverse Mill's ratio, deviation between target and actual leverage, debt level and change in debt. To answer both research questions all available observations with complete data were used. Therefore, some of the observations that were not available for research question one due to missing data were available for research question two. For instance, when an observation was missing data on wages per employee, it was dropped for the analysis for research question one. However, if this were the only missing indicator, the observation would have been available to answer research question two because wages per employee was not a significant predictor of breaches and hence not used to create propensity scores.

When a firm had multiple breaches in the same year, they were treated as a single event. And if a firm had breaches that overlapped event windows, we used the first breach (Corbett, Montes-Sancho, & Kirsch, 2005). For firms with multiple breaches that were 3 or more years apart, each breach was treated as an independent event and the propensity score was calculated separately for each event (Heckman, Ichimura, & Todd, 1998).

Following the above decision rules, the propensity score matching process started with 378 breaches that were committed by 257 firms. We were able to find matches for 298 breaches from 217 firms. Of these 217 firms, 137 had 1 breach, 79 had 2 breaches, and 1 had 3 breaches.

The coefficient of the significant predictors and the actual value of the indicators for each firm were used to calculate the predicted explanatory variables Pr ($Breach_{ij}$). The value of the predicted explanatory variable is the propensity score (a probability from 0 to 1) for each observation. Each firm with a breach was matched to a control firm that did not breach safety regulation in the period of study (from 2006 to 2012) that had the closest propensity score. This approach ensures that the sample and control firms are highly similar, allowing us to test the true impact of a safety breach on financial performance (Sosa, Mihm, & Browning, 2013). This approach performs well when possible sources of bias are controlled for (Smith & Todd, 2005; Levine & Toffel, 2010).

To control for biases, we followed the suggestions of Smith and Todd (2005) and Levine and Toffel (2010) as follows. First, financial data for all firms, regardless of whether they had a breach or not, came from a single database, FAME. Second, we use an extensive number of firm level covariates as well as industry in the matching process. Third, because all firms in the sample have operations in the United Kingdom they are all exposed to the same regulatory requirements and oversight. Fourth, we use nearest neighbour matching with a caliper restriction to match each firm with a breach to the most similar control firm without a breach.

To match each firm with a control based on propensity scores, each sample firm with a breach was matched with a nearest neighbour firm, in the same 2 digit SIC code, without a breach (Barber & Lyon, 1997). This control was the firm with the closest score based on the financial data in the whole event period; 1 year prior to the breach to 2 years post breach. Year 0, the event year, is the year that the firm was convicted of breaching safety regulation. The best match was determined based on the smallest absolute difference between the propensity score for the firm with the breach and the possible control firms.

It is possible that the nearest neighbour is still significantly different from the breach firm despite having the closest propensity score. This can occur in small industries with a limited number of potential matches. Therefore, we followed the procedure of previous studies and dropped pairs for which the propensity scores of the firms with and without a safety breach exceed a caliper size. Levine and Toffel (2010) note that a larger caliper size can increase the matching quality while compromising sample size. Thus, we set our caliper size to 0.1 (Rosenbaum & Rublin, 1985; Levine & Toffel, 2010). The results (Table G) indicate that all of the variables are suitably matched. There were no statistically significant differences between the groups on the matching criteria.

After the matching sample was created the event study was conducted. The event year is the year a firm has a safety breach. The predictions tested in the first research question used a lag between the indicators and the breach. This suggests that if a breach occurs in a given year the firm was likely to be in violation of safety regulations prior to the breach being discovered. This period prior to the breach being discovered is termed the base year and we define it as 1 year prior to the breach (year -1). We investigate abnormal changes in the performance of sample firms as compared to the control firms from 1 year prior to the breach to 2 years post breach in 1, 2 and 3 year increments. Abnormal performance was calculated using a different-in-different (DID) approach:

$$\textit{Abnormal Performance}_{(t+j)} = [\textit{Sample performance}_{(t+j)} - \textit{Sample performance}_{(t)}] - [\textit{Control performance}_{(t+j)} - \textit{Control performance}_{(t)}]$$

where t and j are the start and end year of the comparison respectively. To measure financial performance, we used ROA, profit margin and sales growth. The abnormal performance scores were not normally distributed, therefore the primary discussion of if abnormal performance is significantly different from zero is based on the Wilcoxon significance rank test (WSR), which deals with non-normality (Corbett, Montes-Sancho, & Kirsch, 2005) and is less affected by outliers than other tests (Lo, Pagell, Fan, Wiengarten, & Yeung, 2014).

Endogeneity concerns can arise from reversed causality and the confounding effects from unobservable variables (Ketokivi & McIntosh, 2017). Reversed causality in this case would suggest that safety breaches could result from poor financial performance. Confounding refers to possible selection bias where a firm with some characteristics such as poor managerial skills would be more likely to have poor safety and financial performance (Lo et al., 2014). Our event study research design with propensity score matching should mitigate these endogeneity concerns. First, abnormal financial performance is measured *after* the breach, thus, we rule out reversed causality. Second, the DID approach for calculating abnormal performance eliminates the confounding effects from time-stable factors such as firm structure, industry, public policy and regulations. Third, propensity score matching ensures that the sample and control firms are highly similar in terms of the independent variables included in Table 4 prior to the breach. This mitigates the concern that the captured impact of a safety breach on financial performance was confounded by these variables (Sosa, Mihm, & Browning, 2013).

Table 5 shows the WSR test results for the abnormal change in ROA, profit margin and sales growth. The results for all three models are similar and show that there is a negative and significant abnormal change (compared to zero) in the medians of ROA (-1.336%, $p < .01$), profit margin (-1.270%, $p < .05$) and sales growth (-3.621%, $p < .01$) in the year of the breach (from year -1 to year 0).

[Insert Table 5 about here]

In addition, the cumulative effects in 2 and 3 year increments are also significantly negative for ROA, profit margin and sales growth, indicating that over the long-term there are negative financial implications for putting workers in jeopardy. For example, in the period from year -1 to year 2, the median decrease of abnormal ROA is -0.566% ($p < .05$), profit margin is -0.459% ($p < .05$) and sales growth is -2.328% (p ($p <.1$). Thus, these results provide support for our third hypothesis. Firms with safety breaches have negative abnormal ROA, profit margin and sales growth in the years after the breach occurs. However, our results do not provide support for our second hypothesis. Contrary to the prediction of H2, firms with safety breaches do not have positive abnormal ROA, profit margin and sales growth in the year of the breach.

The event study shows that placing workers in jeopardy provides no short-term financial benefits and harms long-term financial performance. The firms with breaches saw reduced long-term performance when they were compared to firms that were highly similar based on propensity scores. However, this negative impact was not in evidence in the year of (year 0 to year 1) or the year after (year 1-2) the breach, suggesting that managers with short time horizons might not make a connection between their irresponsible behavior at the time of the breach and declining financial performance two years later.

ROBUSTNESS CHECKS

We conducted a number of robustness checks to increase confidence in our results. All of the results of the robustness checks are presented and discussed in the supplement. First, we explore if the choice of change in debt as the indicator of capital structure influenced the results by using change in financial leverage (debt/assets) as an alternative measure of capital structure to examine H1 (Table A). Change in financial leverage is also a significant predictor of breaches, providing additional support to the results for H1.

We also test for endogeneity using both the generalized momentum method (Table B) and an instrumented probit regression analysis (Table C). Based on the results we conclude that endogeneity is not a serious concern in the change in debt-breach relationship.

Additionally, it is important to note the percentage of firms with a breach (the dependent variable – coded as “1” when there is a breach) is only 2.3%. However, this is larger than the percentage in the selection models in the previous literature (e.g., 0.54% in Levine & Toffel, 2010). In addition, Cramer, Franses & Slagter (1999) report that parameter estimations are robust in samples involving large percentages of "0" observations. Finally, Bayus (2013) argue that it is more difficult to find statistical support with a large number of "0" observations. This suggests that the large number of firms without breaches made the hypotheses testing more conservative. To address concerns with the large percentage of "0" or no breach observations, we use a random-effect model (Table D) and rare-event logistic regression model (Table E) to re-estimate the regression model used to examine H1.The results are largely consistent to the fixed-effect model we used in the main analysis.

Next the robustness checks address whether or not changes in regulation altered the results. Amended HSE regulations increasing the fines for breaches came into effect in 2009. Increases in fines were intended to act as a deterrent, and our results suggest they did as the likelihood of a breach decreases after 2009 (Table F). However, the relationship between change in debt and breaches was unchanged by this amended regulation.

Finally, we examined if financial conditions prior to the event window might explain the negative financial impacts of a breach. The results (Table H) suggest that there was no systematic bias in operational performance prior to the breach.

DISCUSSION

The answer to the first research question; *when controlling for industry and firm level factors does the debt component of a manufacturing firm's capital structure predict the firm's likelihood to decide to breach safety regulations?* is yes. As firms decide to increase their debt, the propensity to breach also increases. This result is in line with previous research on capital structure (Chen & Steiner, 1999; Liu et al., 2014; O'Brien et al., 2014). The literature predicts the significant relationship between changes in debt and breaches is due to increased debt focusing managers mainly on short-term economic outcomes at the expense of other priorities; in this case protecting the workforce. This result is also broadly in line with the safety literature, which posits that as managers become more focused on the short-term they will ultimately make decisions that place workers in increased jeopardy.

Research question two; *what are the short and long term financial implications of breaching safety regulations,* examines the short and long-term financial impacts of a breach. This research question was addressed via an event study, providing a longitudinal test, which shows that putting workers in jeopardy harms the firm financially over the long-term (year -1 to year +2). The insignificant results in the year of the breach (year 0 to year +1) and the year after the breach (year +1 to year +2) suggest that the short-term implications of a breach are not as visible to managers. The primary prediction of this research is that the shorter time horizons associated with increased levels of debt will be related to breaches. Hence, it is unlikely that managers with short time horizons will associate behavior in year -1 with decreased financial performance over the long-term, especially if their financial performance in the year of the breach is as expected. In other words, these firms may continue to make decisions that put workers in jeopardy because they do not connect this behavior to their declining financial performance, creating a vicious cycle where financial performance continues to decrease relative to their peers, while workers continue to be put in jeopardy.

This result is what the safety literature would predict. As managers increase their debt their time horizons decrease leading them to at best overlook safety and at worst actively work around regulation to increase sales and production. By adopting such an approach, they are putting operational workers in jeopardy. However, putting workers in jeopardy harms the firm financially over the long-term. This finding is in line with recent work in operations management, which determined that increased worker safety is linked to increased operational effectiveness (e.g., Lo et al., 2014, Pagell, Klassen, Johnston, Shevchenko, & Sharma, 2015).

Chen and Steiner (1999) note that increased financial leverage has long been linked to increased risk. A highly leveraged capital structure is a risky capital structure; as firms take on more debt, they not only shorten managerial decision-making time horizons, they also increase the risk of negative firm outcomes such as default or bankruptcy (e.g., Simerly & Li, 1999). One of the most basic propositions of capitalism and the business literature is that risk-taking leads to increased financial returns. Yet the empirical evidence linking risk to returns is often referred to as Bowman's Paradox because many studies find that risk is not related to or even reduces returns (Bowman, 1980; Nickel & Rodriquez, 2002; Henkel, 2009). Our data set shows evidence of this in that debt and change in debt are negatively correlated with profit margins and ROA in the sample. Additionally, many of the explanations for the risk-paradox revolve around firm performance, with poor performers being those most likely to engage in risky behaviors (Nickel & Rodriquez, 2002). Our results show some evidence of this possibility in that as sales growth declines the propensity to breach safety regulation increases, while increasing debt increase the propensity to breach.

Combining these observations with the event study results suggests that managers of firms in duress will be most likely to place workers in jeopardy and that these managers might not link these behaviors to their negative abnormal financial performance. The lack of long-term visibility could provide incentives to continue placing workers in jeopardy, even when in the long-term it is not in managements' or the workers' interest to do so. Therefore, one reason that worker safety remains a persistent problem may be because the seeming benefits of placing workers in jeopardy are immediate while the benefits of managing a production system that values human capital and is safe are longer term.

Our results show that for operational workers there is no risk paradox; increased debt harms the workforce and their employer. Increased debt might deal with agency problems by focusing managers on the short-term, but the benefits from doing so are offset by reduced investments in human capital (Liu et al., 2014), a reduction in innovation (Kayo & Kimera, 2011), and based on this research an increased propensity to breach safety regulation, all of which harm long-term competitiveness. The complicated relationship between capital structure, short and long-term managerial decision-making and operational outcomes, including safety, will require future research to determine how to meet the needs of multiple stakeholders.

Contribution

The research starts with the knowledge that firms who have breached safety regulations have made decisions that harmed their operational workers. To prevent these actions in the future, workers and related stakeholders need to better understand which firms might be in breach. In addition, all stakeholders need to understand the financial implications of a breach to determine how to respond to this behavior.

The findings should influence the behavior of managers as well as the numerous other stakeholders concerned with the safety of the workforce. We explore the financial implications of breaches because of the continued belief (which is promulgated by many safety researchers) that firms cannot be safe and operationally effective, or that the costs of complying with regulation is a constraint managers need to minimize (e.g. Murray, 2015). Our results, which are in line with other recent research in safe operations (e.g. Lo et al., 2014), show this need not be the case. Yet, the finding that increases debt also lead to more breaches, suggests that many managers still believe that safety regulation is a constraint or an unnecessary cost, which is also in line with the recent research showing that while firms can be safe and operationally effective, many are not (e.g. Pagell et al., 2015).

For managers, even those trying to minimize costs, the implications are clear, skimping on safety is a false economy. Similarly, communities where firms with poor safety records operate need not accept this as a cost of having people employed. Finally, for regulators and other external stakeholders such as unions concerned with worker well-being the results have multiple implications. First, regulators have traditionally focused their limited enforcement budgets on inherently dangerous industries or workplaces. The results suggest that they might also be well served by looking at a firm's capital structure. Capital structure is determined by a set of managerial decisions that seemingly have little to do with safety, yet the results indicate that firms that are increasing their debt will be significantly more likely to put workers in jeopardy. Rather than assuming all firms in an industry are likely to be (un)safe regulators could better target enforcement by focusing on individual firm attributes such as changes in debt.

Second, the real costs of poor safety need to be better communicated by regulators, unions and the like to overcome the continuing perception that safety is costly. Third, there needs to be more regulatory enforcement, at least in the short-term. The evidence is clear that inspections make workers safer (Levine, Toffel, & Johnson, 2012). Yet in most of the developed world accidents are still very common and inspections are rare. For instance, OSHA data indicates that only about 100,000 of the approximately 7 million workplaces in the USA are inspected in any given year: a 1.4% probability of being inspected (OSHA 2017). A manager who believed that safety was a cost and safety regulation was a constraint on profitability could rightfully look at those figures and assume that there was no need to comply. Our results suggest that this attitude will ultimately lead to more harm to workers and their employers.

CONCLUSIONS

The role of capital structure in managerial decision-making has traditionally been explored from the firm's perspective. In this research, we explore capital structure from a perspective that examines how these decisions impact workers and the firm.

The research contributes to the how and why of creating safer operations by reinforcing that a short-term focus and protecting the operational workforce are not compatible. Decisions on capital structure are seemingly unrelated to worker safety. Yet this research suggests that one of the reasons why poor safety persists, even in highly regulated settings, is that as debt increases managers are more likely to ignore their responsibility to the workforce when under pressure to improve short-term profitability. In addition, while the research is clear in showing that placing workers in jeopardy harms the firm over the long-term, it also suggests that managers with short-term time horizons will be unlikely to make these connections. Therefore, other stakeholders such as regulators, unions and academics need to do a better job disseminating the implications of managers not meeting their responsibilities to the workforce.

The sample used to predict the propensity of a breach is large and covers a majority of the overall population of UK based manufacturing firms. The event study methodology created robust matches and provides longitudinal rather than cross sectional results. However, like all studies this research has limitations that should be addressed by future research. The data comes from a single, relatively small country with high costs of labor, hence future research needs to explore the role of placing workers in jeopardy in other contexts.

Future research could also explore alternative measures of placing workers in jeopardy. Breaches are rare and being prosecuted indicates that a firm that has failed its workforce and that the HSE does not see other more common means as being likely to change managerial behavior. Our sample of firms with breaches is, in effect, a sample of the least responsible (in terms of safety) manufacturing firms in the UK. An obvious extension would be to look at accident rates. Accident rates would have the benefit of capturing harm that breaches do not always indicate, but at the cost of including an element of individual behavior that breaches do not have. The other proxies used in this research, for instance overtime which was measured at the industry and not firm level, due to limitations with the FAME database, are other areas that future research should explore.

More broadly, the use of secondary data allowed for causal / longitudinal tests of the relationship between changes in debt and breaches. However, this research, like all research using secondary data to explore managerial decisions, is making untestable assumptions about the timing and motives of specific decisions; in this case when the decision to breach was made. Breaches provide insight into a decision that managers would not likely disclose willingly. The trade-off is that while we do know when the decision to increase debt was made we don't know when the decision to ignore regulation was made, only when it was discovered. Future research, perhaps using operational workers as the respondents, should directly explore the actual decision to breach.

Future research should also clarify the links between capital structure and operational decisions. We start with the assumption that as debt increase time horizons get shorter which has implications for numerous decisions that operations managers make such as the timing of maintenance or the likelihood of adopting third party certifications.

However, with the exception of productivity and overtime, operational decisions are not captured in the analysis. Instead, we assume that other operational decisions are driven by the strategic choice of capital structure. Future research should explore these operational decisions to understand how operations managers can respond to the pressure of increased debt without putting the workforce in jeopardy. And this future research would be well served by taking a broader perspective on how operational and financial decisions are intertwined, because with a few recent exceptions (see for instance Steinker et al., 2016) linkages between financial and operational decisions have been mainly unexplored. Their results and ours suggest this is a gap that needs to be addressed.

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Table 1: Probit analysis for missing data; two-tailed test

DV: Have missing data at year t-1 (1=missing; 0=no missing), data used from 2005 to 2014			
IVs data at t-2 （used from 2004 to 2013)	Coef.	Standard error	p
Intercept	65.7771	8.926	0.000
Firm sales	-0.148	0.012	0.000
Employee number (Log)	-0.048	0.014	0.000
Financial leverage	0.0007	0.000	0.127
ROA	-0.0004	0.001	0.499
Breach history	0.2116	0.000	0.000
Industry missing data percentage	-0.0021	0.002	0.000
Industry breaches	-0.0305	0.036	0.000
Industry	Included		
Year of the DV	Included		
Log-likelihood	-9013.14		0.000
R-squared	6.81%		

Table 2: Descriptive Statistics and Correlations

	Variables	**Mean**	**S.D.**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
1	Breach	0.023	0.150														
2	Industry median overtime	13.375	13.920	-.056													
3	Industry accident rate	132.784	97.797	.028	.220												
4	Industry average leverage	0.389	4.053	-.007	-.009	-.028											
5	Wages per employee (Log)	10.400	0.446	-.005	.053	-.016	.003										
6	Productivity (Log)	11.672	0.005	.001	.006	.008	.004	.011									
7	Inverse Mill's ratio (Missing data)	1.964	0.303	.005	-.113	.035	.004	.116	.038								
8	Sales growth	3.675	184.106	-.003	-.011	-.019	.003	-.009	-.009	-.039							
9	Profit margin	0.039	0.125	.004	.032	.007	.037	.031	.110	.021	-.030						
10	Employee number (Log)	4.912	1.270	.117	-.056	.026	-.013	.106	-.022	.631	-.004	.005					
11	Change in assets	0.104	1.460	-.006	-.030	-.014	.006	.010	.000	.018	.012	.027	-.002				
12	Change in debt	0.012	0.176	.007	-.130	-.018	.013	-.002	-.013	.080	.020	-.006	.022	.159			
13	Debt level (log)	9.001	1.684	.110	-.011	.008	-.024	.159	.016	.593	.005	-.028	.768	-.016	-.075		
14	Deviation between target and actual leverage level	0.512	2.790	-.004	.012	-.001	.062	-.021	-.005	-.054	.000	-.027	-.071	.008	.009	-.096	
15	ROA	0.066	2.498	.003	-.002	.002	.000	-.004	.217	-.008	-.297	.184	-.017	.000	-.013	-.019	-.003

Table 3: Variable Descriptions

Variables	Description	Initial data source	Reference
Breach	"1" was coded for observations having breach, otherwise "0"	HSE	Fan & Zhou, 2018
Industry median overtime	Median overtime hours of the industry	HSE	White & Beswick, 2003
Industry accident rate	Number of accidents per 100,000 employees of the industry	HSE	HSE, 2018
Industry average leverage	The average debt/assets ratio of the industry	FAME	Flannery & Rangan, 2006
Wages per employee (Log)	Wage expenses per employee	FAME	Pagell et al., 2014
Productivity (Log)	Operating income per employee	FAME	Fan, Lo, Yeung & Cheng, 2018
Inverse Mill's ratio (Missing data)	The Inverse Mill's ratio derived from the probit analysis (Table 1)	FAME	Allison, 2002
Sales growth	Yearly percentage change of sales	FAME	Lo et al., 2014
Profit margin	Operating income divided by annual sales	FAME	Lo et al., 2014
Employee number (Log)	Number of employee	FAME	Levine & Toffel, 2011
Change in assets	Yearly percentage change of total assets	FAME	Sweeney, 1993
Change in debt	Yearly percentage change of total debt	FAME	Standard and Poor's, 2003
Debt level (log)	Total debt	FAME	Standard and Poor's, 2003
Deviation between target and actual leverage level	Actual debt/assets ratio minus target debt assets ratio	FAME	Flannery & Rangan, 2006

Table 4: Logistic analysis of breach; two-tailed test						
Dependent variable: Breach of safety regulation ("1" = yes; "0" = no); n=15324						
	Control Model			Full Model		
	Coef.	Robust S.E.	*p*	Coef.	Robust S.E.	*p*
Industry median overtime	0.052	0.057	0.358	0.051	0.057	0.372
Industry accident rate	0.001	0.001	0.383	0.001	0.001	0.426
Industry average leverage	0.010	0.012	0.373	0.011	0.012	0.357
Wages per employee (Log)	-0.112	0.132	0.393	-0.112	0.132	0.399
Productivity	7.849	19.931	0.694	7.359	19.729	0.709
Inverse Mill's ratio (Missing data)	-4.794	0.568	0.000	-4.842	0.572	0.000
Sales growth	-0.057	0.039	0.143	-0.058	0.039	0.140
Profit margin	0.878	0.383	0.022	0.919	0.377	0.015
Employee number	0.875	0.099	0.000	0.861	0.099	0.000
Change in assets	-0.090	0.126	0.475	-0.284	0.217	0.191
Debt level	0.357	0.060	0.000	0.376	0.060	0.000
Deviation between target and actual leverage level	0.020	0.010	0.049	0.020	0.010	0.049
Change in debt				0.895	0.424	0.035
Pseudo R^2	18.44%			18.59%		
Incremental Log-likelihood				2.5679		0.002

Table 5: Event study of safety breach on firm performance

		Wilcoxon sign rank tests		
Abnormal Performance	N	Median	Wilcoxon-Z	*p*
ROA				
year -1 to year 0	298	-1.336%	-2.825	0.005
year 0 to year 1	282	-0.229%	-0.489	0.625
year 1 to year 2	274	0.357%	0.582	0.560
year -1 to year 1	282	-0.777%	-2.327	0.020
year -1 to year 2	274	-0.566%	-2.204	0.028
Profit Margin				
year -1 to year 0	297	-1.270%	-2.236	0.025
year 0 to year 1	282	0.088%	0.065	0.948
year 1 to year 2	273	0.666%	0.583	0.560
year -1 to year 1	282	-0.324%	-1.845	0.065
year -1 to year 2	273	-0.459%	-2.018	0.044
Sales Growth				
year -1 to year 0	298	-3.621%	-3.004	0.003
year 0 to year 1	283	-1.945%	-0.877	0.380
year 1 to year 2	273	2.370%	1.756	0.079
year -1 to year 1	283	-2.500%	-2.770	0.006
year -1 to year 2	273	-2.328%	-1.750	0.080

Note: two-tailed tests

Supplementary Material

Robustness check using an alternative measure of capital structure

Financial leverage (debt/assets ratio) is another widely adopted measurement for capital structure and risk level (Cole, Daniel & Naveen, 2006). Therefore, we used change in financial leverage as an alternative for change in debt. We also replaced the control variable of debt level with financial leverage level. The results in Table A indicate that the coefficient of change in financial leverage is positively significant (coefficient=0.005, $p < .05$). These results offer additional support to H1.

Table A: Logistic analysis of breach

Dependent variable: Breach of safety regulation ("1" = yes; "0" = no)			
	Full Model		
	Coef.	Robust S.E.	*p*
Industry median overtime	0.068	0.057	0.234
Industry accident rate	0.002	0.001	0.201
Industry average leverage	0.004	0.010	0.716
Wages per employee (Log)	0.017	0.127	0.895
Productivity (Log)	35.776	20.559	0.082
Inverse Mill's ratio (Missing data)	-5.151	0.404	0.000
Sales growth	-0.047	0.033	0.152
Profit margin	0.653	0.432	0.131
Employee number (Log)	1.342	0.079	0.000
Change in assets	-0.147	0.149	0.322
Financial leverage level	0.028	0.025	0.263
Deviation between target and actual leverage level	0.001	0.018	0.937
Change in financial leverage	0.005	0.002	0.036
Pseudo R^2	18.44%		

Note: Two-tailed tests; n=15324

Robustness checks for endogeneity

Endogeneity may affect the results for H1. Endogeneity concerns can arise from reversed causality between the independent and dependent variables, which should not be a concern in this study because the independent variables have a time-lag to the dependent variables. However, *endogeneity* could also be due to a confounding effect from unobserved variables. The significant relationship between changes in debt and breaches could be due to unobserved variable(s). For example, a firm with a weak cash flow may increase its debt level while also cutting corners on safety practices. Statistically, this concern arises because of the potential correlation between the endogenous variable (i.e., change in debt) and error term (Semadeni, Withers, & Trevis Certo, 2014).

The instrumental variable technique is widely used to cope with endogeneity resulting from the confounding effect of unobserved variable(s) (Wooldridge, 2015). The instrumental variable technique works by splitting out the part of the endogenous variable that correlates with the error term. A satisfactory instrumental variable should correlate with the endogenous variable and be an exogenous variable; not correlated with the error term (Wooldridge, 2015).

We used two instrumental variable techniques to address endogeneity; difference Generalized Method of Momentum (GMM) and instrumented probit regression. We used STATA 14.0 to conduct the robustness tests.

Difference GMM is suitable for addressing endogeneity in panel data analysis, thus it fits our data structure (e.g., Lam, Yeung, & Cheng, 2016; Wiengarten, Fan, Lo, & Pagell, 2017). The difference GMM estimator first conducts a difference transformation[1] to the variables. This transformation removes the confounding effects from the time-invariant fixed effects. However, 2,919 observations are lost due to this transformation. The year and industry dummy variables were also omitted from the model because they are fixed effects. Then, the GMM analysis used the lagged values of the endogenous variables (the lagged values of change in debt and debt level) as instrumental variables (e.g., Lam et al., 2016; Wiengarten et al., 2017). The Arellano–Bond and Sargan tests were used to examine the quality of instrumental variables (Sargan, 1958; Arellano & Bond, 1991; Roodman, 2009).

The GMM analysis results are shown in Table B. The coefficient of change in debt remains significant ($p<.05$). The Arellano-Bond test shows that the first order autocorrelation (AR1) is significant while the second order correlation (AR2) and Sargan test are not significant ($p > .1$). Thus, the instrumental variables are exogenous and not correlating with the corresponding error terms (Lam et al., 2016; Wiengarten et al., 2017). The results of the GMM analysis mitigate endogeneity concerns.

Table B: GMM analysis of breach

Dependent variable: Breach of safety regulation ("1" = yes; "0" = no)			
	Coef.	Standard error	*p*
Industry median overtime	-0.0001	0.0004	0.883
Industry accident rate	0.0000	0.0001	0.963
Industry average leverage	-0.0043	0.0205	0.834
Wages per employee (Log)	-0.1334	0.1328	0.315
Productivity (Log)	12.6020	23.1289	0.586
Inverse Mill's ratio (Missing data)	-0.0018	0.0372	0.962
Sales growth	-0.0002	0.0003	0.565
Profit margin	-0.2536	0.4950	0.608
Employee number (Log)	0.0991	0.0499	0.047
Change in assets	-0.0621	0.0316	0.049
Debt level (Log)	0.0017	0.0096	0.862
Deviation between target and actual leverage level	0.0035	0.0125	0.779
Change in debt	0.1099	0.0464	0.018
Chi^2	33.52		0.002
AR(1)			0.006
AR(2)			0.264
Sargan test			0.627

Note: two-tailed test n=12405;

[1] For example, firm size$_{t-1\&t-2}$ will be transformed to delta firm size = firm size$_{(t-1\&t-2)}$ – firm size$_{(t-2\&t-3)}$

An instrumented probit regression was also conducted as an additional robust check for endogeneity. The probit regression model is suitable for testing models with a binary dependent variable (Cappellari & Jenkins, 2003). We followed previous econometric literature to use the industry average of the endogenous variable (industry change in debt) as the instrumental variable (Lin, Lin, Song, & Li, 2011). Industry change in debt is a satisfactory instrumental variable because it correlates with the endogenous variable (change in debt for the firm) and it is an exogenous (environmental) variable. Table C shows the instrumented probit regression results. The coefficient of change in debt is significant ($p <.01$). And the significance of Wald test of exogeneity ($p < .05$) suggests that the instrumental variable is valid.

Table C: Instrumented probit analysis of breach

Dependent variable: Breach of safety regulation (“1” = yes; “0” = no)			
	Coef.	Standard error	*p*
Industry median overtime	0.011	0.018	0.539
Industry accident rate	0.000	0.000	0.964
Industry average leverage	0.003	0.004	0.410
Wages per employee (Log)	-0.060	0.045	0.185
Productivity (Log)	1.901	7.551	0.801
Inverse Mill's ratio (Missing data)	-1.908	0.318	0.000
Sales growth	-0.020	0.011	0.070
Profit margin	0.434	0.155	0.005
Employee number (Log)	0.227	0.089	0.011
Change in assets	-0.144	0.086	0.095
Debt level (Log)	0.228	0.021	0.000
Deviation between target and actual leverage level	0.006	0.004	0.100
Change in debt	4.081	1.122	0.000
Chi^2	916.76		0.000
Wald test of exogeneity	5.16		0.023

Note: two-tailed test n=15324;

Robustness checks for alternative estimation models

Our primary analysis for H1 used fixed-effect logistic regression, which controls for the time-invariant factors. We also used a random effect model to estimate the specified model for testing H1. Table D presents the random-effect logistic regression model. The coefficient of change in debt remains significantly positive (coefficient = 0.846, $p < 0.1$).

Table D: Random effect logistic analysis of breach			
Dependent variable: Breach of safety regulation (“1” = yes; “0” = no)			
	Full Model		
	Coef.	Robust S.E.	*p*
Industry median overtime	-0.035	0.005	0.000
Industry accident rate	0.002	0.001	0.004
Industry average leverage	0.009	0.007	0.188

Wages per employee (Log)	-0.168	0.183	0.358
Productivity (Log)	8.048	23.919	0.737
Inverse Mill's ratio (Missing data)	-2.118	0.259	0.000
Sales Growth	-0.026	0.024	0.282
Profit margin	0.912	0.538	0.090
Employee number (Log)	0.676	0.101	0.000
Change in assets	-0.235	0.241	0.329
Debt level (Log)	0.320	0.072	0.000
Deviation between target and actual leverage level	0.027	0.017	0.110
Change in debt	0.846	0.480	0.078
Chi^2	254.800		0.000
Note: two-tailed tests; n=15324			

In addition, it can be argued that the relatively low proportion of breaches in the dependent variable may have biased the results. We conducted a rare-event logistic regression to examine this possibility. Table E shows that the coefficient of change in debt remains significantly positive (coefficient = 0.859, p <.05). Therefore, the results for testing H1 are robust across different estimation methods.

Table E: Rare event logistic analysis of breach

Dependent variable: Breach of safety regulation ("1" = yes; "0" = no)			
	Full Model		
	Coef.	S.E.	*p*
Industry median overtime	0.088	0.053	0.100
Industry accident rate	0.003	0.001	0.018
Industry average leverage	0.008	0.012	0.530
Wages per employee (Log)	-0.119	0.133	0.370
Productivity (Log)	74.858	19.975	0.000
Inverse Mill's ratio (Missing data)	-4.759	0.570	0.000
Sales growth	-0.046	0.039	0.249
Profit margin	0.697	0.378	0.065
Employee number (Log)	0.838	0.099	0.000
Change in assets	-0.251	0.212	0.236
Debt level (Log)	0.377	0.060	0.000
Deviation between target and actual leverage level	0.013	0.011	0.213
Change in debt	0.859	0.420	0.041
Note: two-tailed tests; n=15324			

Robustness check for changes in regulation

We used year dummy variables to control for the time-invariant fixed effect in Table 3. This controls for year on year changes in economic conditions or fluctuations in investigations, but does not directly cope with the one regulatory change during our analysis window. In January 2009, new regulation came into force raising the maximum fines for breaches (HSE, 2017). The increased penalties could have a larger deterrent effect. Thus, we conducted an additional analysis by replacing the year dummy variables in the logistic regression with a binary variable of year after 2009. The variable was coded as "1" if *t* is before 2009, and "0" if *t* is 2009 or after. Table F shows that the coefficient of change in debt remains significantly positive (coefficient = 0.706, p<.1). In addition, the coefficient of year after 2009 is significantly negative (p<.01), indicating the deterrent effects of the new regulation.

Table F: Logistic regression analysis of breach

Dependent variable: Breach of safety regulation ("1" = yes; "0" = no)			
	Coef.	S.E.	*p*
Industry median overtime	-0.041	0.006	0.000
Industry accident rate	0.000	0.001	0.721
Industry average leverage	0.009	0.010	0.394
Wages per employee (Log)	-0.156	0.138	0.261
Productivity (Log)	-4.578	7.759	0.555
Inverse Mill's ratio (Missing data)	-3.273	0.380	0.000
Sales growth	-0.046	0.031	0.138
Profit margin	0.803	0.358	0.025
Employee number (Log)	0.696	0.087	0.000
Change in assets	-0.253	0.205	0.217
Debt level (log)	0.309	0.057	0.000
Deviation between target and actual leverage level	0.021	0.011	0.067
Year after 2009	-0.813	0.194	0.000
Change in debt	0.706	0.412	0.087
Chi2	456.460		0.000

Note: two-tailed test n=15324;

Robustness check for event study

The primary goal of propensity score matching is to match each sample firm to the most similar control firm on the significant indicators. Table G indicates that there were no statistically significant differences between the groups on the matching criteria. However, it is possible that the negative abnormal performance during the event period (year -1 to year 2) was driven by changes in performance in year -2 to year -1. Thus, we conducted WSR tests for all the indicators of abnormal performance from year -2 to year -1 (Lo, Pagell, Fan, Wiengarten, & Yeung, 2014). Table H shows that there were no significant changes in the performance indicators over the period. The causal relationship does not seem to be due to a systematic bias in operational performance prior to the breach.

Table G: Matching Quality (after caliper cut): Difference between sample and control firms prior to breach

Variables	*p*-value of pair t-tests
Sales Growth	0.283

Employee number (Log)	0.209
Profit margin	0.451
Wages per employee (Log)	0.593
Productivity (Log)	0.604
Change in ROA	0.413
Debt level (Log)	0.273
Deviation between target and actual leverage level	0.739
Change in debt	0.222

Two-tailed tests

Table H: Tests for performance change prior to breach

		Wilcoxon sign rank tests		
Abnormal Performance	n	Median	Wilcoxon-Z	*p*
ROA				
year -3 to year -2	292	1.493%	1.542	0.123
year -2 to year -1	301	1.178%	1.362	0.173
Profit Margin				
year -3 to year -2	292	0.953%	1.461	0.144
year -2 to year -1	301	0.290%	0.769	0.442
Sales Growth				
year -3 to year -2	292	-0.940%	-0.233	
year -2 to year -1	301	-1.099%	-0.133	0.894

Note: two-tailed tests

Supplementary analysis

Table I: paired t-test and Sign test of abnormal performance

Abnormal performance	n	Pair t-tests Mean	t	*p*	Sign tests %	Sign-Z	*p*
ROA							
year -1 to year 0	298	-2.678%	-3.651	0.000	42.62%	-2.491	0.013
year 0 to year 1	282	-0.884%	-0.962	0.337	48.94%	-0.298	0.766
year 1 to year 2	274	0.521%	0.462	0.644	52.90%	0.903	0.367
year -1 to year 1	282	-3.338%	-3.364	0.001	46.81%	-1.012	0.311
year -1 to year 2	274	-2.590%	-2.251	0.025	47.45%	-0.785	0.432
Profit Margin							
year -1 to year 0	297	-1.028%	-1.643	0.101	44.78%	-1.741	0.082
year 0 to year 1	282	-1.109%	-1.394	0.164	50.71%	0.179	0.858
year 1 to year 2	273	4.733%	0.668	0.505	54.18%	1.327	0.185
year -1 to year 1	282	-2.169%	-3.111	0.002	47.87%	-0.655	0.512
year -1 to year 2	273	-4.060%	-1.985	0.048	48.35%	-0.484	0.628
Sales Growth							
year -1 to year 0	298	-6.433%	-3.358	0.001	43.62%	-2.143	0.032
year 0 to year 1	283	-2.587%	-1.099	0.273	47.35%	-0.832	0.405
year 1 to year 2	273	2.349%	1.322	0.187	58.18%	2.653	0.008
year -1 to year 1	283	-4.412%	-2.768	0.006	41.55%	-2.789	0.005
year -1 to year 2	273	-2.787%	-1.812	0.071	46.67%	-1.066	0.286

Note: two-tailed tests.

Table J: Regression for estimating target financial leverage

Dependent variable: Financial leverage*ijt*			
	Coef.	S.E.	*p*
Financial leverage$_{ijt-1}$	0.794	0.080	0.000
EBIT ratio$_{ijt-1}$	0.266	0.203	0.190
Total assets$_{ijt-1}$	-0.219	0.215	0.309
Industry leverage$_{jt-1}$	-0.002	0.017	0.906
Industry Leverage Change$_{jt-1}$	1.044	0.014	0.000
Intercept	1.921	2.086	0.357
R2	17.40%		

Note: two-tailed test

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